Machine learning and quantum computing applied to particle physics

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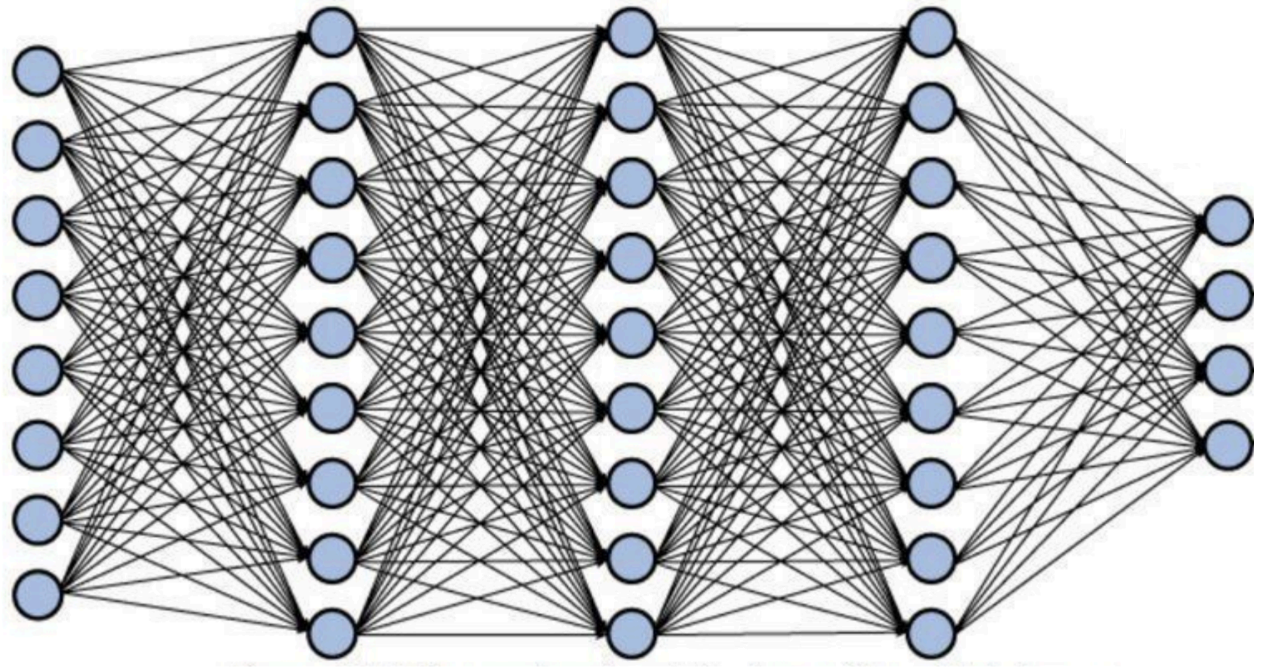
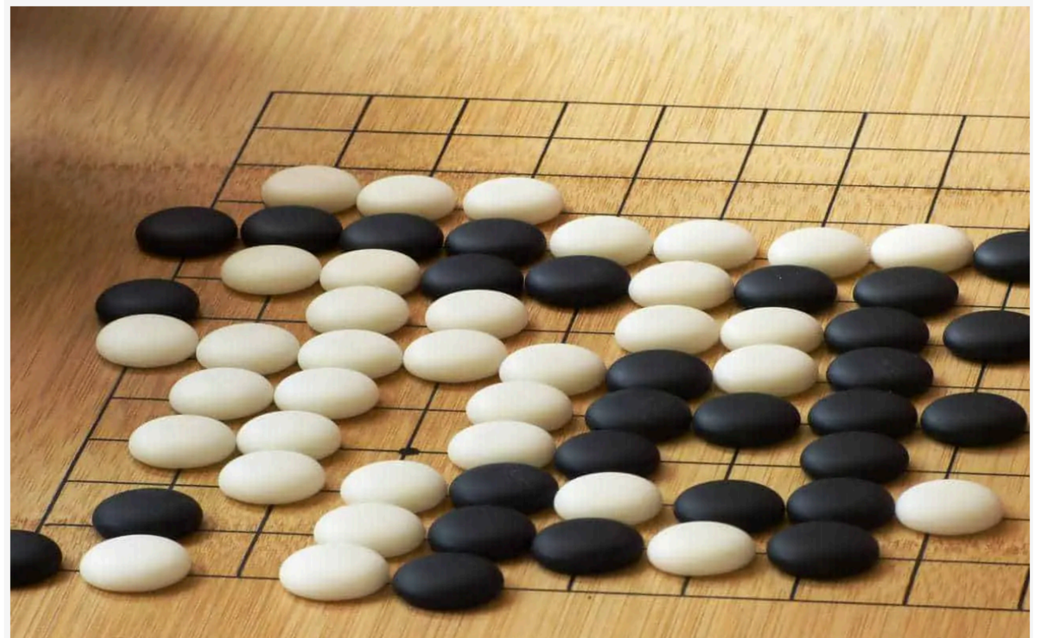
A Virtual Tribute to Quark Confinement and the Hadron Spectrum 2021, 08/05/21

Machine learning applications

- Machine learning (ML) has revolutionized many industries
- Efficient training of neural networks



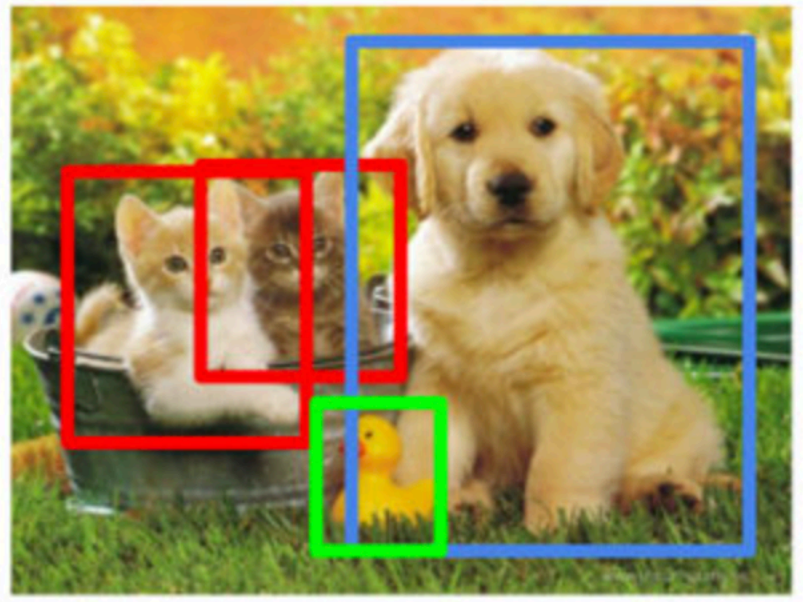
Adobe stock



Go

Boston dynamics

CAT



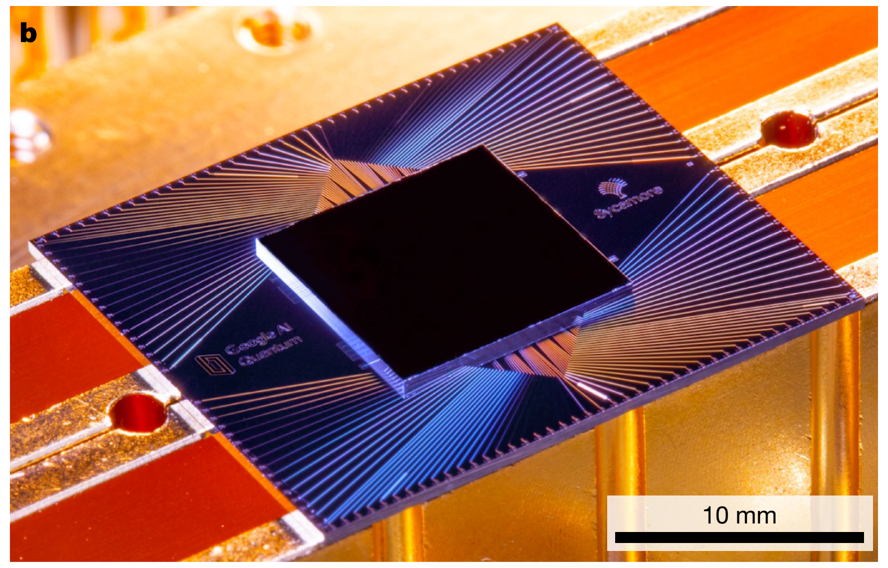
CAT, DOG, DUCK

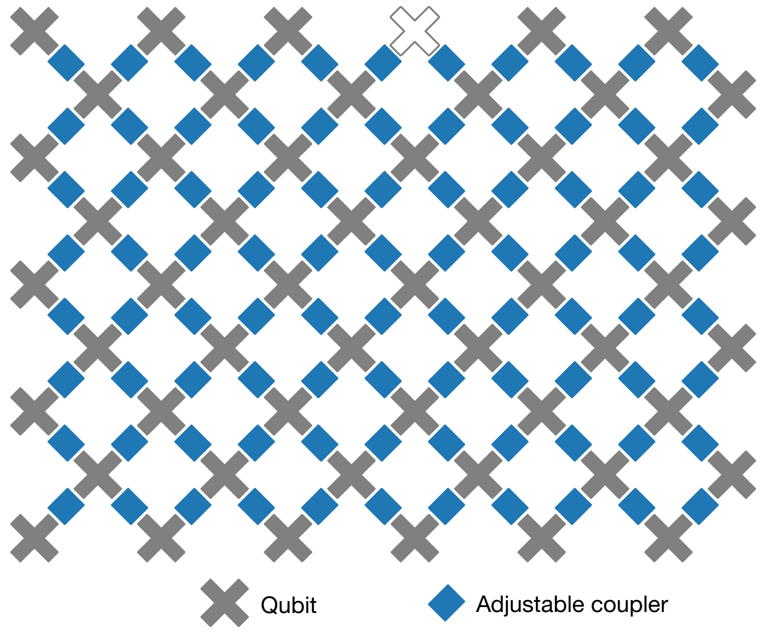
Recent progress in quantum computing

- Quantum supremacy experiments
- Noisy Intermediate Scale Quantum (NISQ) era
- Digital & analog quantum computing via cloud services

Article

Quantum supremacy using a programmable superconducting processor





Google

Random circuit sampling *Martinis et al. `19*

REPORT

Quantum computational advantage using photons

Han-Sen Zhong[1,2,*], Hui Wang[1,2,*], Yu-Hao Deng[1,2,*], Ming-Cheng Chen[1,2,*], Li-Chao Peng[1,2], Yi-Han Luo[1,...]
+ See all authors and affiliations

Science 18 Dec 2020:
Vol. 370, Issue 6523, pp. 1460-1463
DOI: 10.1126/science.abe8770

Boson sampling *Zhong et al. `20*


ATLAS
EXPERIMENT
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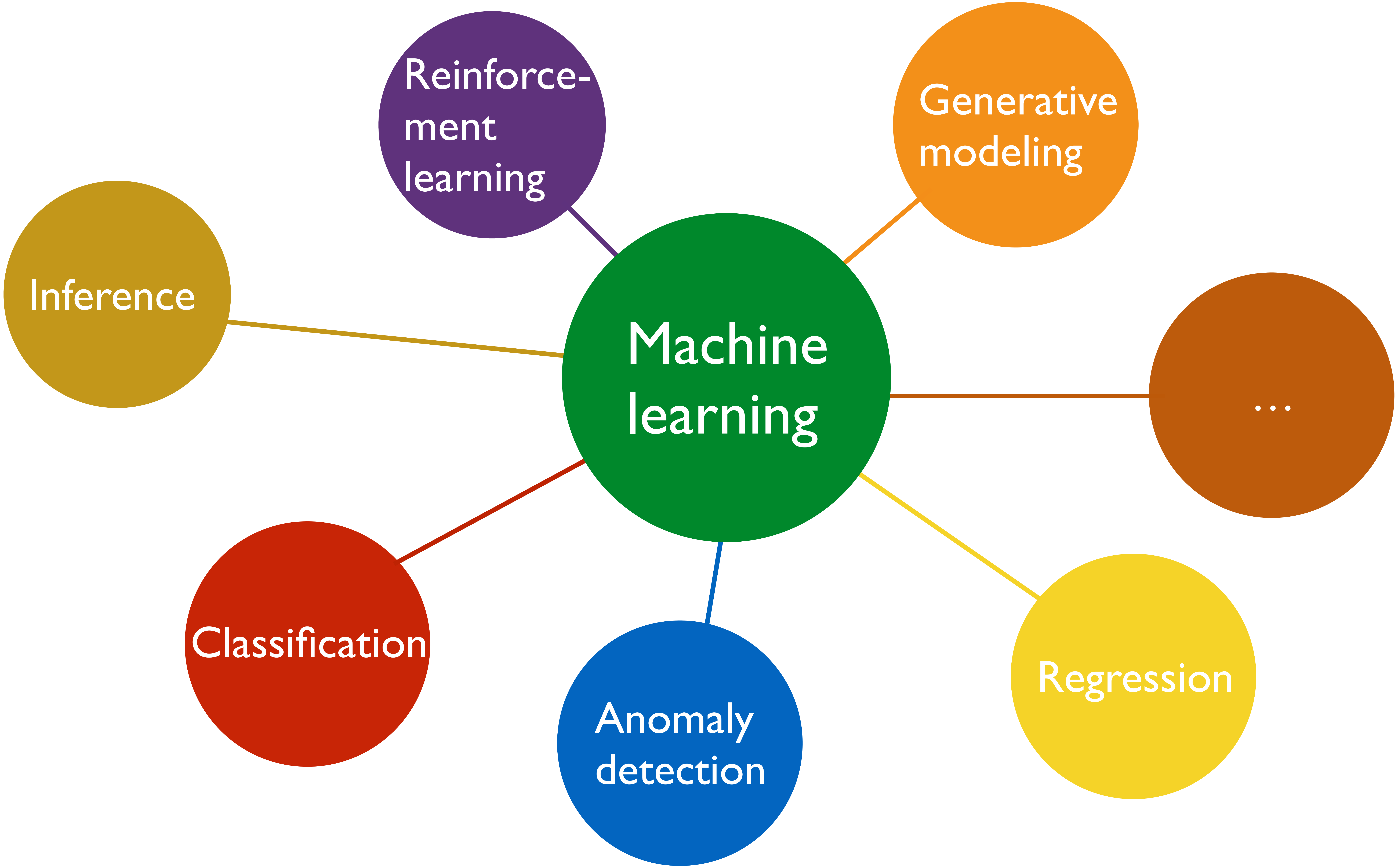
Outline

Machine learning

Quantum computing

Conclusions & Outlook

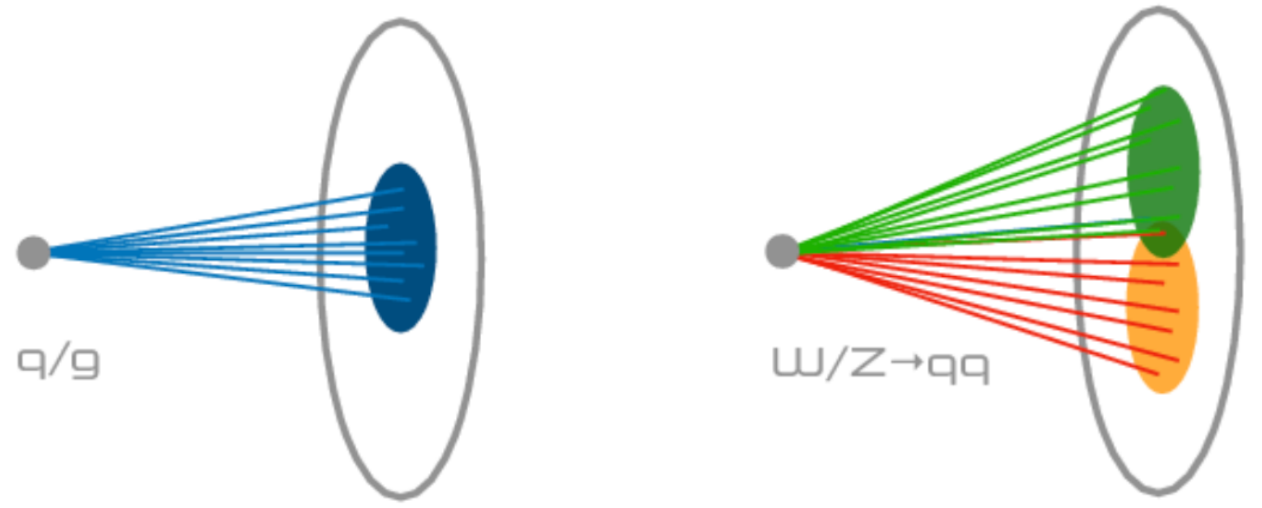
Selection of topics

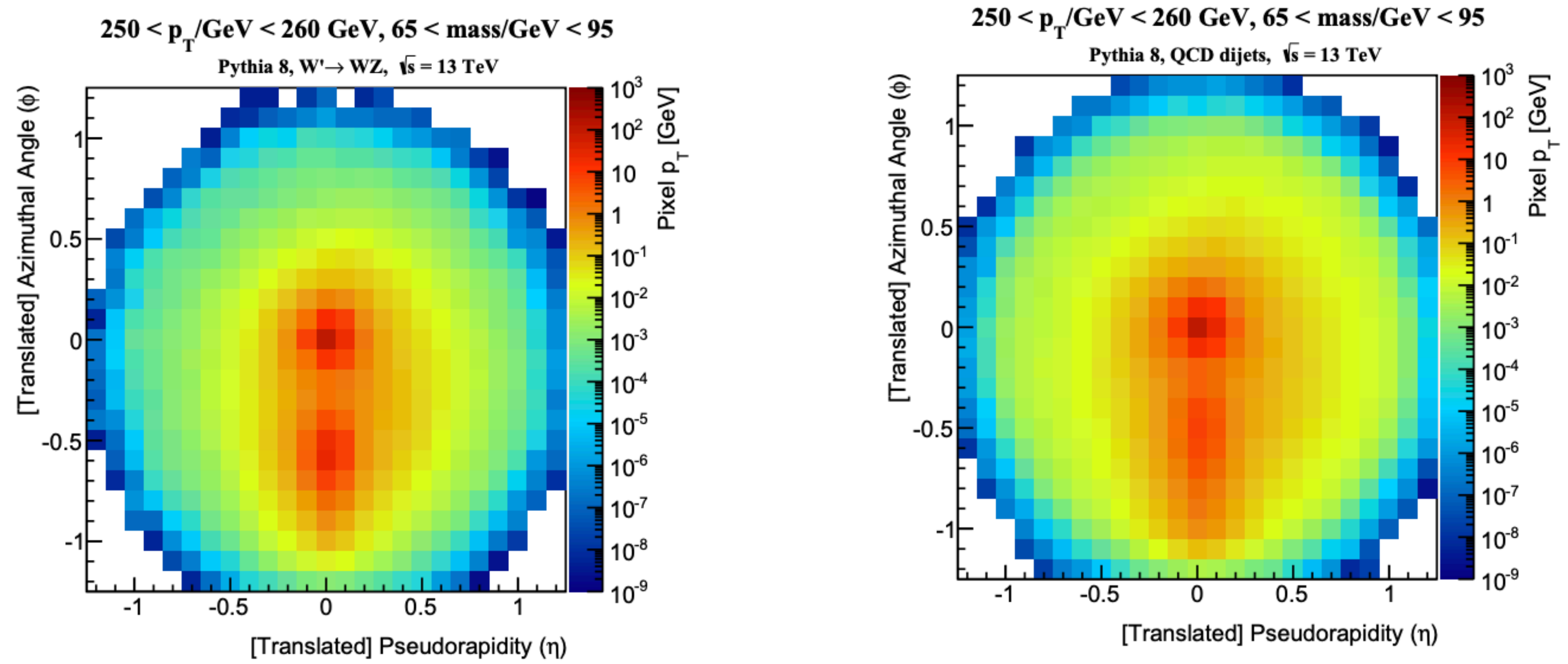

Reinforce-
ment
learning
Generative
modeling
Inference
Machine
learning
...
Classification
Anomaly
detection
Regression

