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U.S. DEPARTMENT OF ENERGY

UNIVERSITY OF CALIFORNIA

Survey: Status of A.I. in Experimental Analysis

Yue Shi Lai

Nuclear Science Division

Thanks to: Wahid Bhimji, Eric Church, Mario Cromaz, Jacob Daughhetee, Markus Diefenthaler, Andrey Elagin, Cristiano Fanelli, Gian Michele Innocenti, Gaosong Li, Kate Scholberg, Nu Xu, Liang Yang

Disclaimer

- Both A.I. and NP are highly diverse fields
- The materials I will cover is largely limited to what I have received as response
- I will only briefly mention edge-cases such as Bayesian optimization

Overview, Terminology

Artificial Intelligence (A.I.), Andrew Moore 2017:

“Artificial intelligence is the science and engineering of making computers behave in ways that, until recently, we thought required human intelligence.”

Forbes, “Carnegie Mellon Dean Of Computer Science On The Future Of AI” (2017)
https://www.forbes.com/sites/peterhigh/2017/10/30/carnegie-mellon-dean-of-computer-science-on-the-future-of-ai/

Machine learning (ML), Arthur Samuel 1959:

“Programming computers to learn from experience should eventually eliminate the need for much of this detailed programming effort.”

A. Samuel, IBM J. Res. Dev. 3(3), 210–229 (1959)

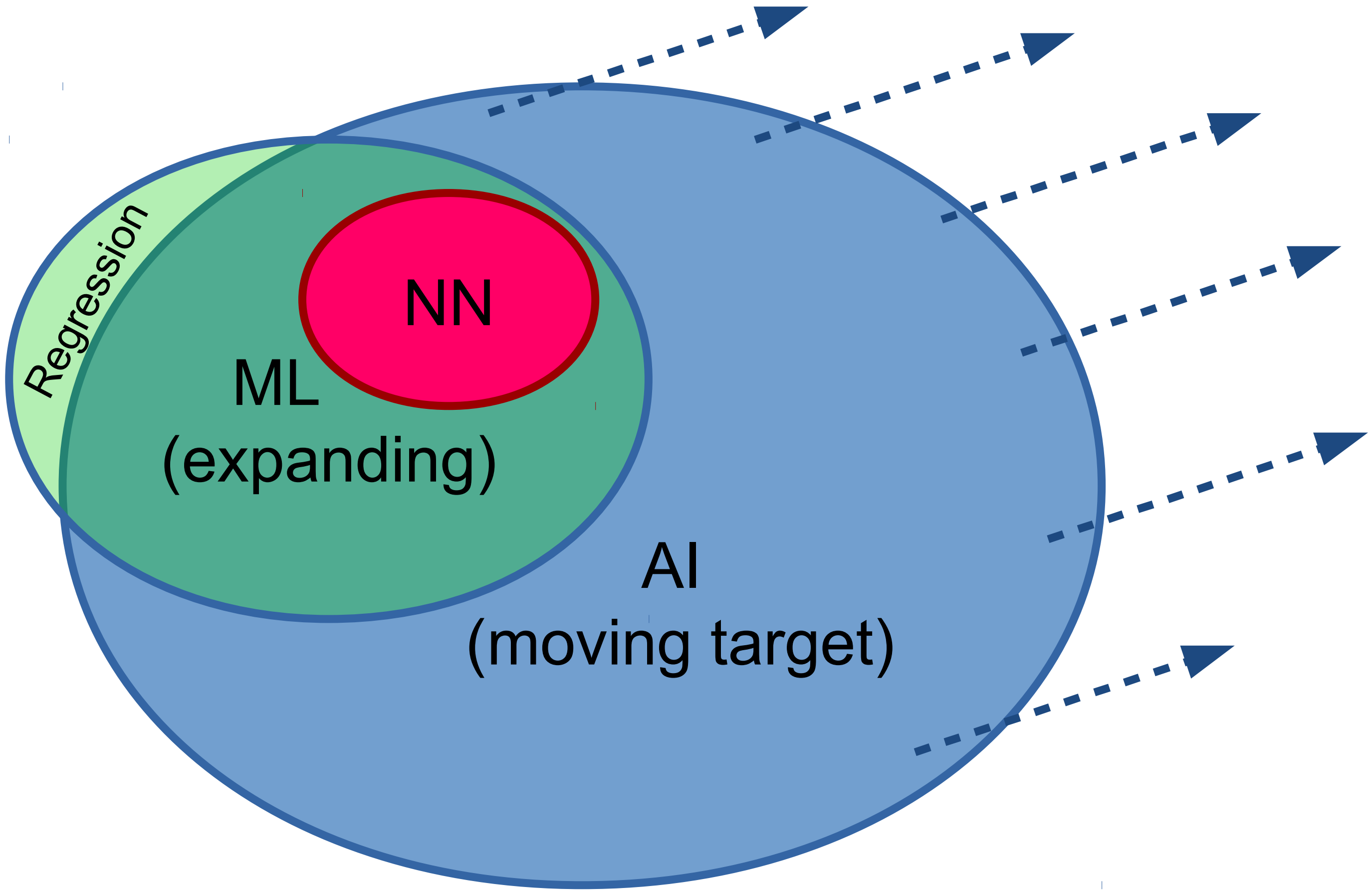
(Artificial) neural network [(A)NN], Warren McCulloch, Walter Pitts 1943 (many thereafter):