Classification - jet identification

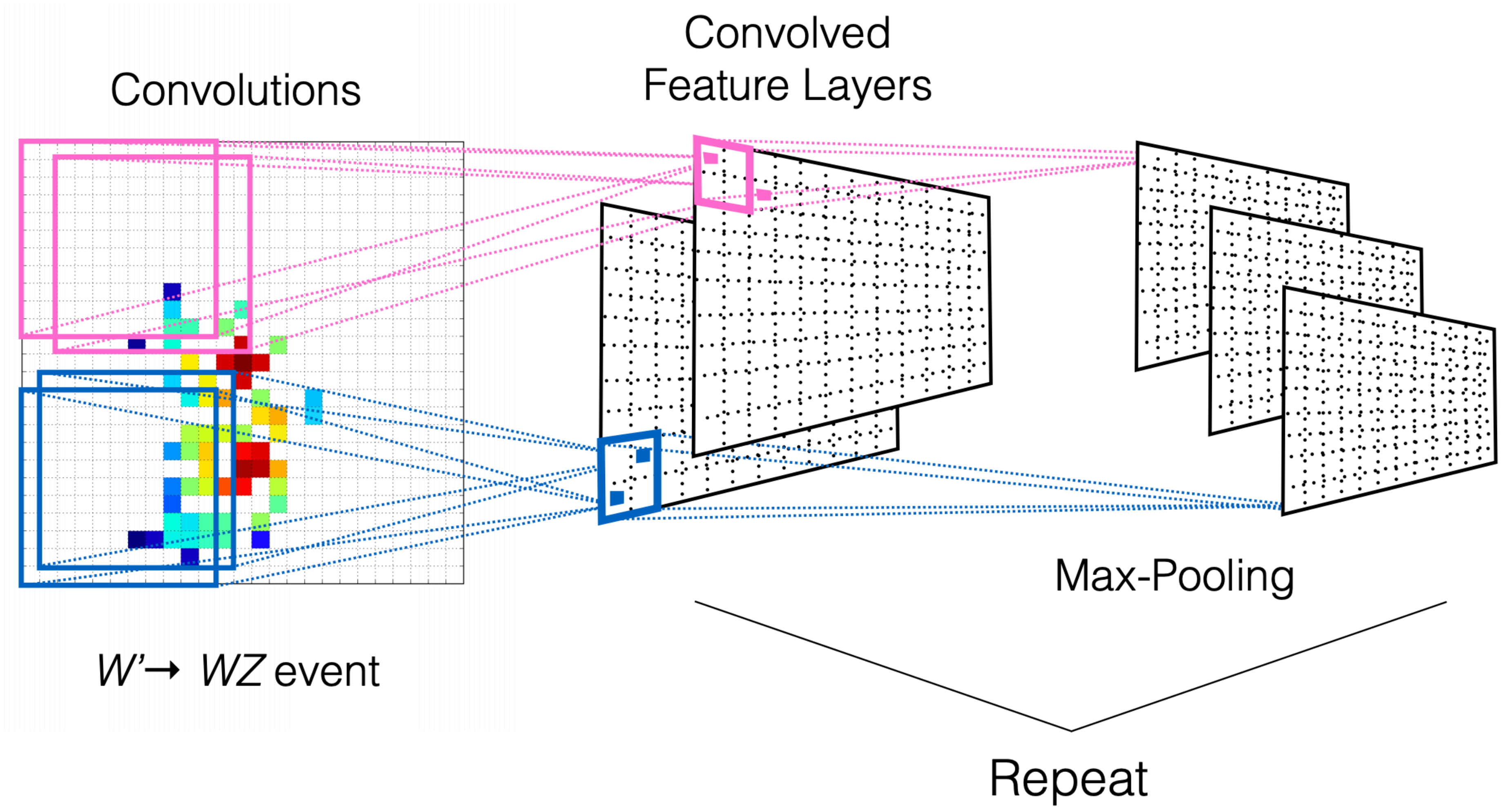
Oliveira, Kagan, Mackey, Nachman, Schwartzman `15

- Quark vs gluon tagging
- QCD vs boosted Z/W-jet
- Boosted top-quarks





Average images of W and QCD jets



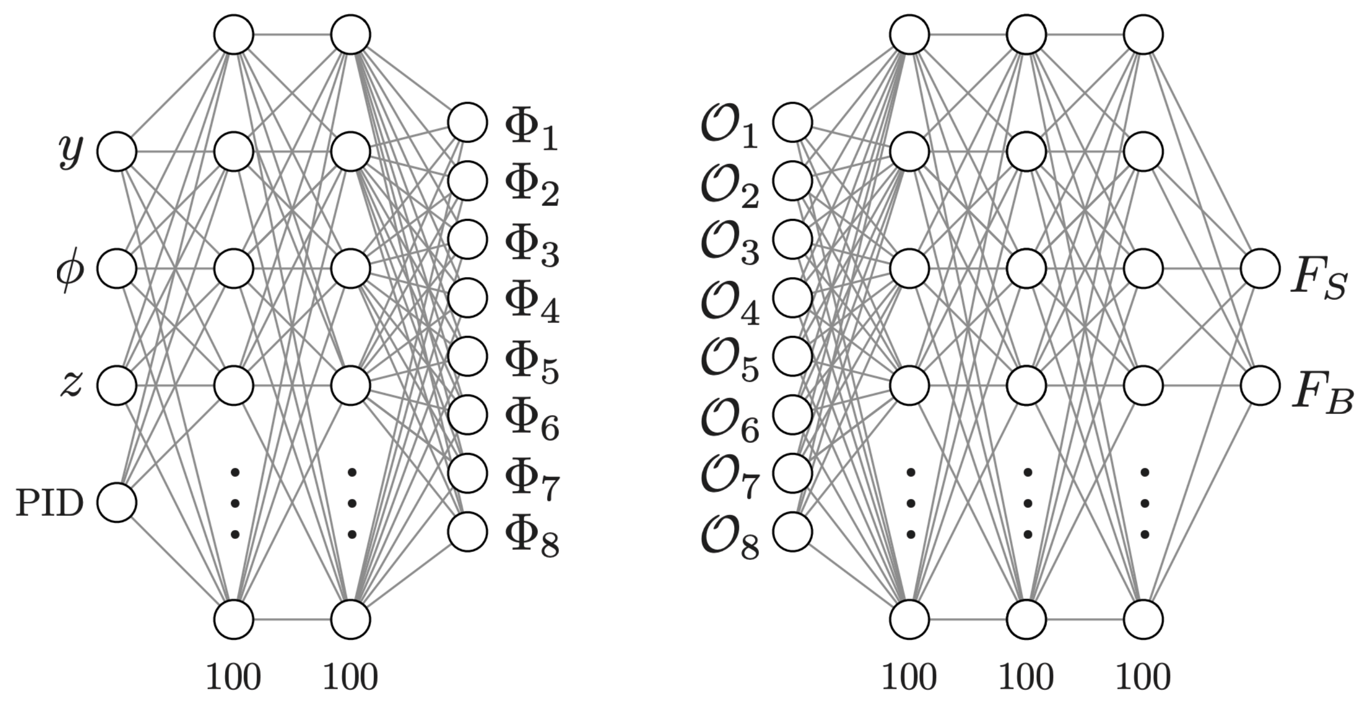
Convolutional Neural Networks (CNNs)

- Sparse data sets
- Machine learned taggers can significantly outperform QCD theory-inspired methods

Deep sets and probabilistic models

- Inspired by point clouds
- Permutation invariant sets
- Particle/Energy Flow Networks

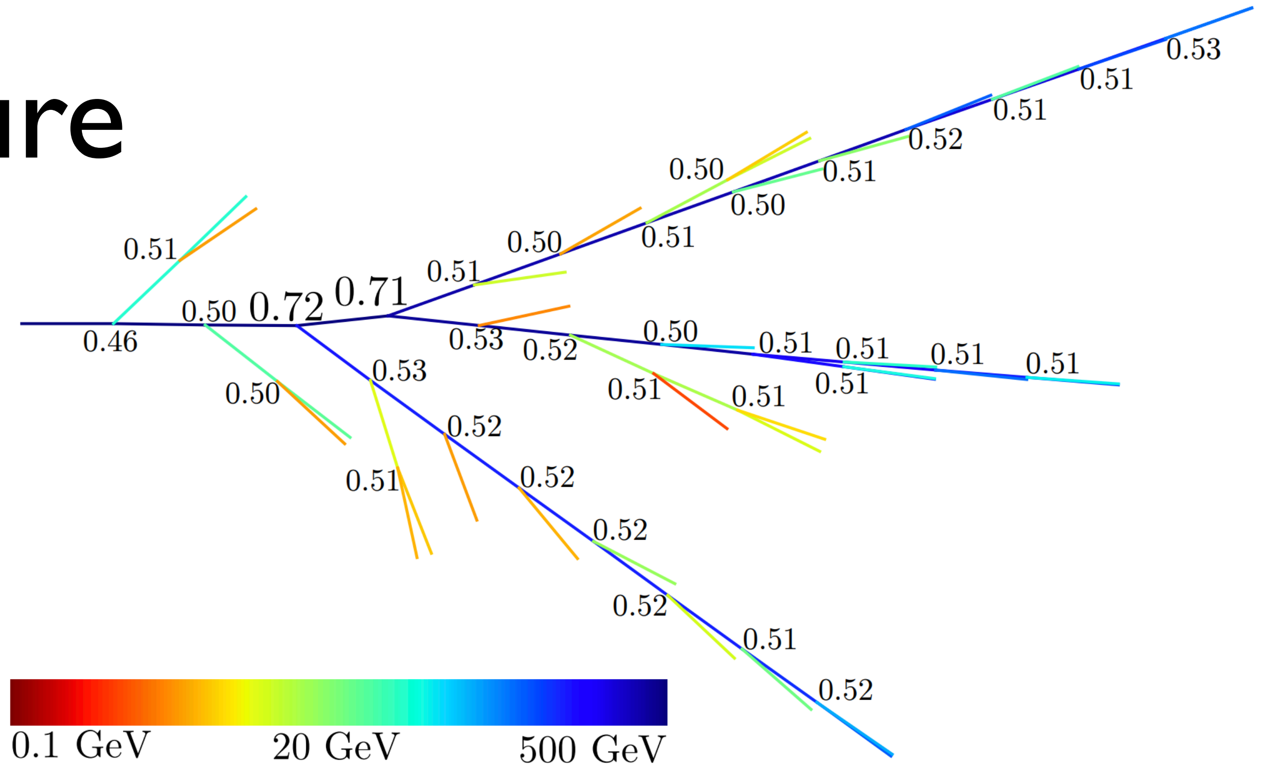
$$\mathcal{O}(\{p_1,\ldots,p_M\}) = F\left(\sum_{i=1}^{M}\Phi(p_i)\right)$$

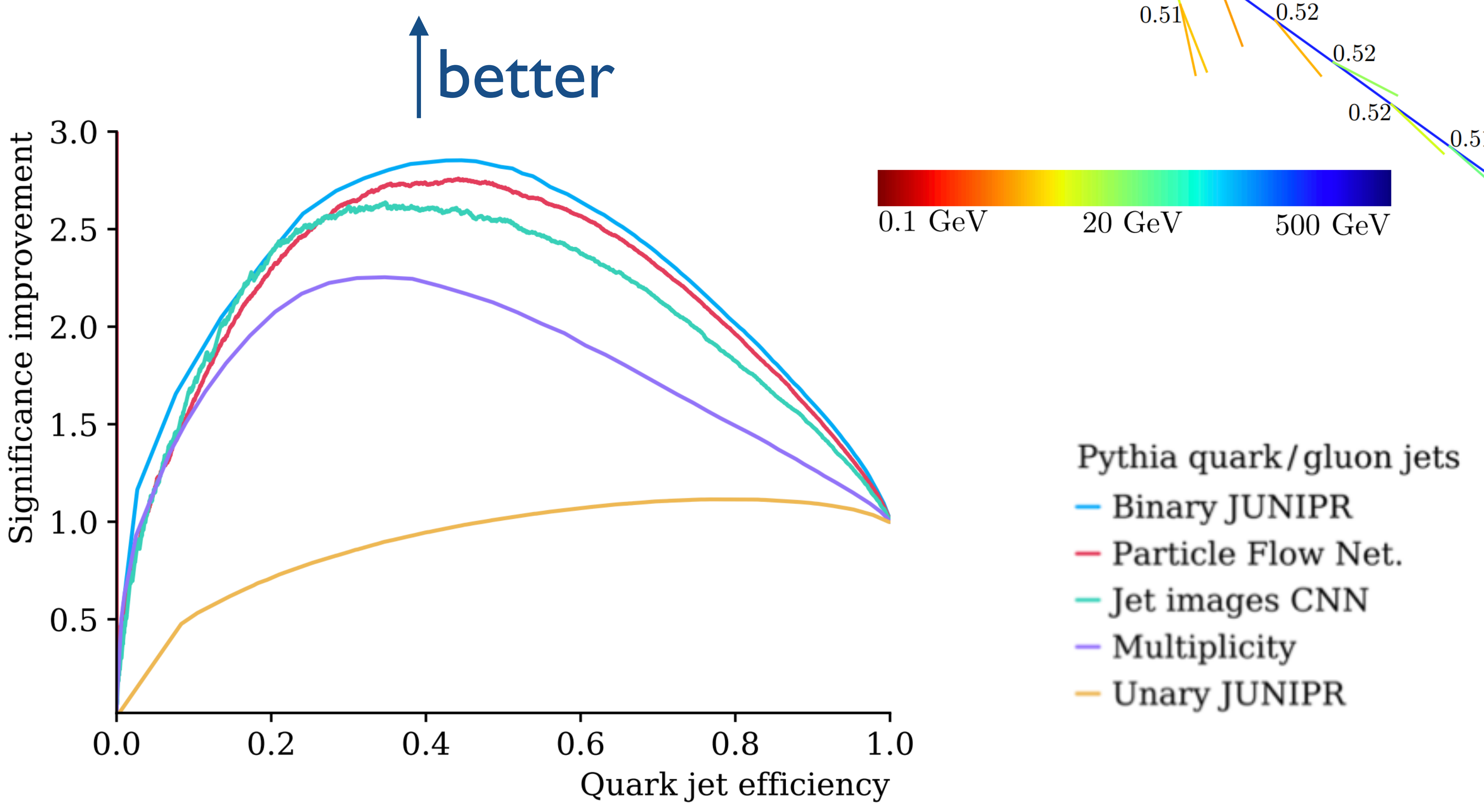


Infrared-Collinear Safety can be built in

Komiske, Methodiev, Thaler `19

- Probabilistic model
- JUNIPR
- Jet/tree-like structure





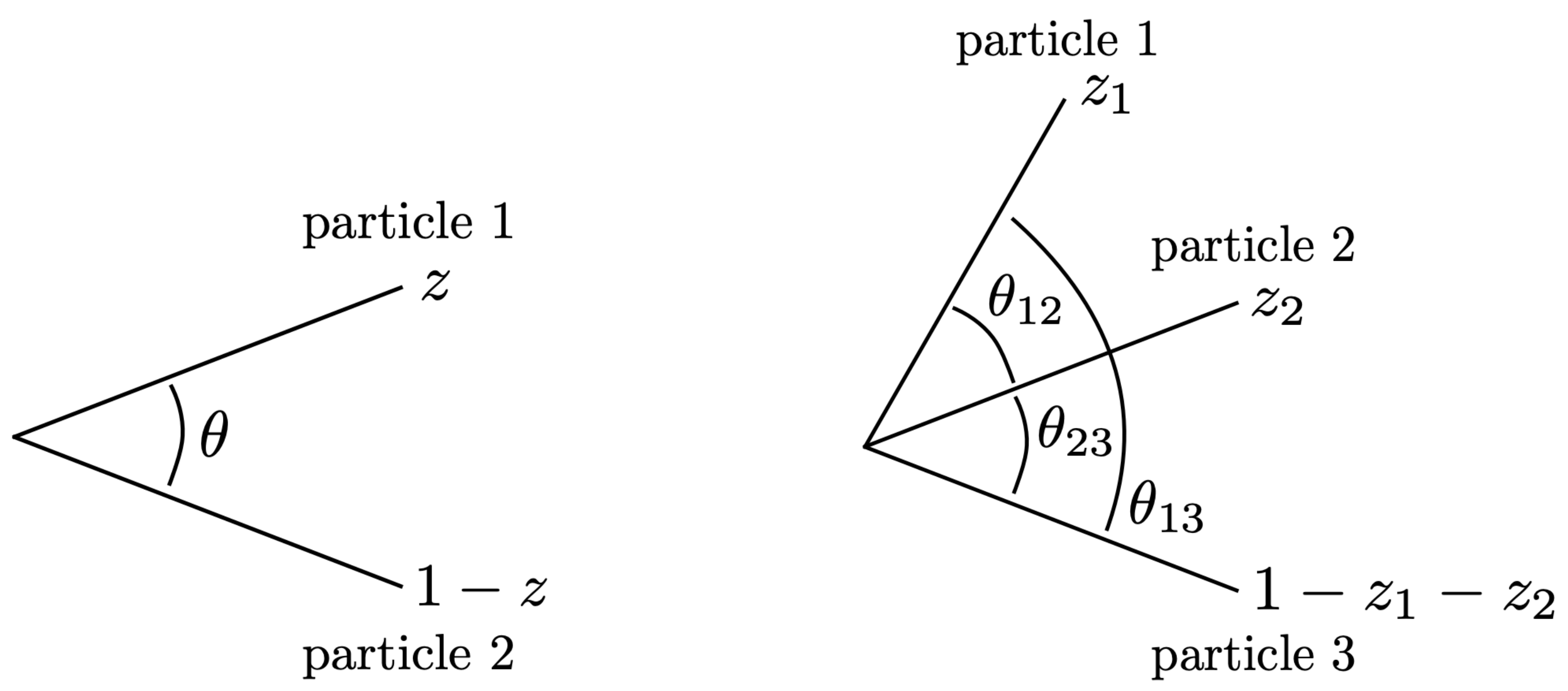
Andreassen, Feige, Frye, Schwartz `18, `19

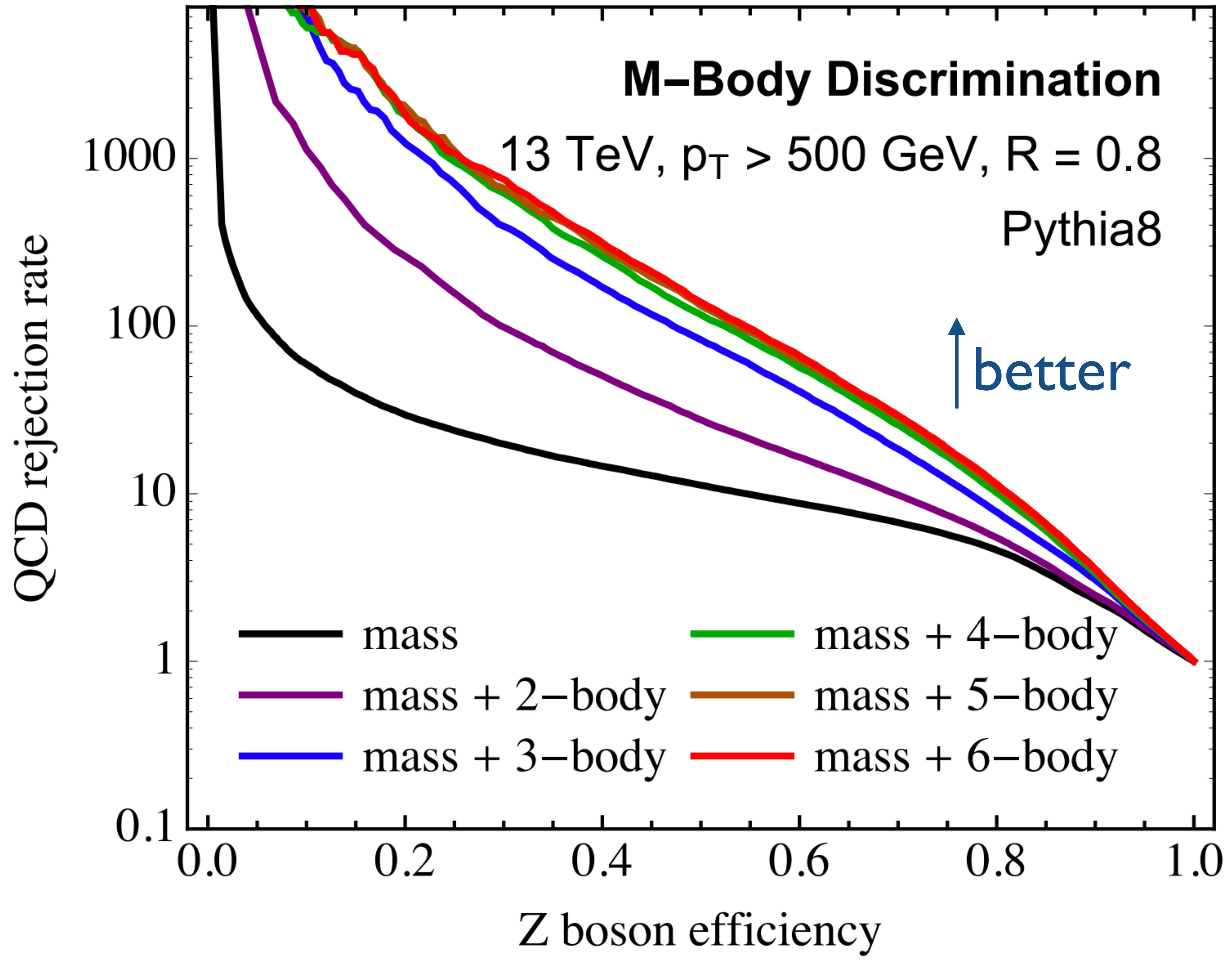
See also Cranmer, Drnevich, Macaluso, Pappadopulo `21

Quantifying the information content of jets

- Complete set of observables
- N-subjettiness basis
- Observe convergence of ROC curve

$$\tau_N^{(\beta)} = \frac{1}{p_{TJ}} \sum_{i\in \mathrm{Jet}} p_{Ti} \min\left\{R_{1i}^{\beta}, R_{2i}^{\beta}, \ldots, R_{Ni}^{\beta}\right\}$$



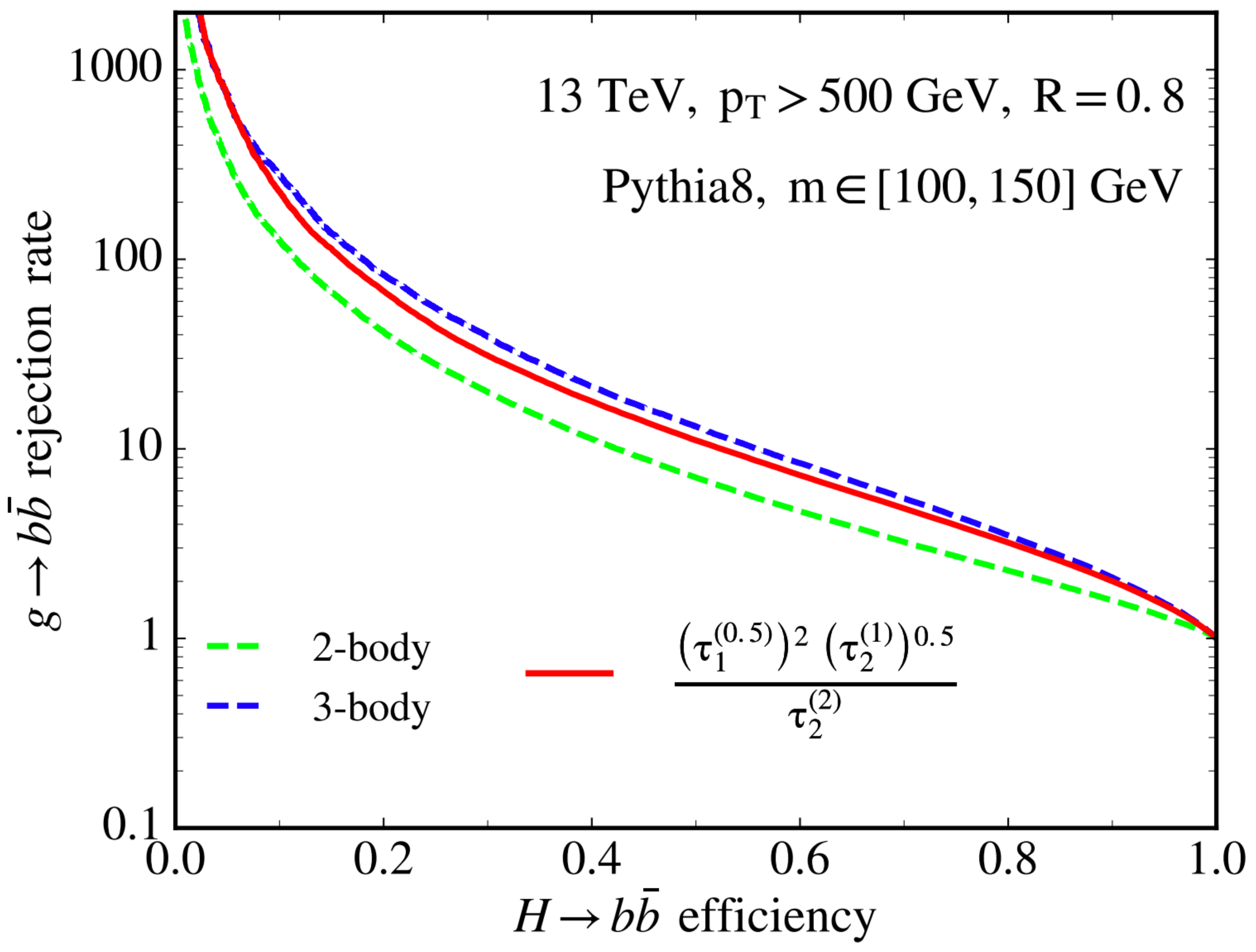


- Convergence related to entropy production in the jet after the hard-scattering

Datta, Larkoski `17, Datta, Larkoski, Nachman `19
Neill, Waalewijn `19

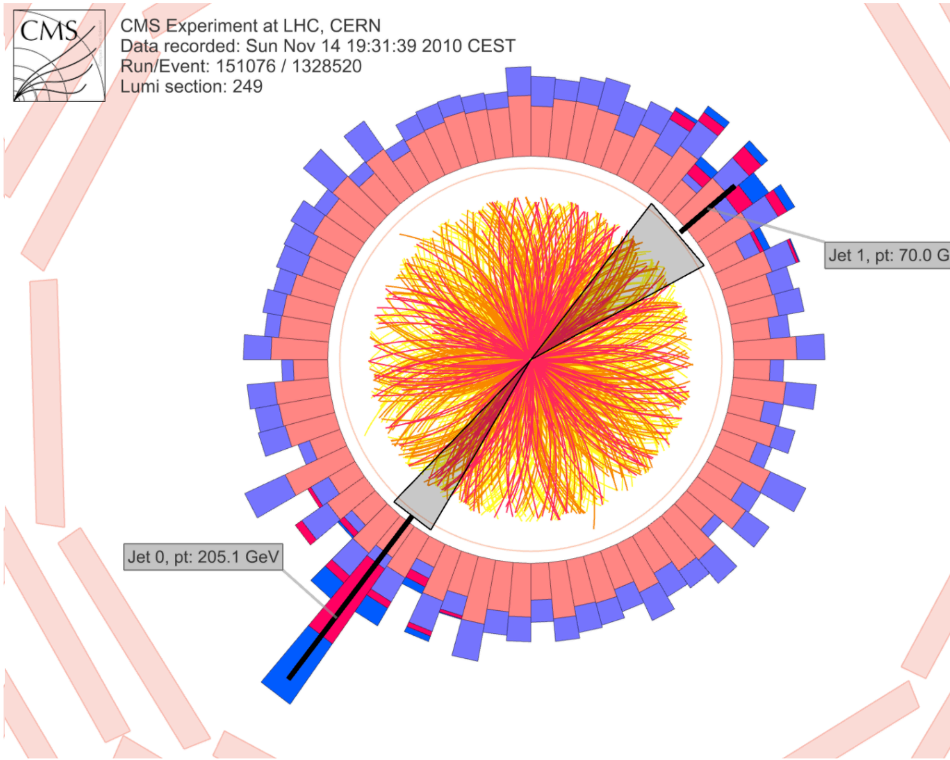
Automated design of observables

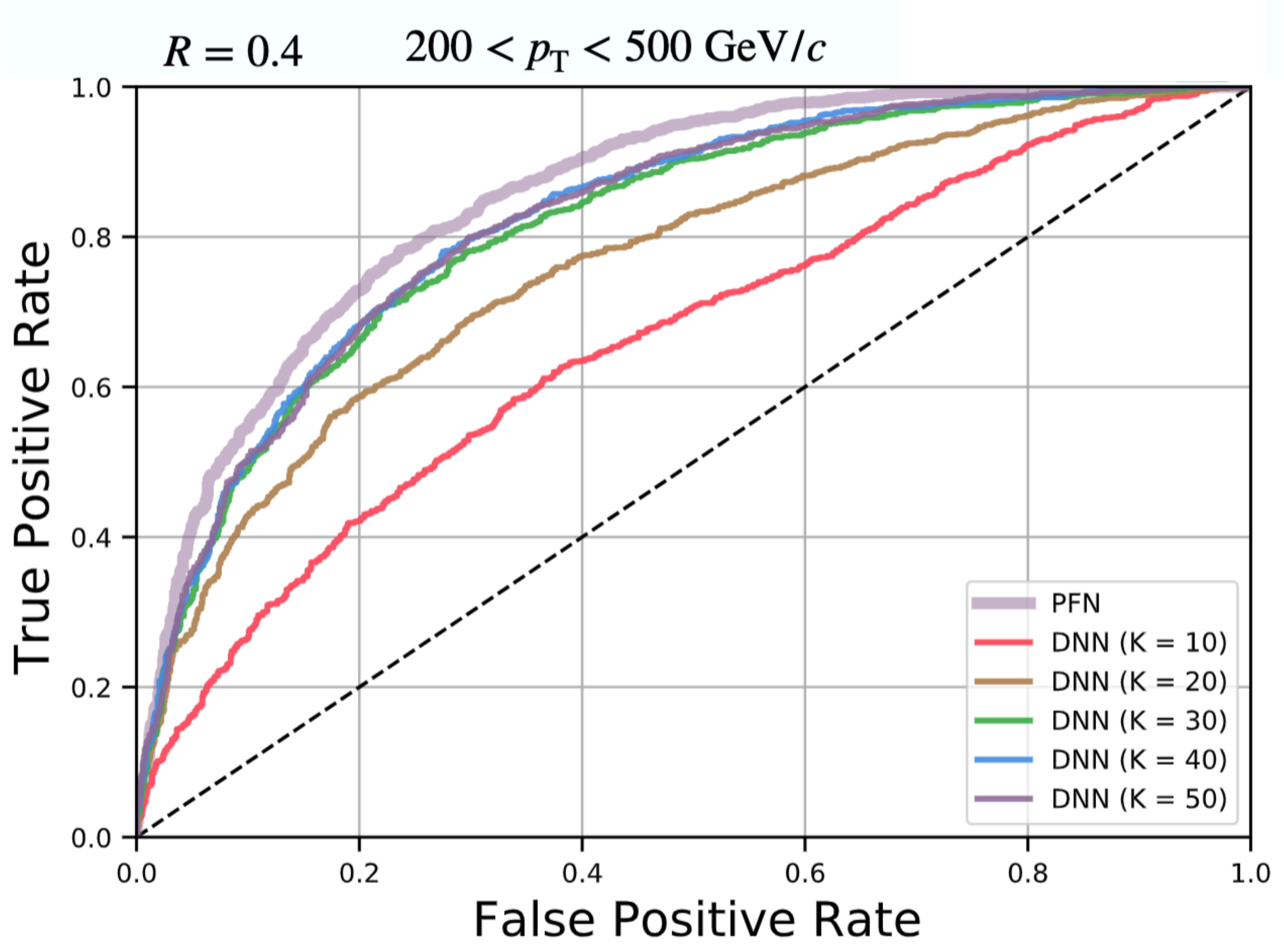
- Single product observable
- Interpretability



Datta, Larkoski `17

- Quantify the information content of quenched jets
- Identify optimal observables

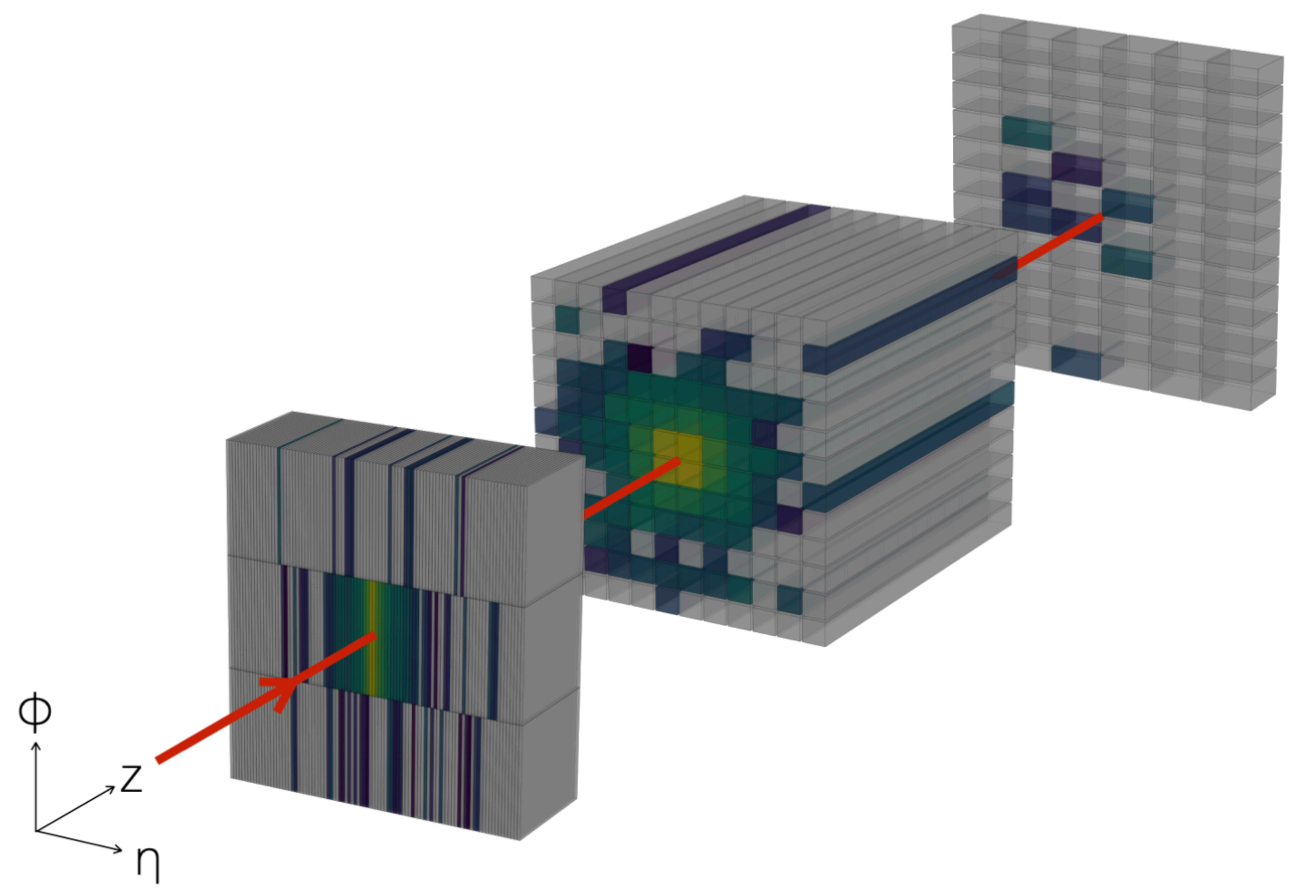


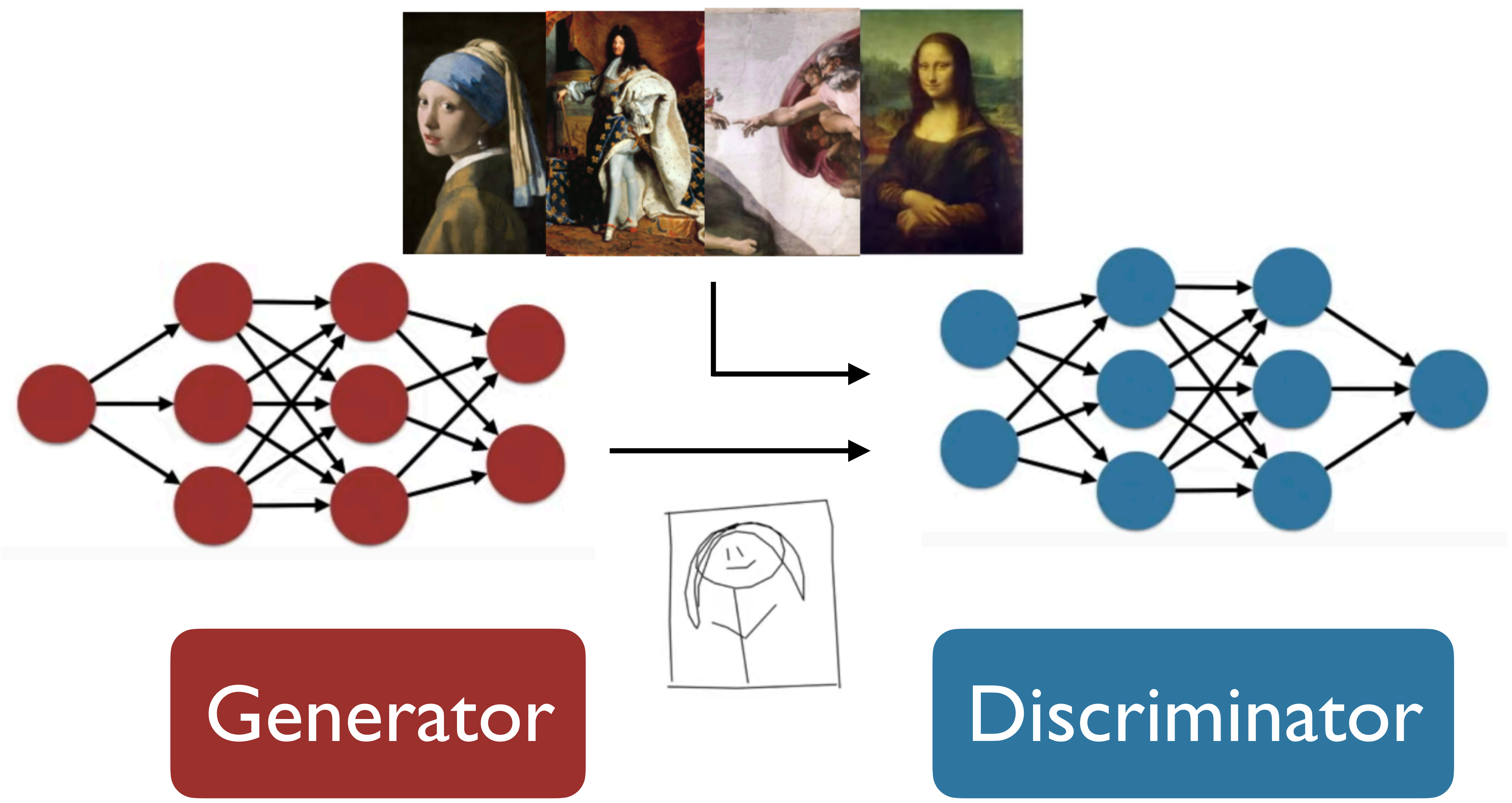


Lai, Mulligan, Ploskon, FR - in preparation
see also Lai `18

Generative modeling

- Generative Adversarial Networks (GANs) *Goodfellow et al. `14*
- GEANT detector simulations
- Reduction of the computational cost of simulations *Paganini, Oliveira, Nachman `17*



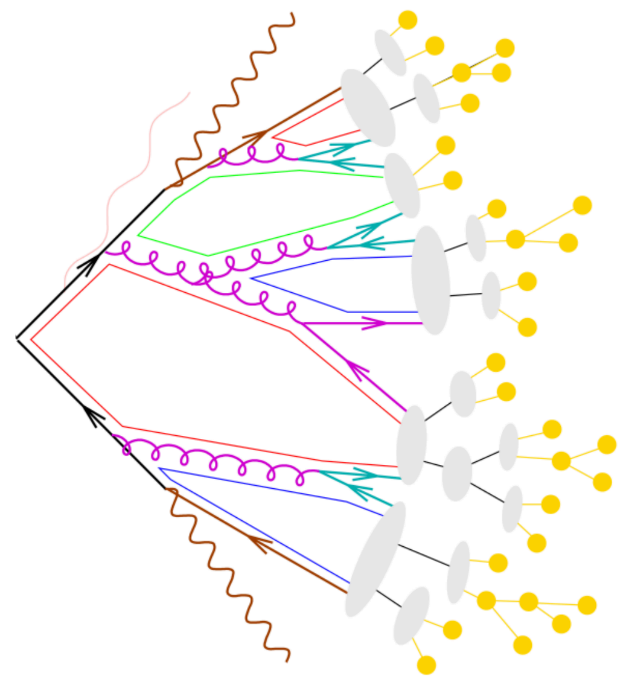


- With Normalizing Flows

  see Krause, Shish `21

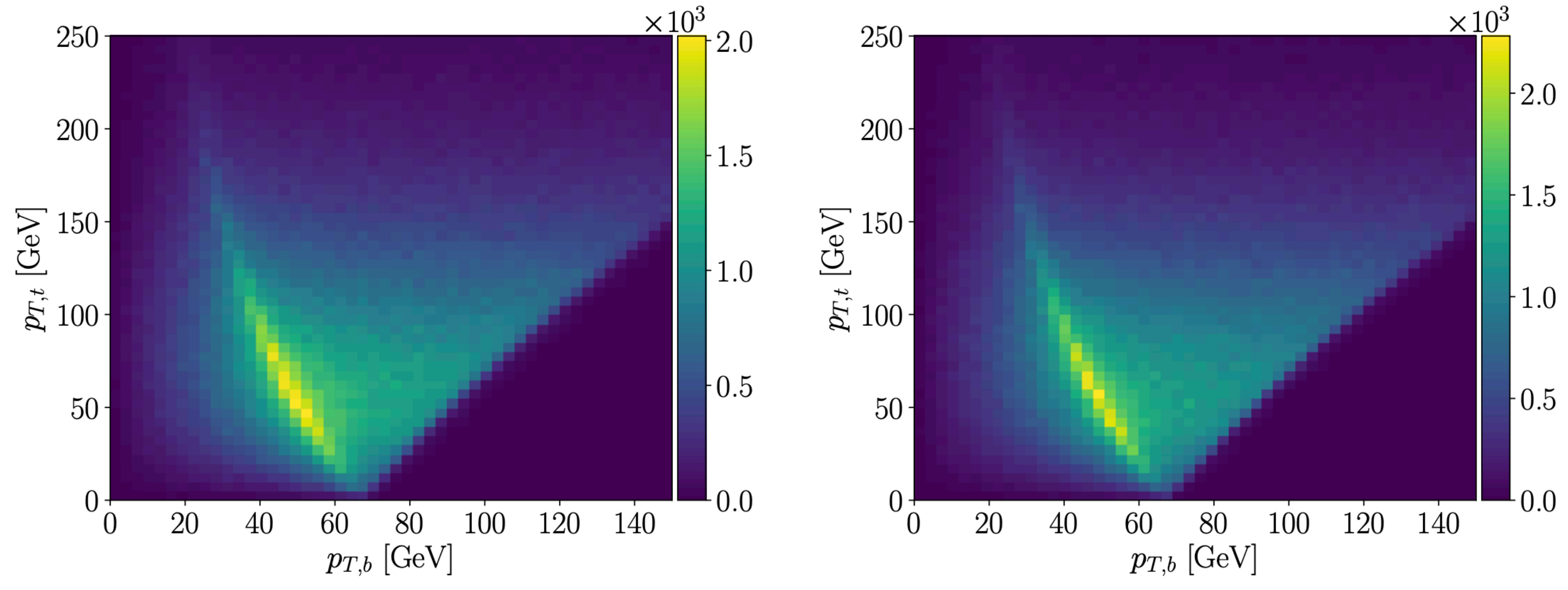
Generative modeling

- GANs for event simulation
- LHC energies *Butter, Plehn, Winterhalder `19-`20



Train GAN on the final output of the shower

$pp \to t\bar{t} \to (bq\bar{q}')\ (\bar{b}\bar{q}q')$ correlations



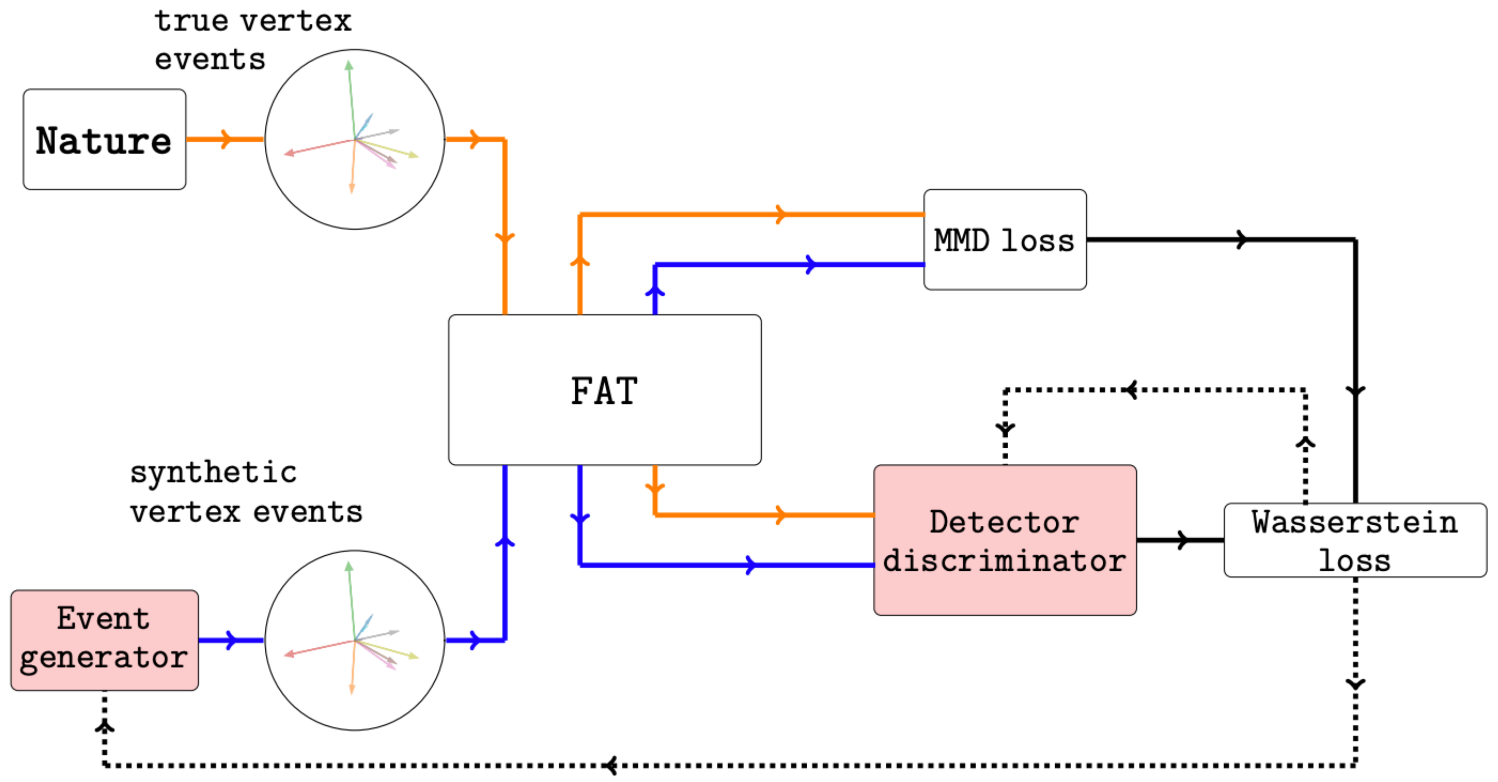
Shower GAN

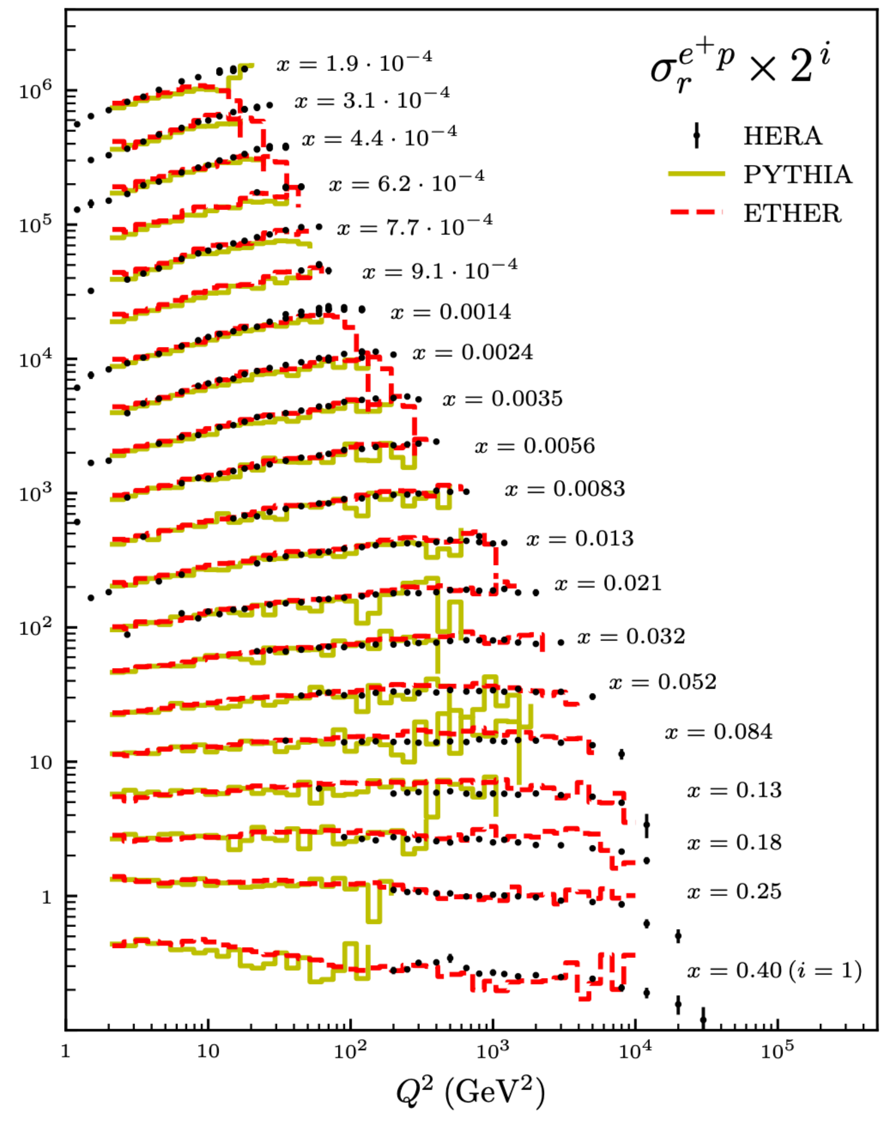
- JLab/EIC energies

Feature augmented GAN

Alnazi, Sato, Liu et al. `20

→ (Un)folding

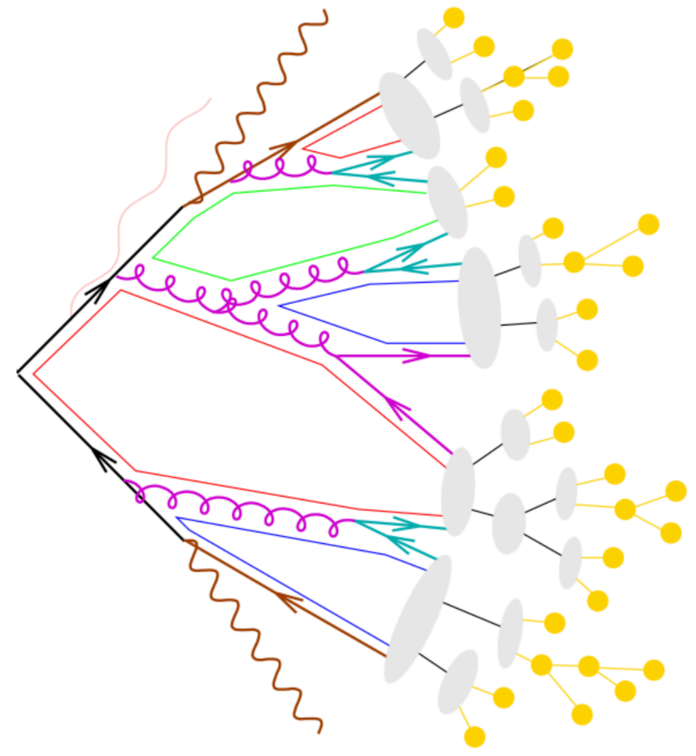




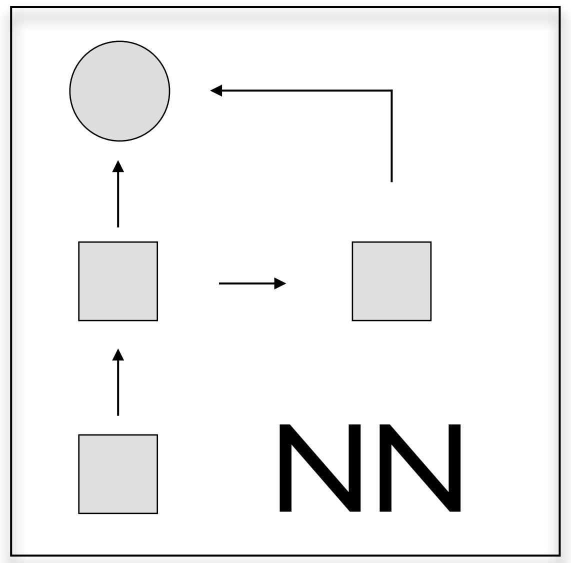
Explainable machine learning

Lai, Neill, FR, Ploskon `20

- White-box AI
- Learn the underlying physics of the parton shower

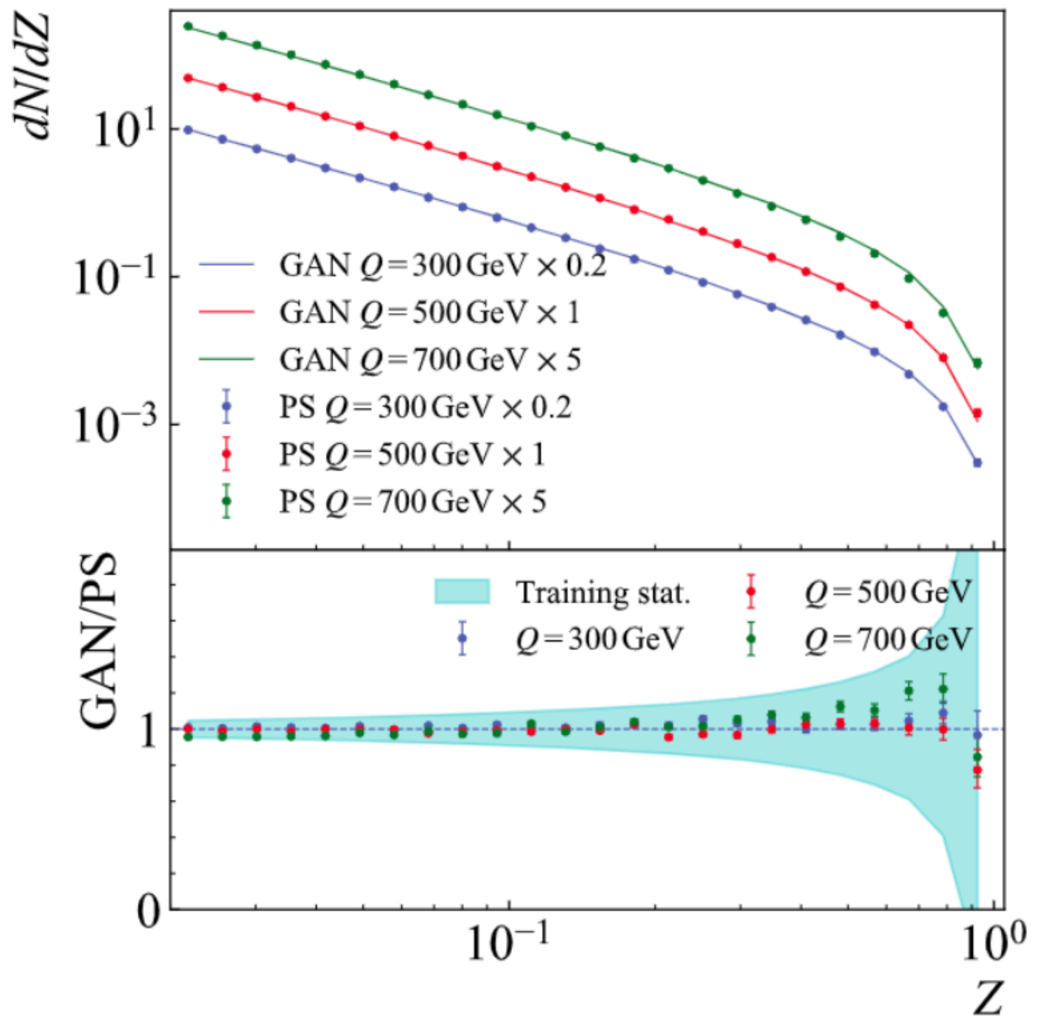


Train GAN on the final output of the shower

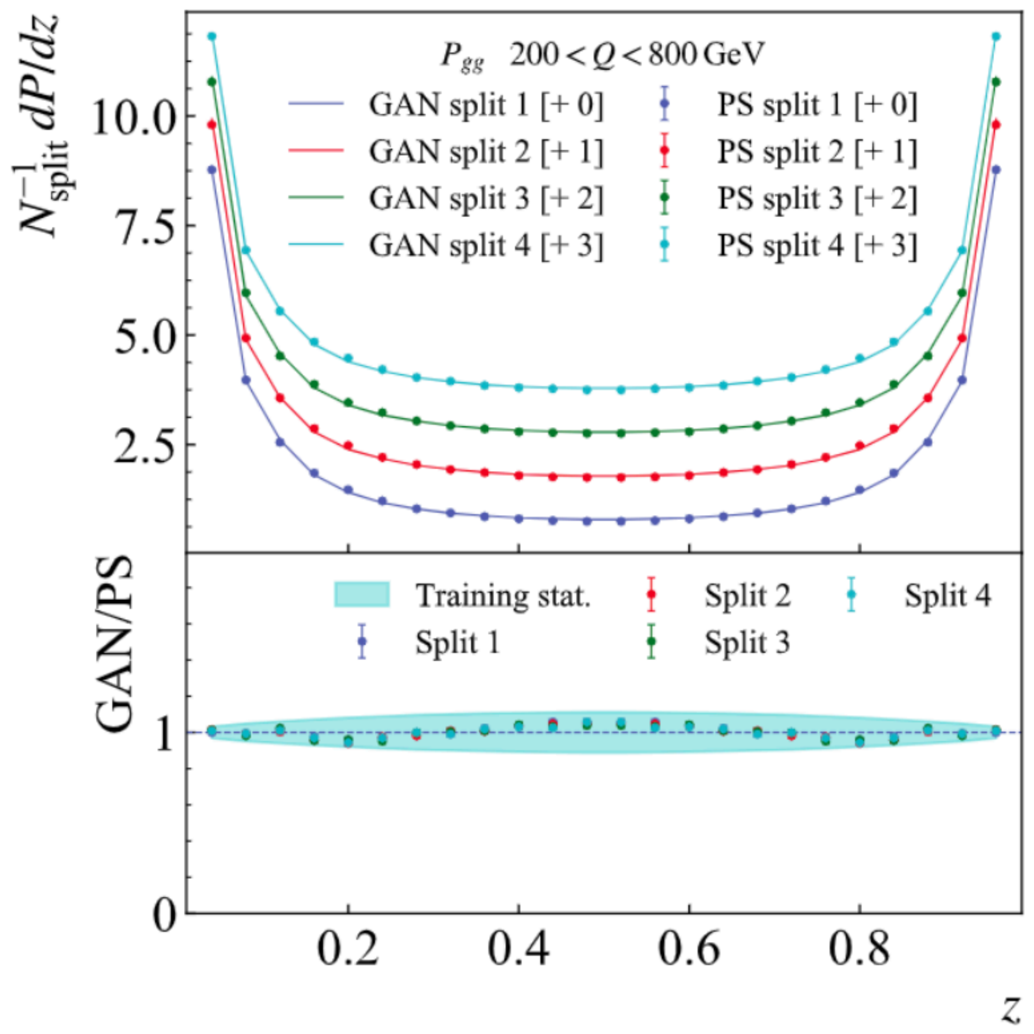


- Generator is a Recurrent Neural Nework (RNN)

$n \to n+1$ partons



Final energy distribution



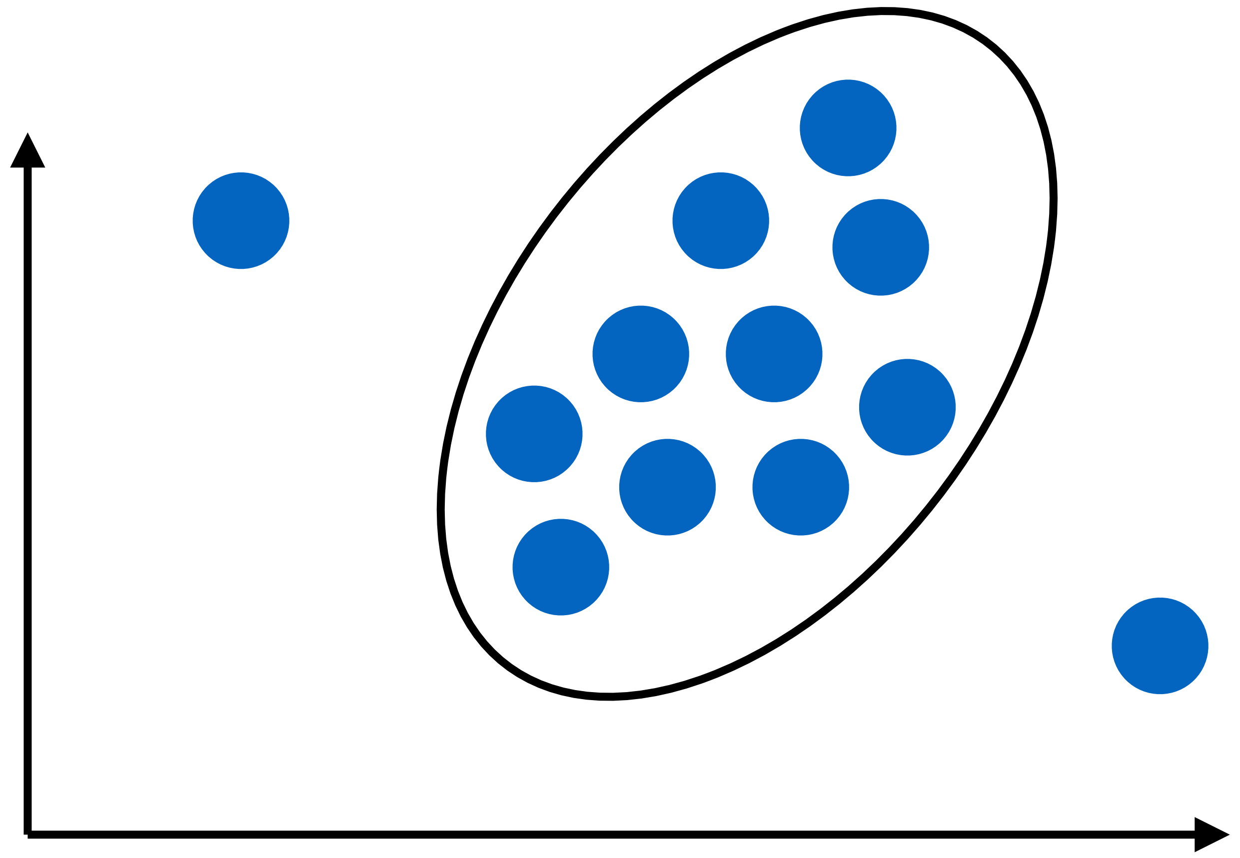
Intermediate splittings

see also Bieringer, Butter, Heimel, Höche et al. `20

Anomaly detection

Heimel, Kasieczka et al. `19
Andreassen, Nachman, Shih `19
Pierini, Wulzer et al. `20
Atkinson, Spannowsky et al. `21
…

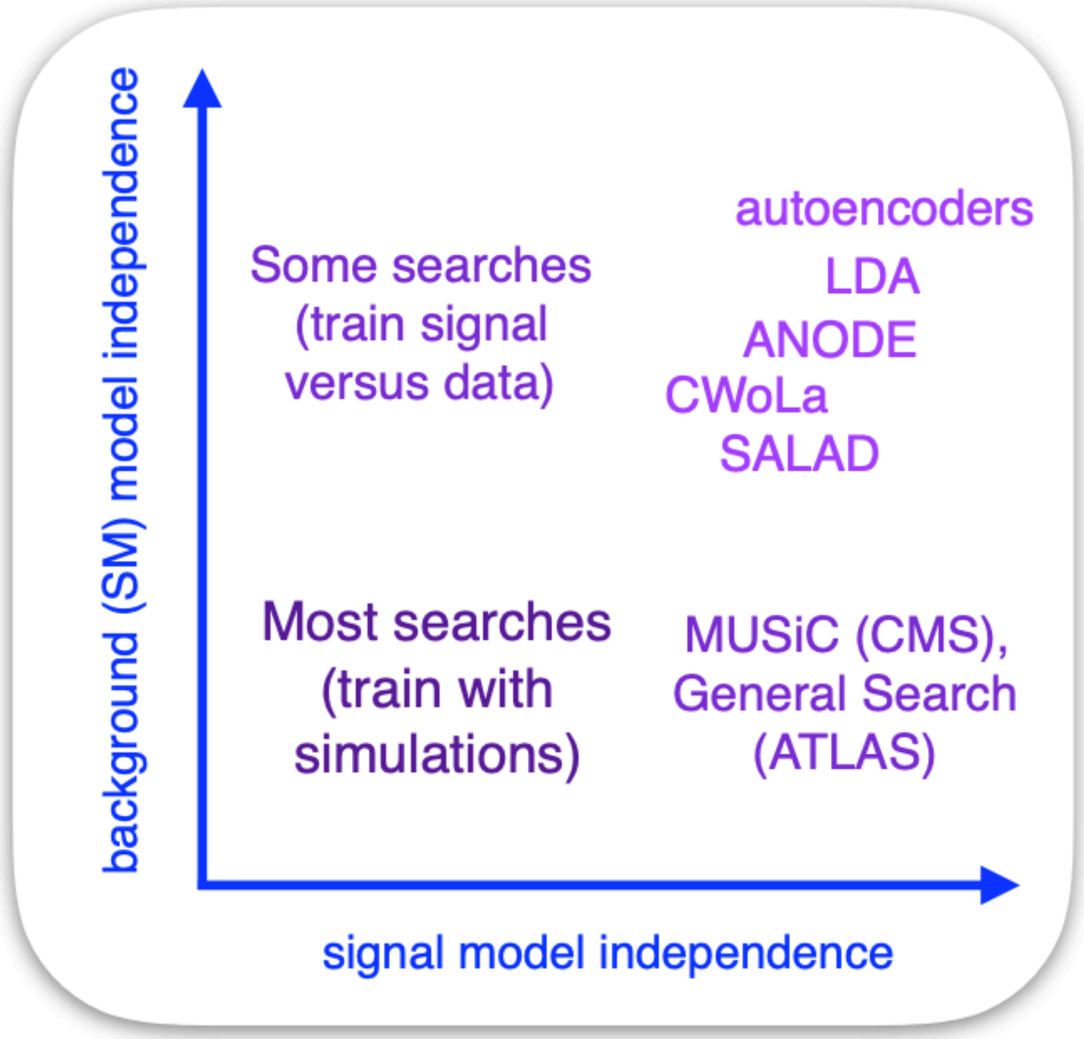
- Use low-level event-by-event information for BSM searches
- Can use weakly supervised or unsupervised learning
- Improvement of traditional searches



Many new ideas →

Applied at the LHC

see e.g. ATLAS, PRL 125 (2020) 131801



Nachman, Shih `20

HEP ML - Living Review

Feickert, Nachman `21

HEPML-LivingReview

A Living Review of Machine Learning for Particle Physics

Modern machine learning techniques, including deep learning, is rapidly being applied, adapted, and developed for high energy physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

download review

The purpose of this note is to collect references for modern machine learning as applied to particle physics. A minimal number of categories is chosen in order to be as useful as possible. Note that papers may be referenced in more than one category. The fact that a paper is listed in this document does not endorse or validate its content - that is for the community (and for peer-review) to decide. Furthermore, the classification here is a best attempt and may have flaws - please let us know if (a) we have missed a paper you think should be included, (b) a paper has been misclassified, or (c) a citation for a paper is not correct or if the journal information is now available. In order to be as useful as possible, this document will continue to evolve so please check back before you write your next paper. If you find this review helpful, please consider citing it using \cite{hepmllivingreview} in HEPML.bib.

- Reviews
  - Modern reviews
    - Jet Substructure at the Large Hadron Collider: A Review of Recent Advances in Theory and Machine Learning [DOI]
    - Deep Learning and its Application to LHC Physics [DOI]
    - Machine Learning in High Energy Physics Community White Paper [DOI]
    - Machine learning at the energy and intensity frontiers of particle physics
    - Machine learning and the physical sciences [DOI]
    - Machine and Deep Learning Applications in Particle Physics [DOI]

…

https://iml-wg.github.io/HEPML-LivingReview/

- ML with uncertainties *e.g. Bellagente, Plehn et al. `21*
- Monte Carlo tuning *e.g. Nachman, Thaler `20*
- Pileup mitigation *e.g. Komiske, Metodiev, Nachman, Schwartz `17*
- Neural networks with symmetries *e.g. Bogatskiy et al. `20*
- Efficient sampling for lattice field theory *Cranmer, Shanahan et al. `20-`21*
- …

See today's round-table discussion

Outline

Machine learning

Quantum computing

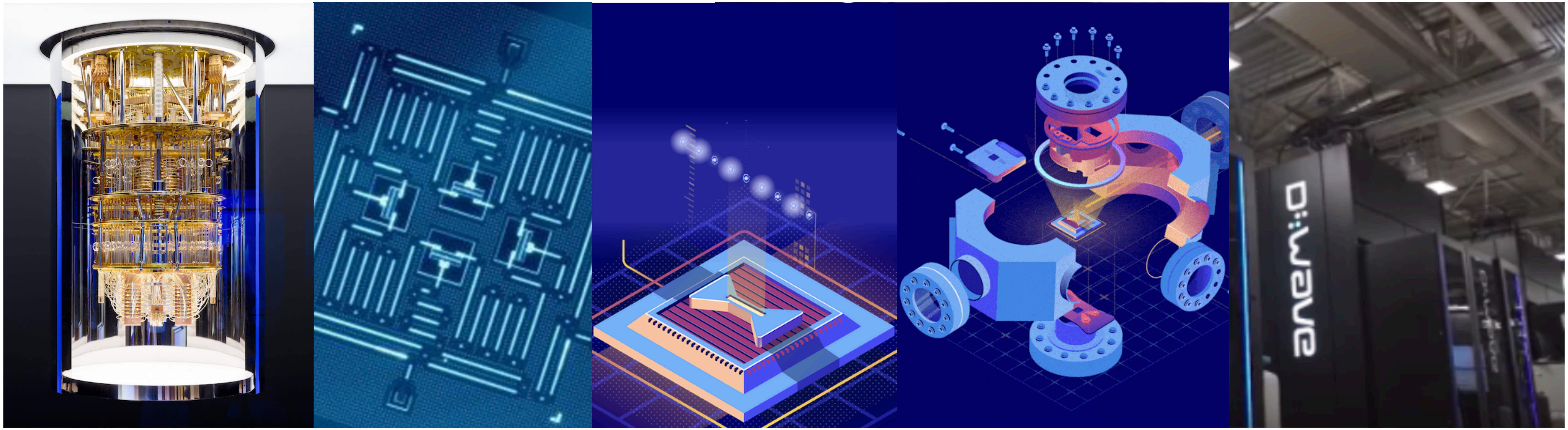
Conclusions & Outlook

Quantum computing platforms

For example

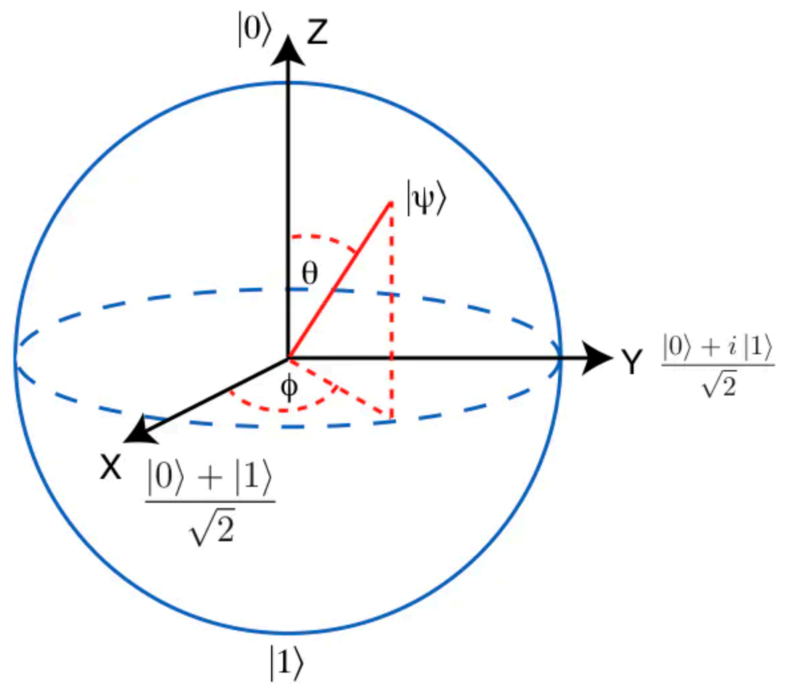
- Superconducting qubits
- Trapped ion devices

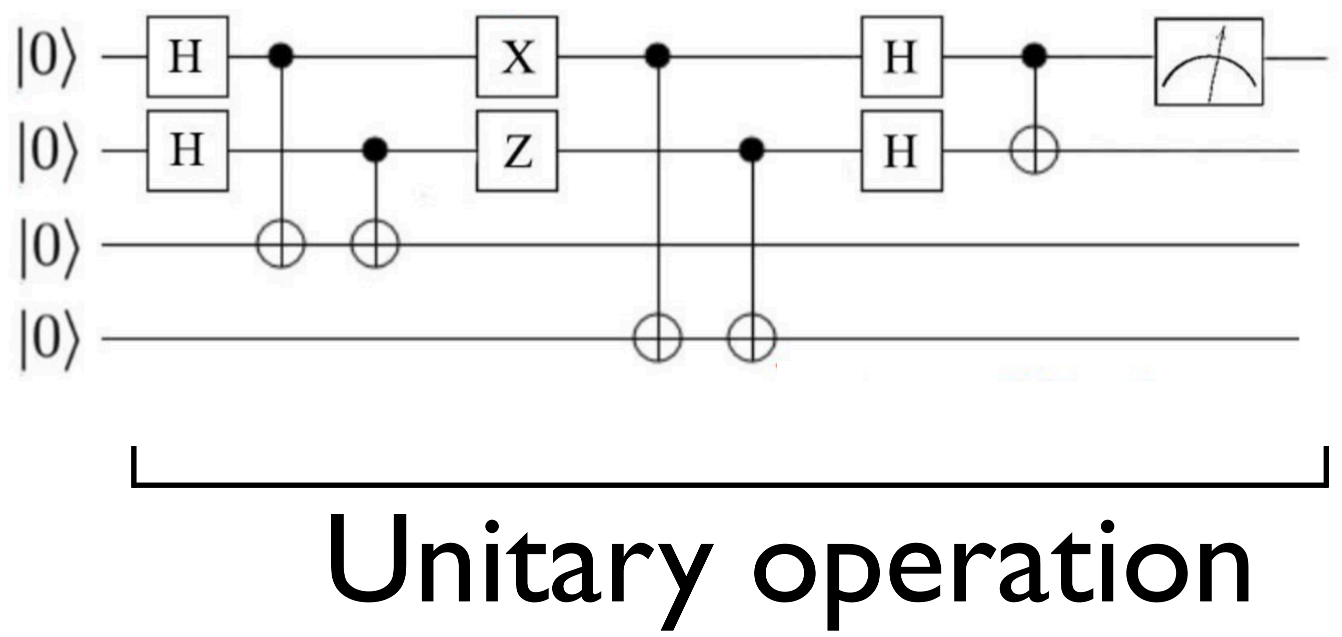
IBM Q rigetti
Google IONQ
Honeywell D:Wave …



Digital quantum computing

- Universal gate set: single-qubit rotations and CNOT





IBM Q rigetti
Google IONQ
Honeywell …

- Well suited for computational complexity analyses
  cf. Turing machines for classical computing

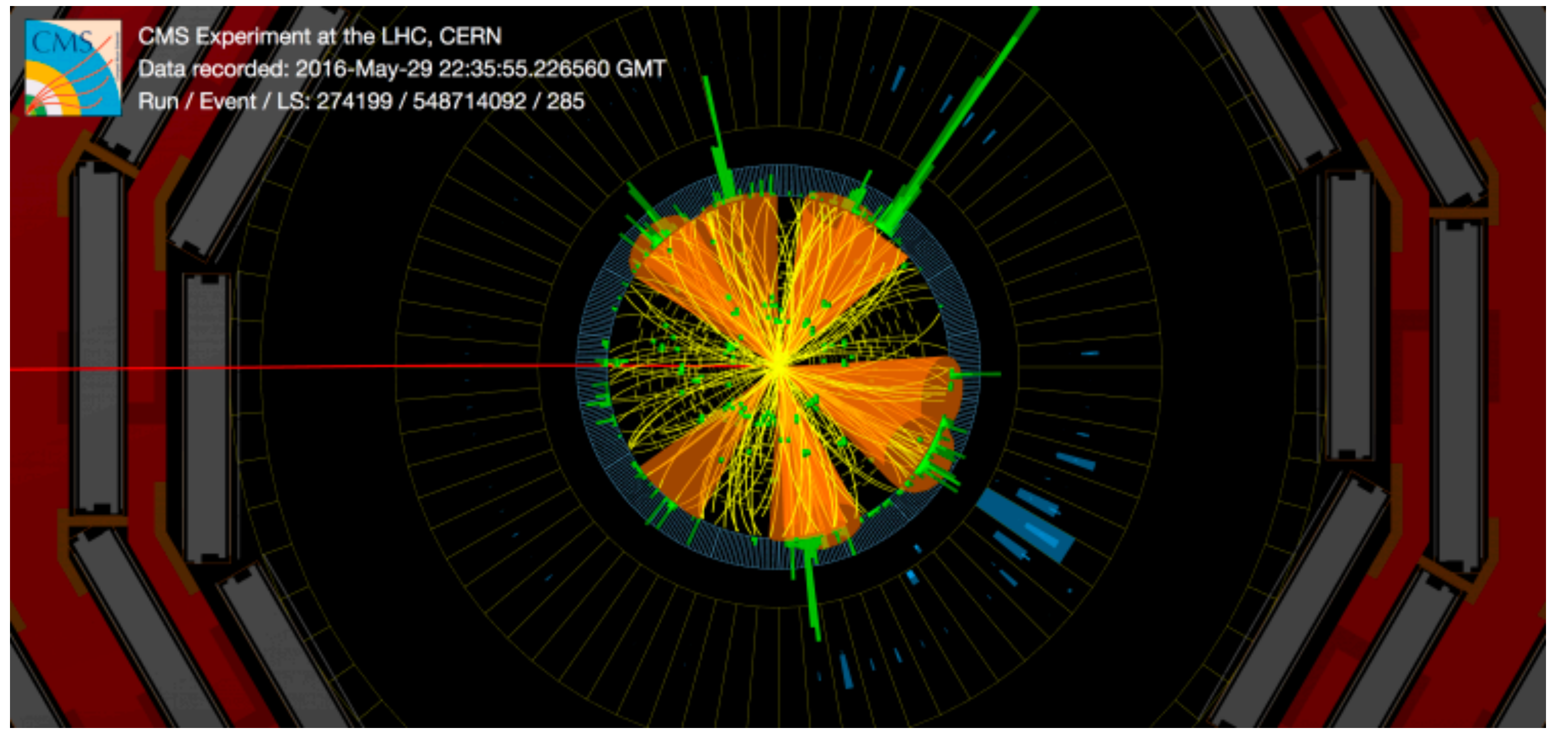
Real-time dynamics of QCD

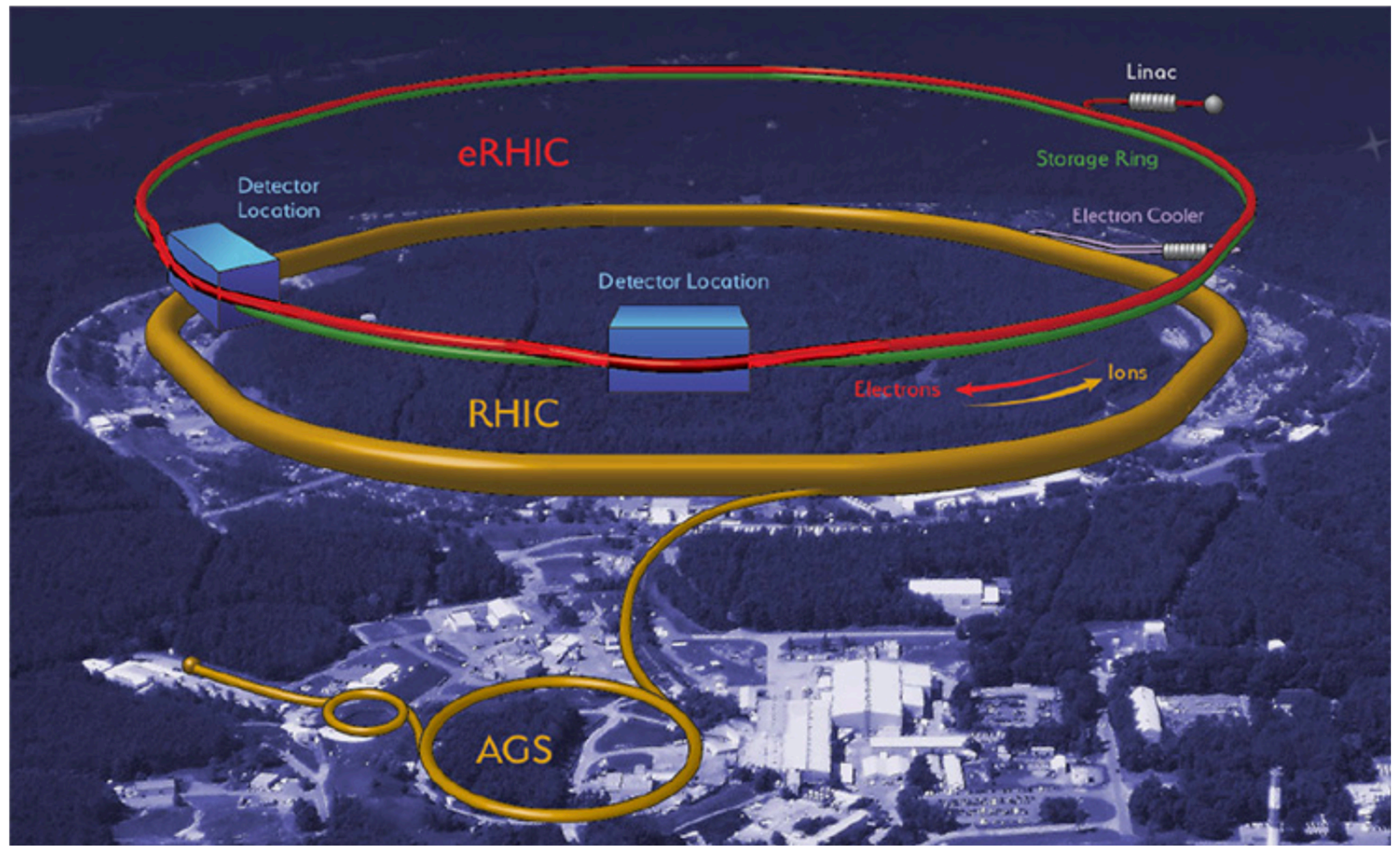
- Perturbative QCD - weakly coupled regime, requires factorization

- Euclidean-time lattice QCD - computation of e.g. PDFs but eventually runs into the sign problem

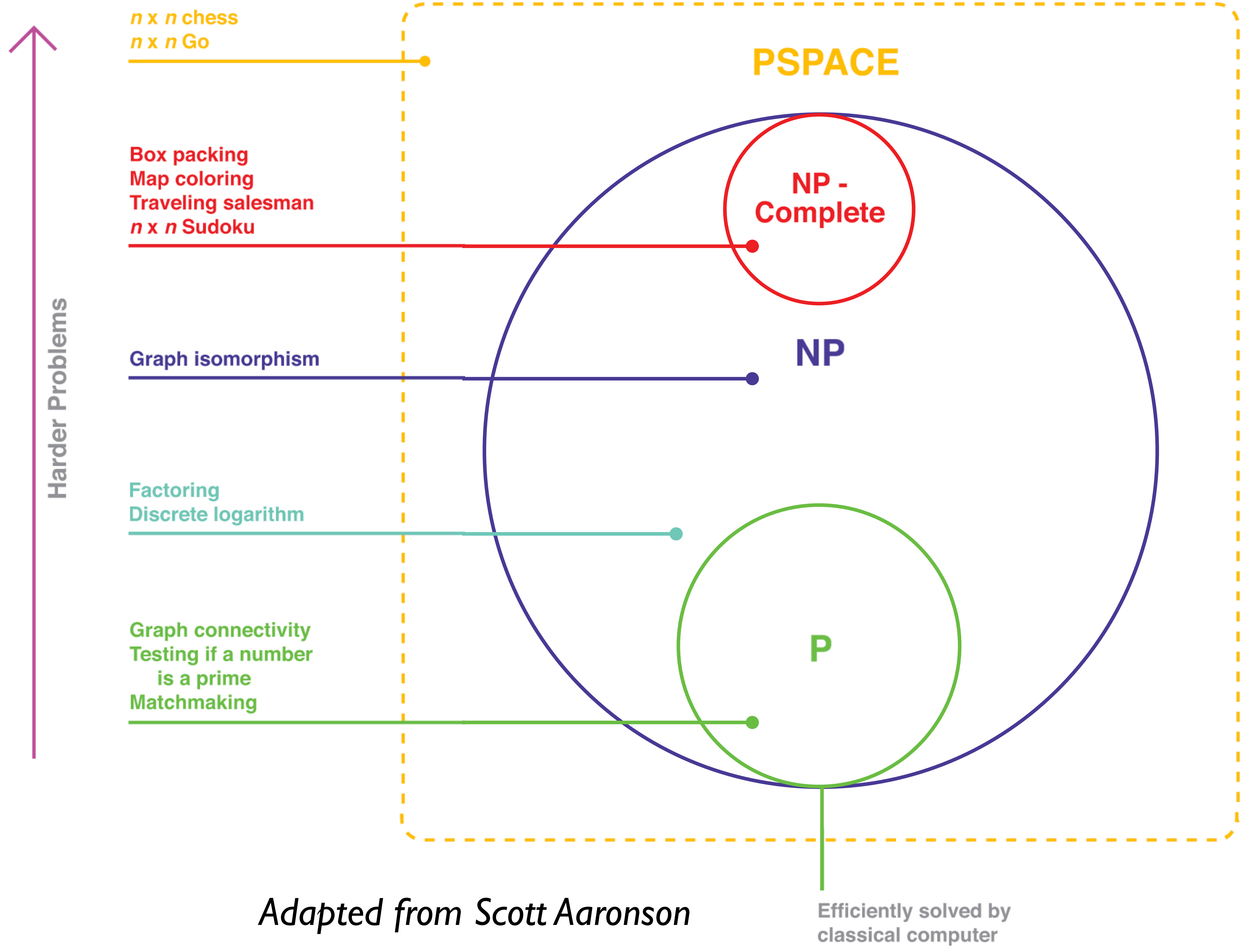
→ Solve real-time lattice QCD with the help of quantum computing?

Kogut, Susskind `70s, Jordan, Lee, Preskill `11-`17





Computational complexity



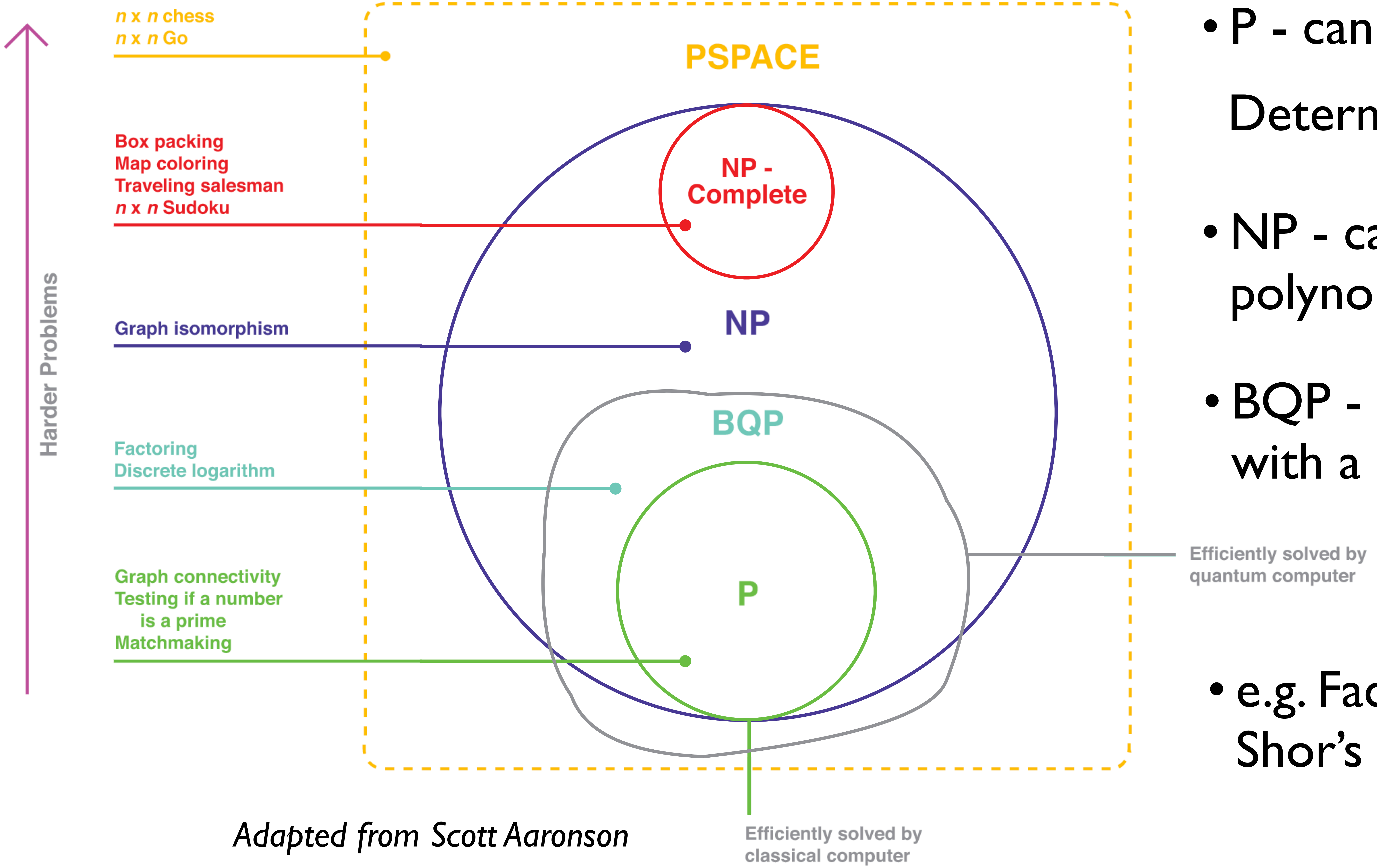
Adapted from Scott Aaronson

- P - can solve in polynomial time

  Deterministic & probabilistic

- NP - can check solution in polynomial time

Computational complexity



Adapted from Scott Aaronson

- P - can solve in polynomial time

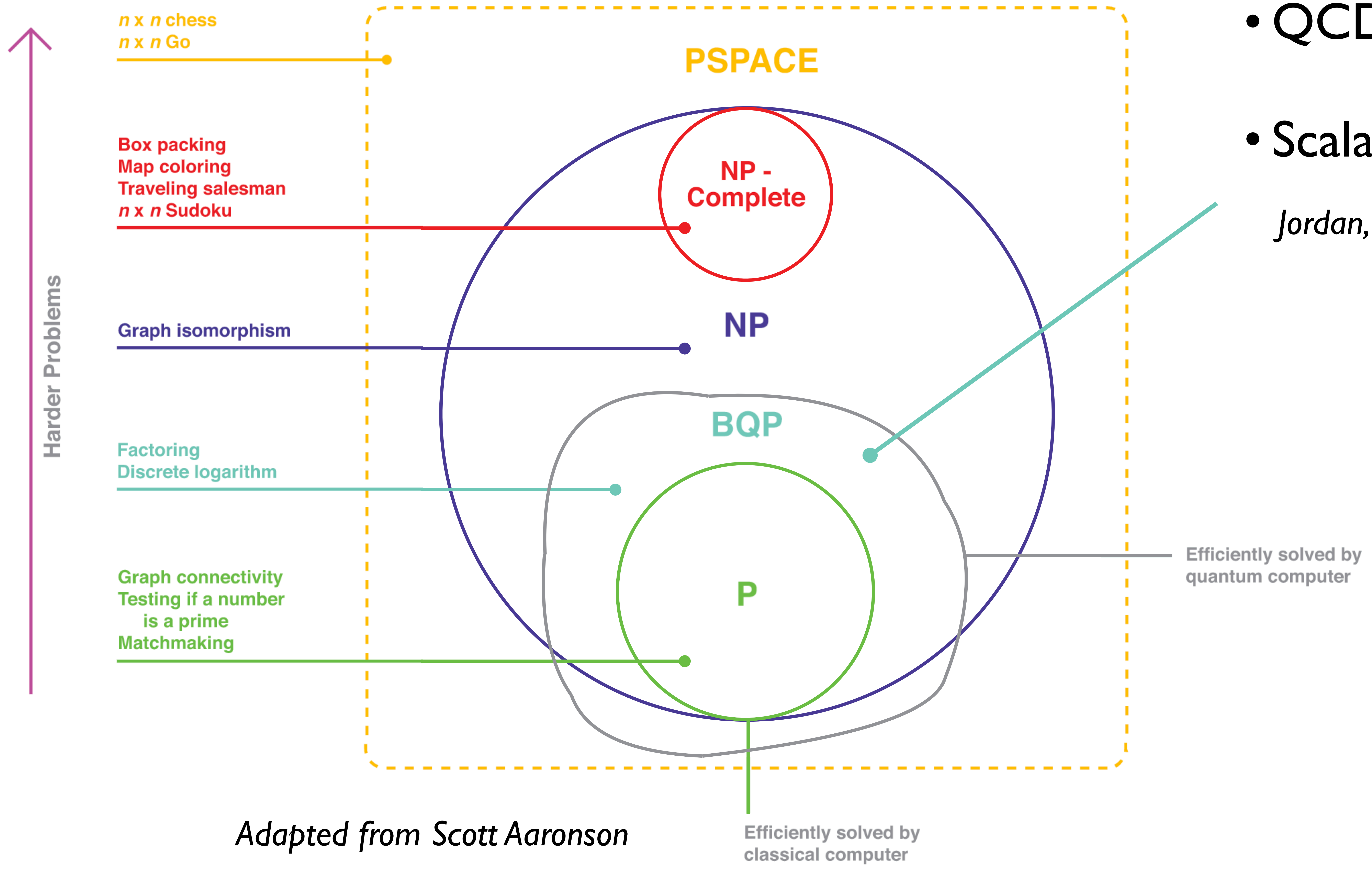
  Deterministic & probabilistic

- NP - can check solution in polynomial time

- BQP - can solve in polynomial time with a quantum computer

- e.g. Factoring is in BQP
  Shor's algorithm

Computational complexity



Adapted from Scott Aaronson

- QCD/Standard Model?
- Scalar field theory

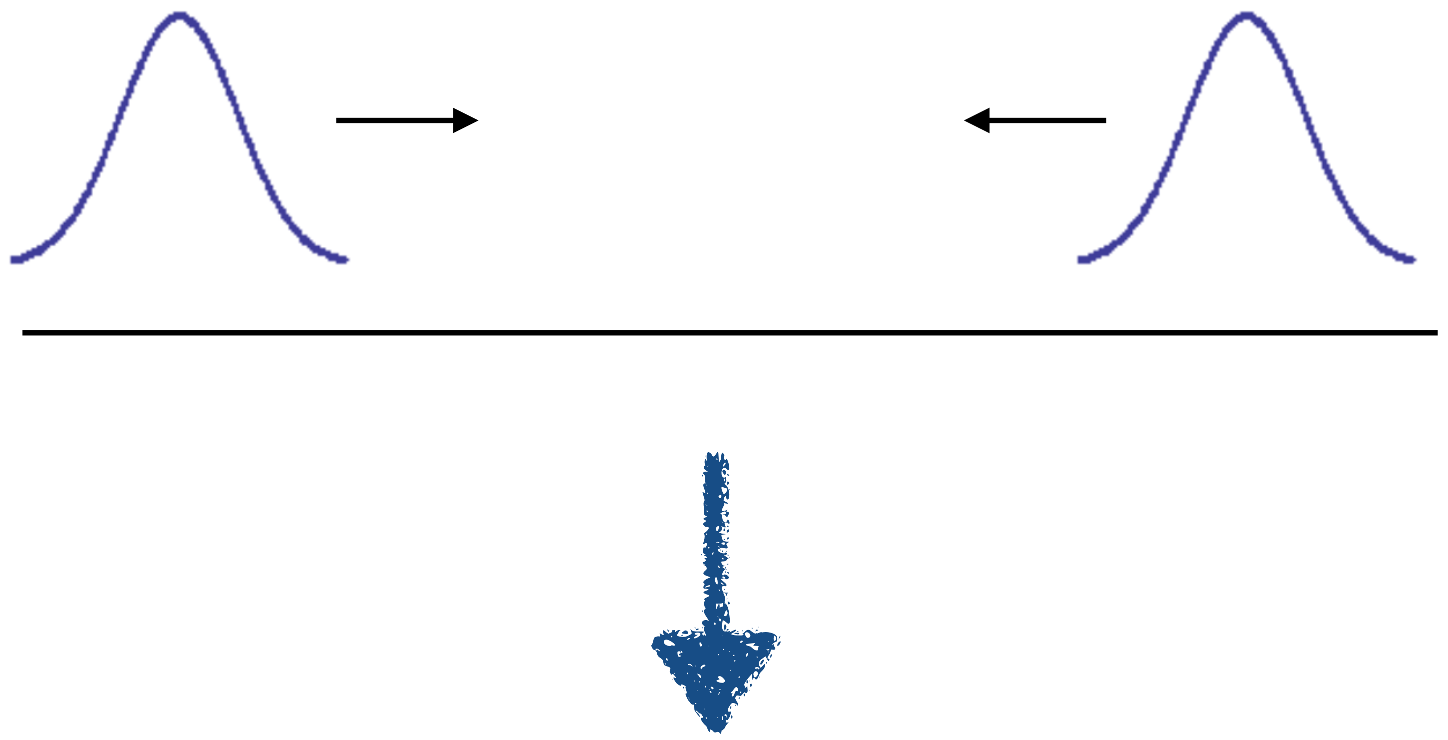
Jordan, Lee, Preskill `10-`17

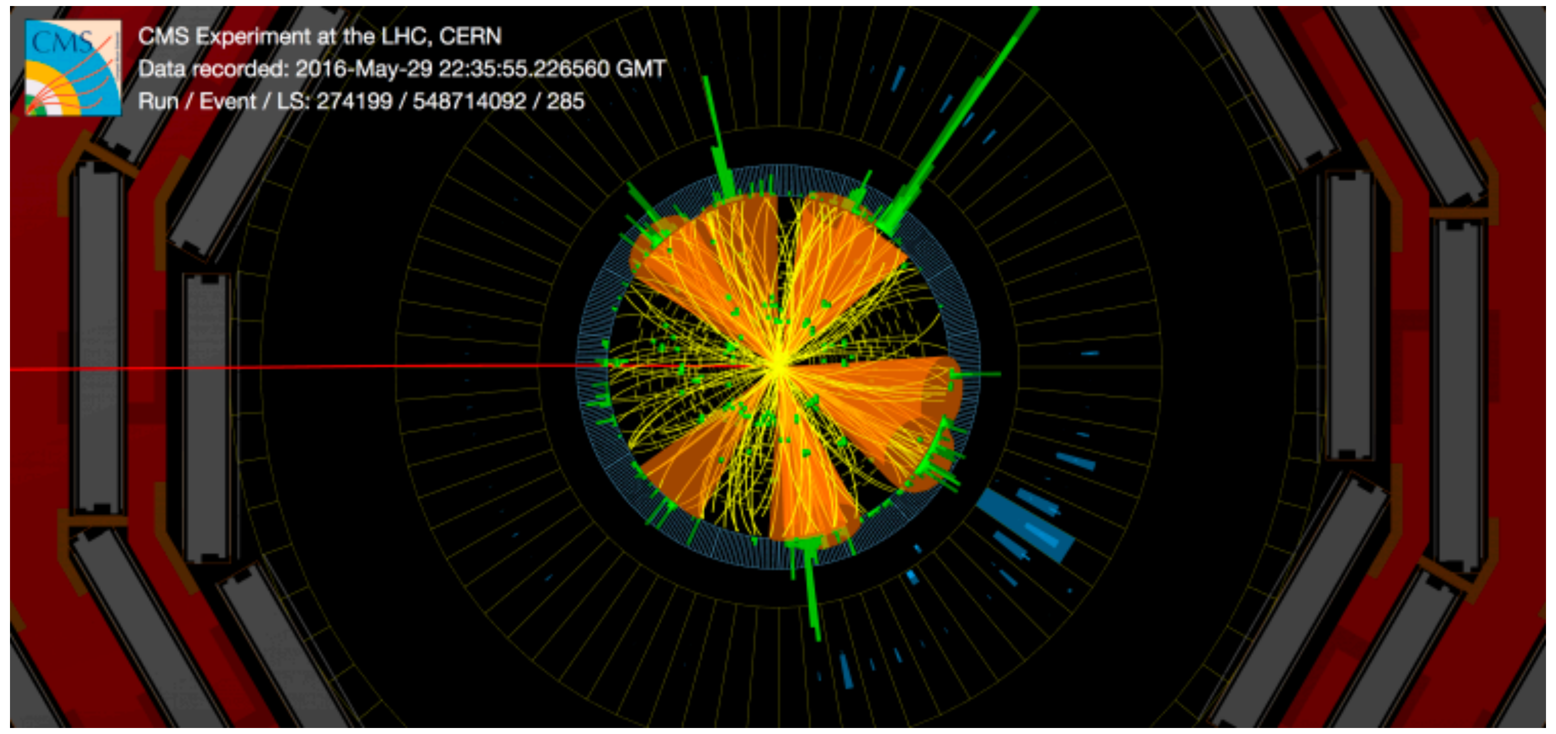
Hamiltonian formulation of field theories

Simulation protocol

Kogut, Susskind `70s, Jordan, Lee, Preskill `11-`17

1. Digitize the field theory on a spatial lattice
2. Prepare wave packets of the free field theory
3. Turn on interactions adiabatically
4. Unitary time evolution
5. After the scattering turn interactions off adiabatically
6. Perform measurement



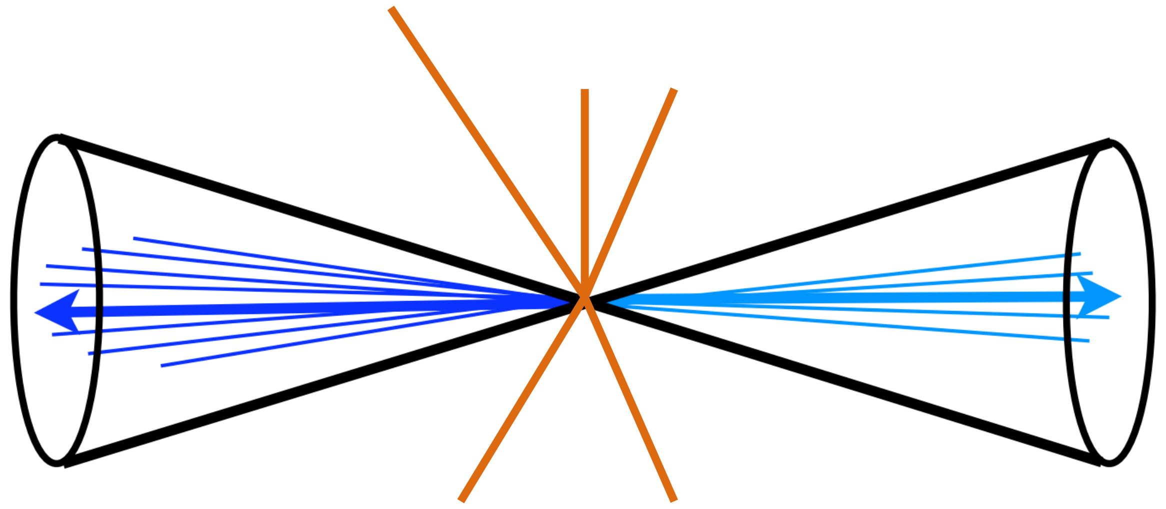


→ Scalar field theory is in BQP but at high energies significant resources are required

Applications in Soft Collinear Effective Theory

Bauer, Freytsis, Nachman `21

- Factorization of jet cross sections
- Hard, jet and soft functions
- Exclusive n-jets



$$\sigma = H \otimes J_1 \otimes \cdots \otimes J_n \otimes S$$

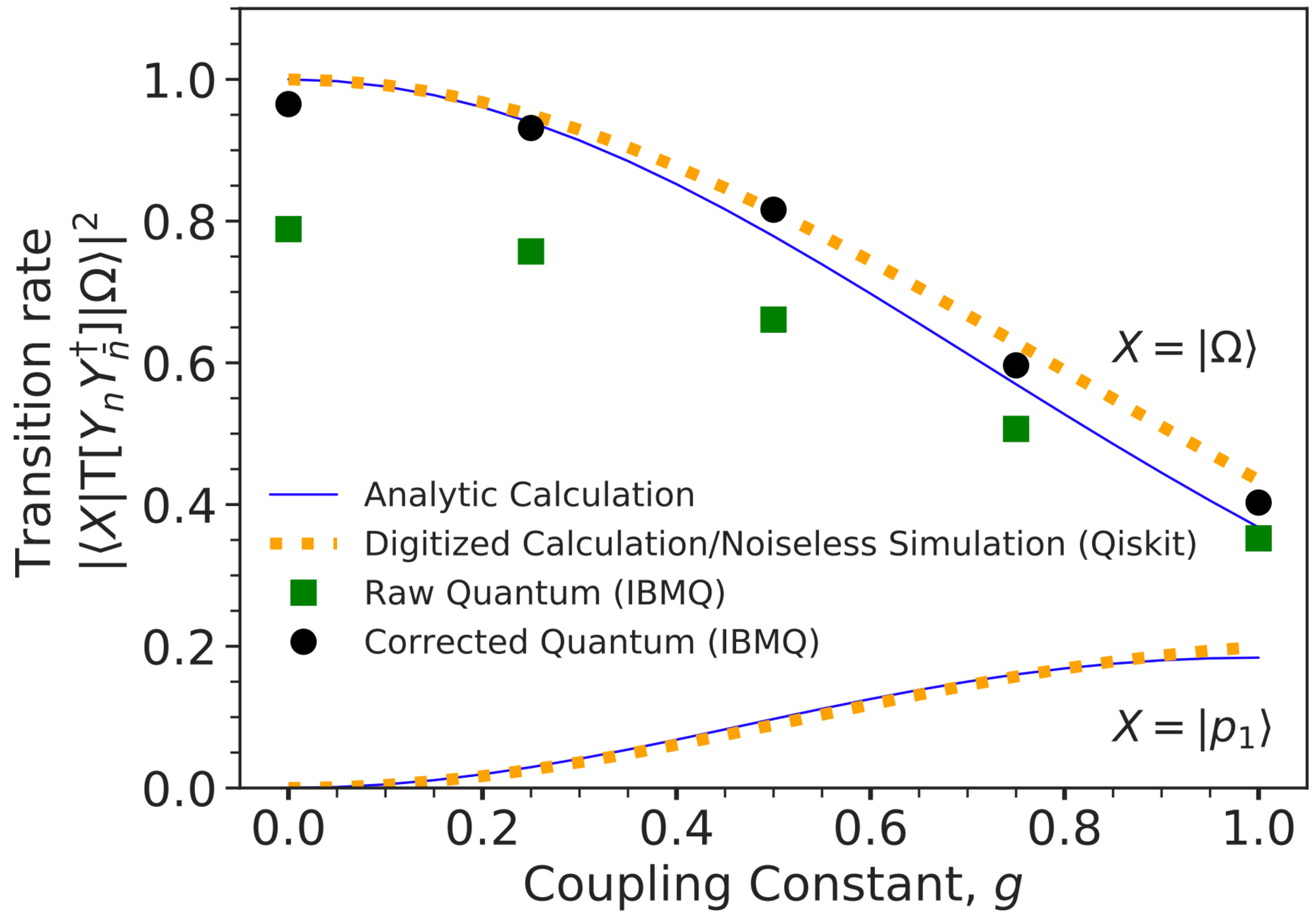
IBM **Q**

- Soft sector matrix element

$$\langle X | \mathrm{T}[Y_n \, Y_{\bar{n}}^\dagger] | \Omega \rangle$$

- Simulation with (scalar field theory) Wilson lines

$$Y_n = \mathrm{P} \exp \left[ig \int_0^\infty \mathrm{d}s \; \phi(x^\mu = n^\mu s) \right]$$



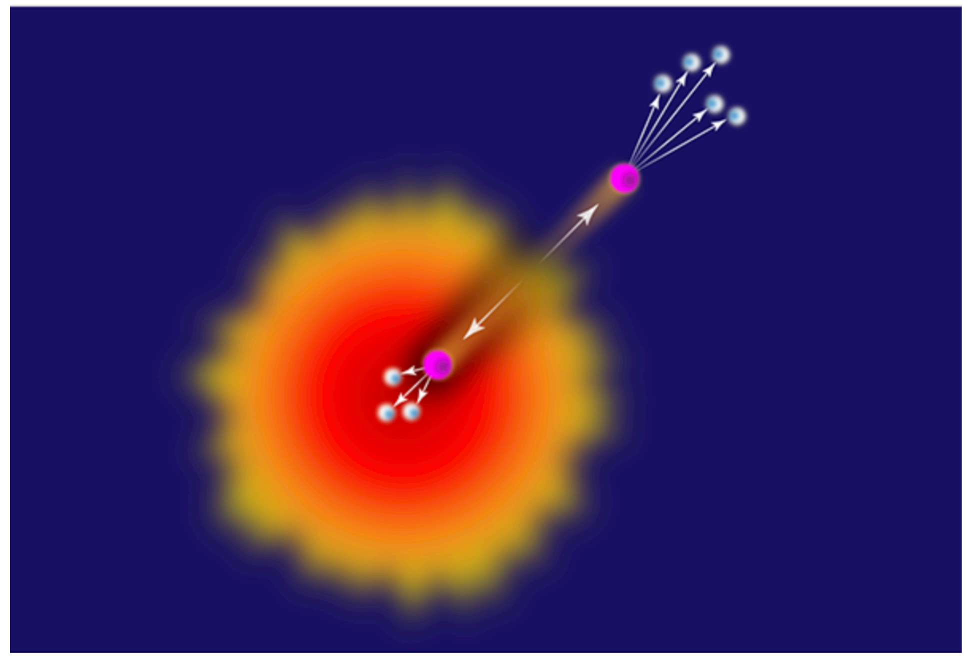
Open quantum systems

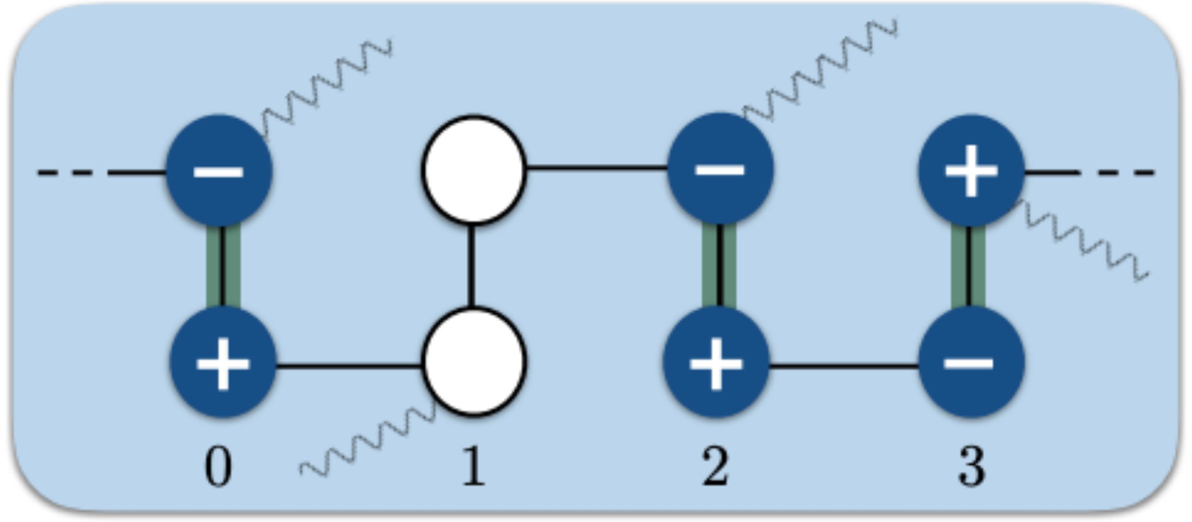
de Jong, Lee, Mulligan, Ploskon, FR, Yao `21

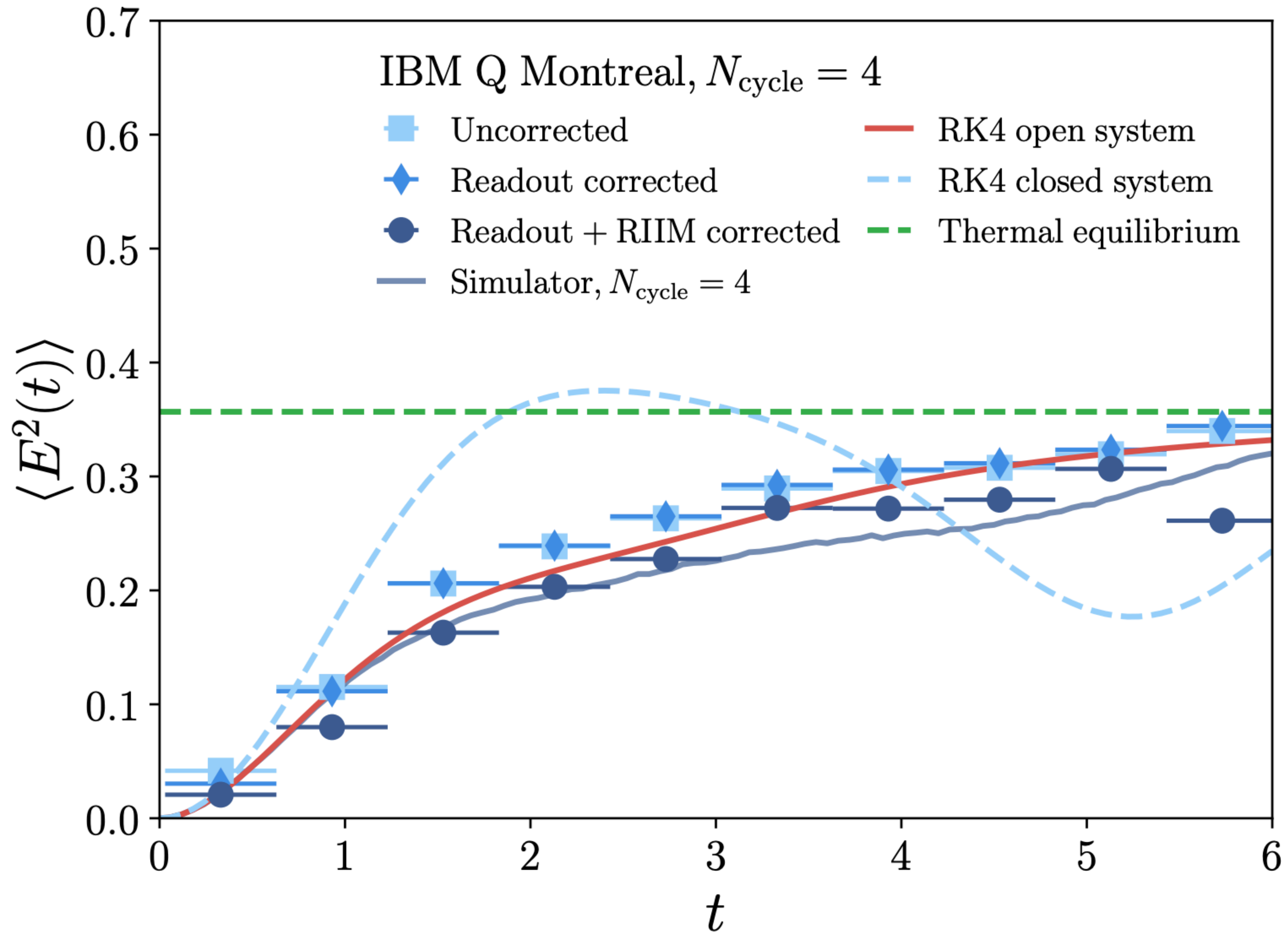
- Thermalization and non-equilibrium dynamics
- Nuclear medium modification
- Non-global resummation

IBM Q

- Schwinger model coupled to a thermal scalar field theory
- Non-unitary Lindblad evolution







See yesterday's round-table discussion

see also Klco, Savage et al. `18,
Akamatsu, Rothkopf et al., Brambilla, Escobedo, Vairo et al., Yao, Vaidya, Mehen et al.

Quantum algorithms for transport coefficients

Cohen, Lamm, Lawrence, Yamauchi `21

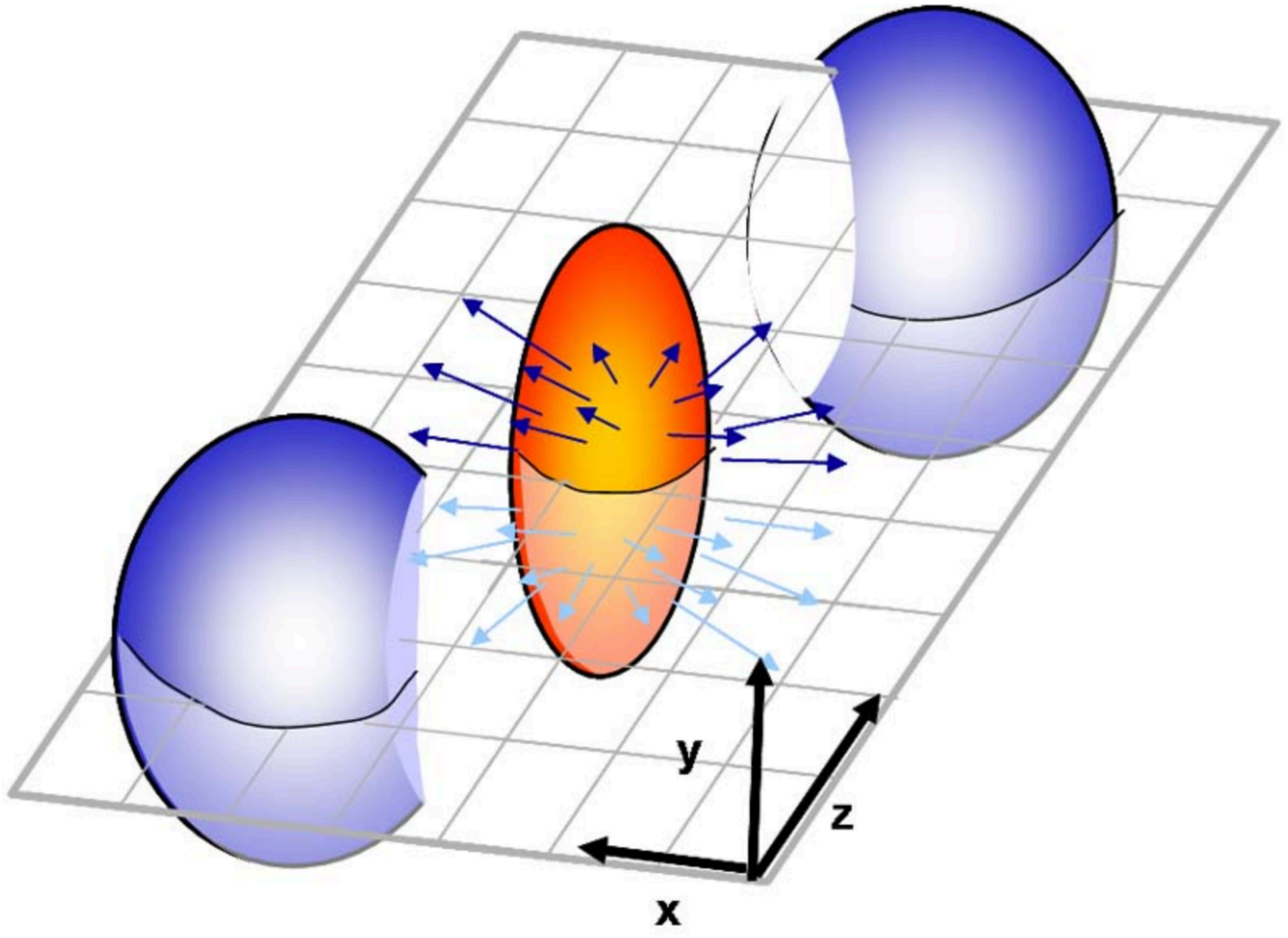
- Hydrodynamic flow of the quark-gluon plasma in heavy-ion collisions
- Non-perturbative input e.g. viscosity
- Potential near-term application

$\sim 10^4$ qubits for pure glue $3+1\mathrm{d}\ \ \mathrm{SU}(3)$

$\sim 10^2$ qubits for $2+1\mathrm{d}\ \ \mathbb{Z}_N$

- Energy-momentum tensor in the Hamiltonian formulation

$$T_{\mu\nu} = \frac{1}{4} g_{\mu\nu} \mathrm{Tr}\left[F_{\alpha\beta}F^{\alpha\beta}\right] - \mathrm{Tr}\left[F_{\mu\alpha}F^{\alpha}_{\nu}\right]$$

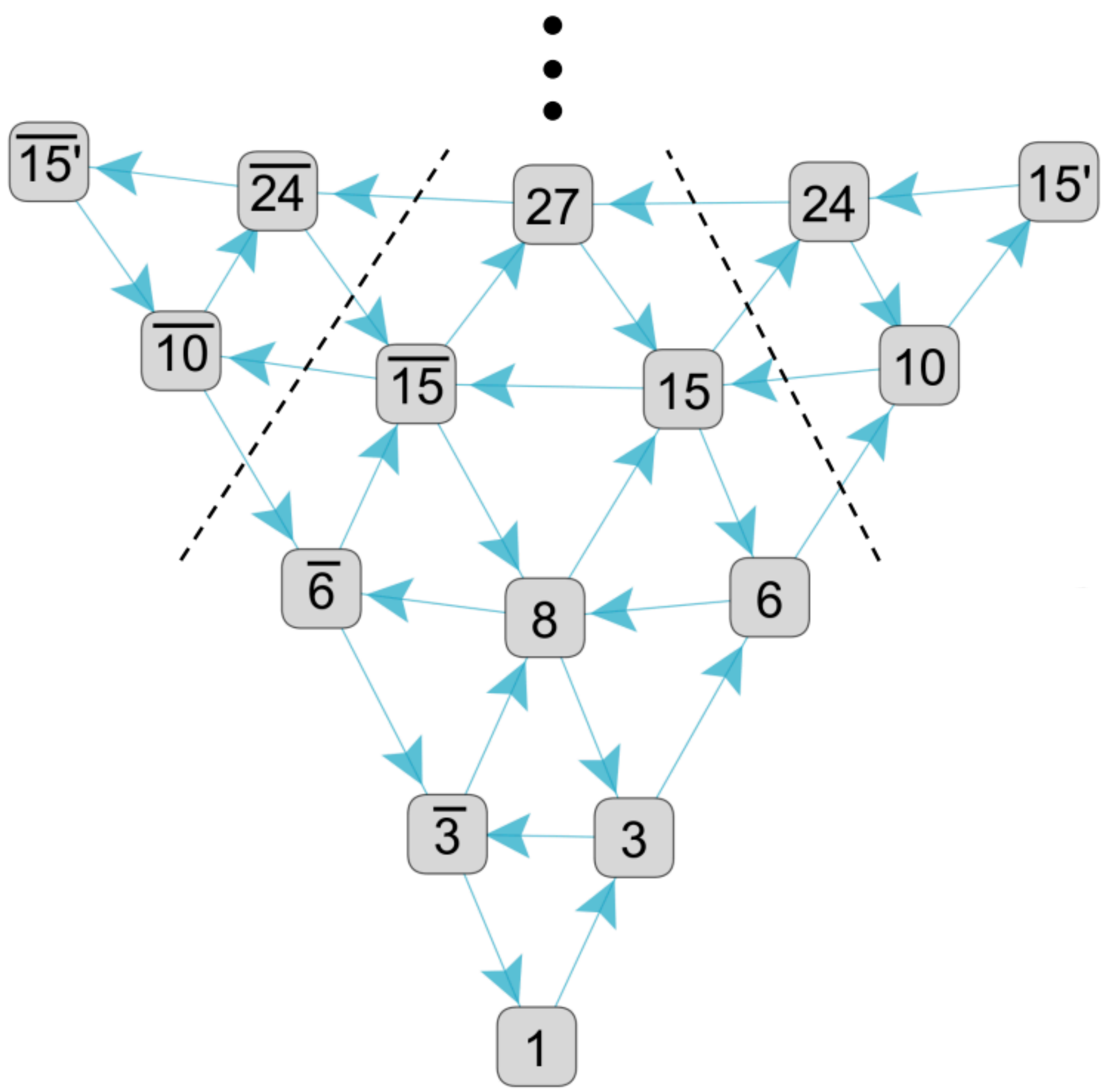


see also Barata, Salgado `21

Trailhead for SU(3)

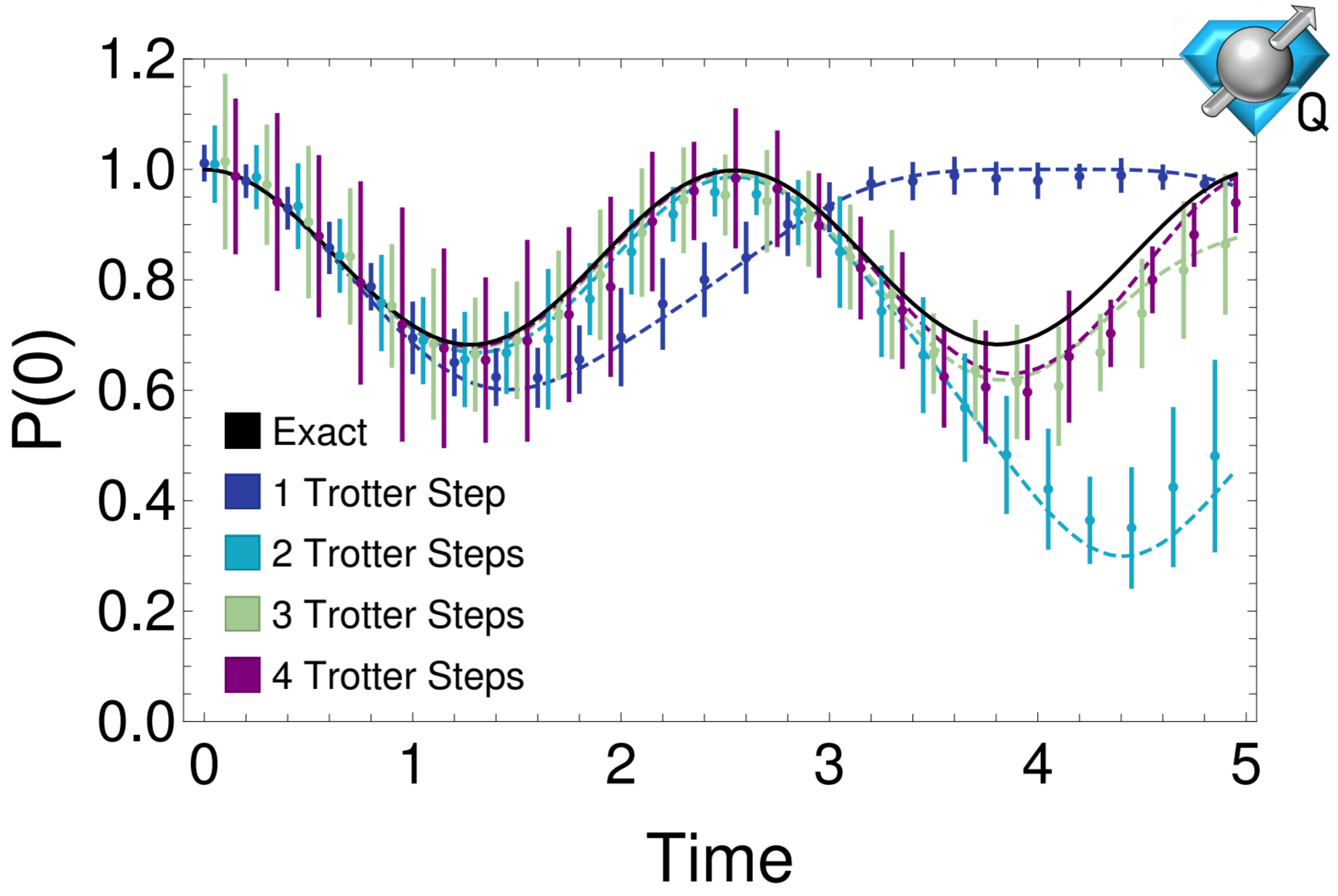
Ciavarella, Klco, Savage `21

- Quantum simulation of SU(3) Yang-Mills
- 1 and 2 plaquettes in the local multiplet basis



- Vacuum-to-vacuum persistence probability $|\langle 00|\,\hat{U}(t)\,|00\rangle|^2$

- Up to 4 Trotter steps



IBM **Q**

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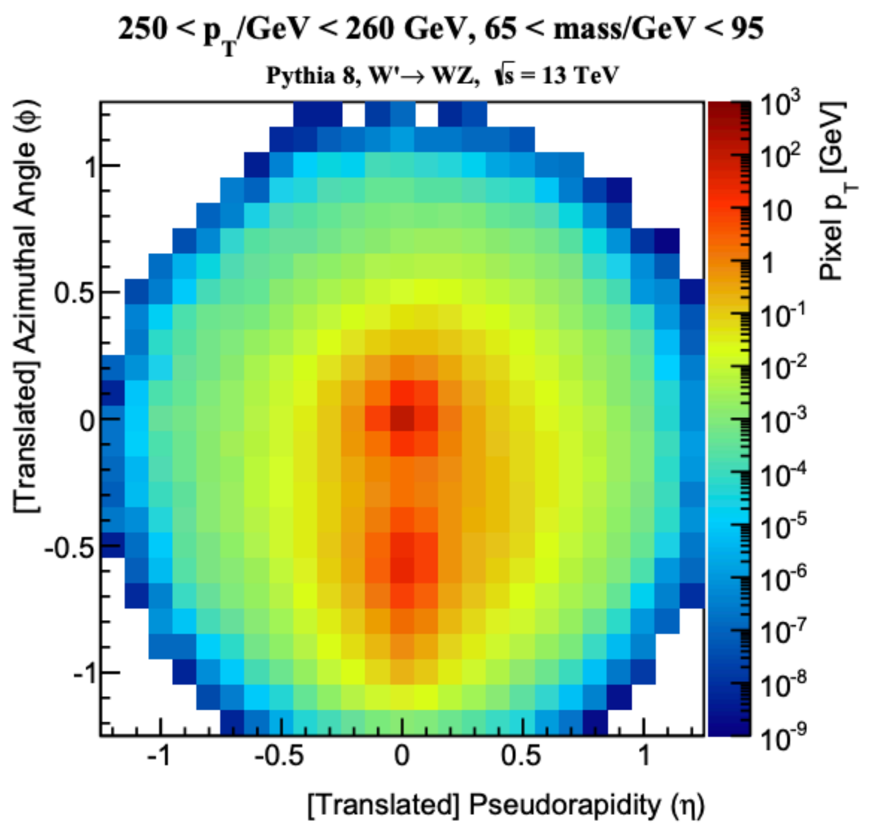
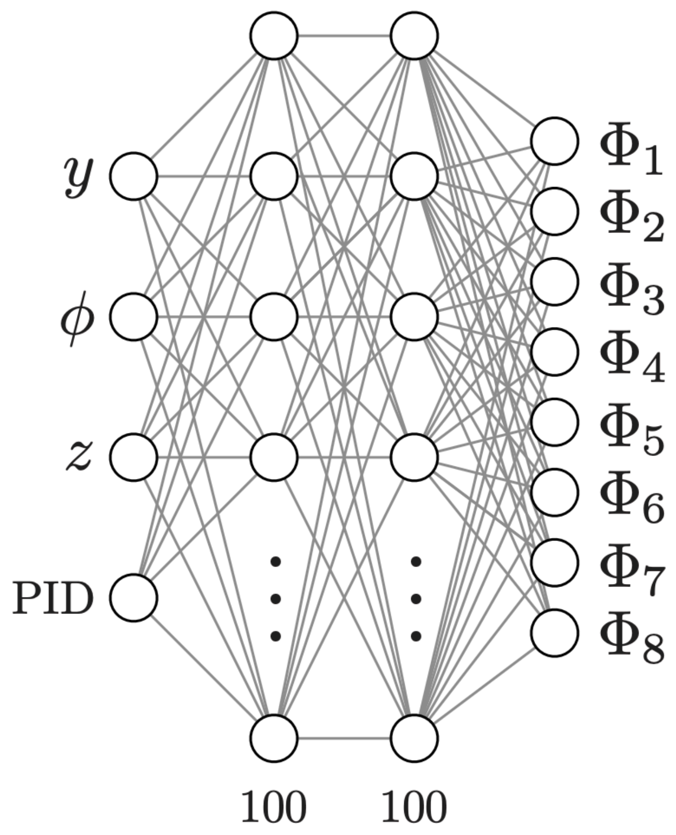
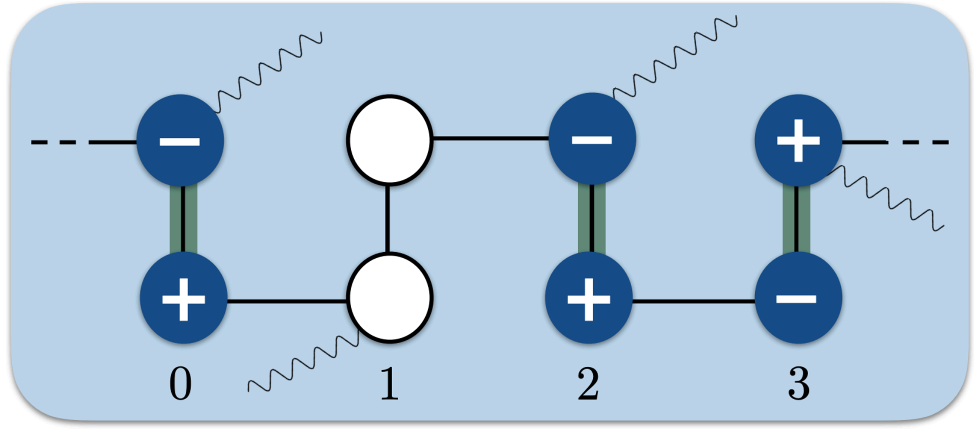
Conclusions



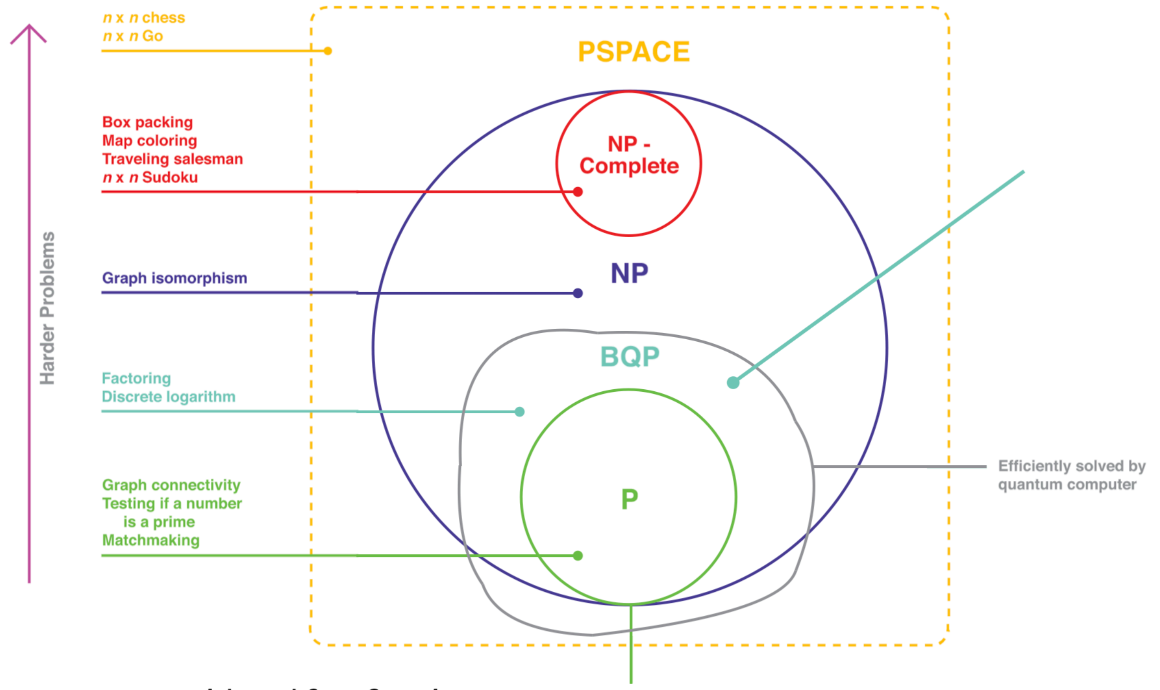
- Various machine learning applications for fundamental physics
- Unsupervised learning for searches of BSM physics
- Learning the underlying physics



- Quantum simulations of real-time dynamics of field theories
- Proposals of near-term applications
- Many interesting things to learn along the way



- Quantum machine learning



Adapted from Scott Aaronson