Computation model loosely modeled after the biological axon-synapse-dendrite connections

Why is it useful?

- Eliminates the need for human programming
- Outperforms programming with structured human knowledge (“symbolic AI”)

A.I. vs. ML vs. NN



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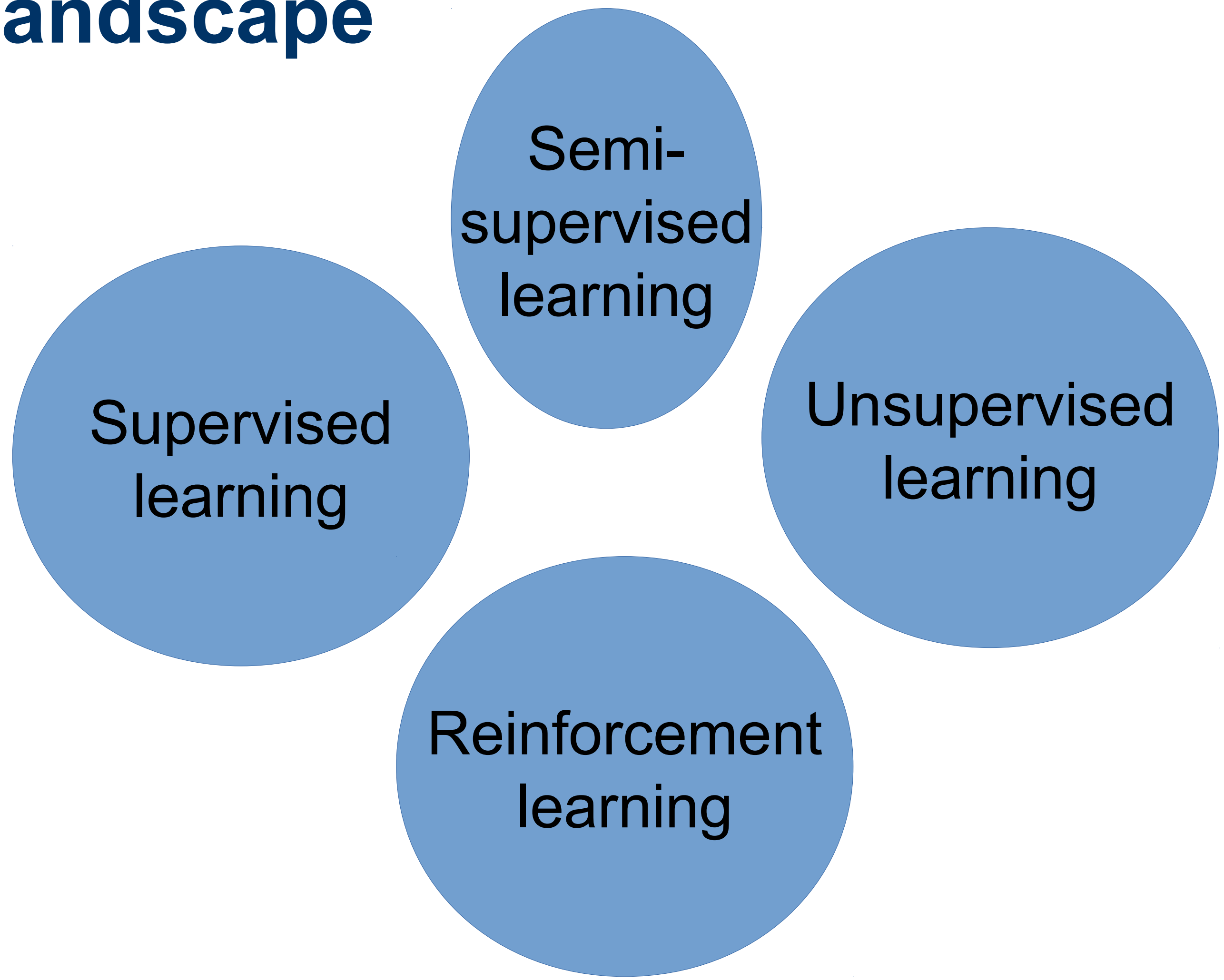
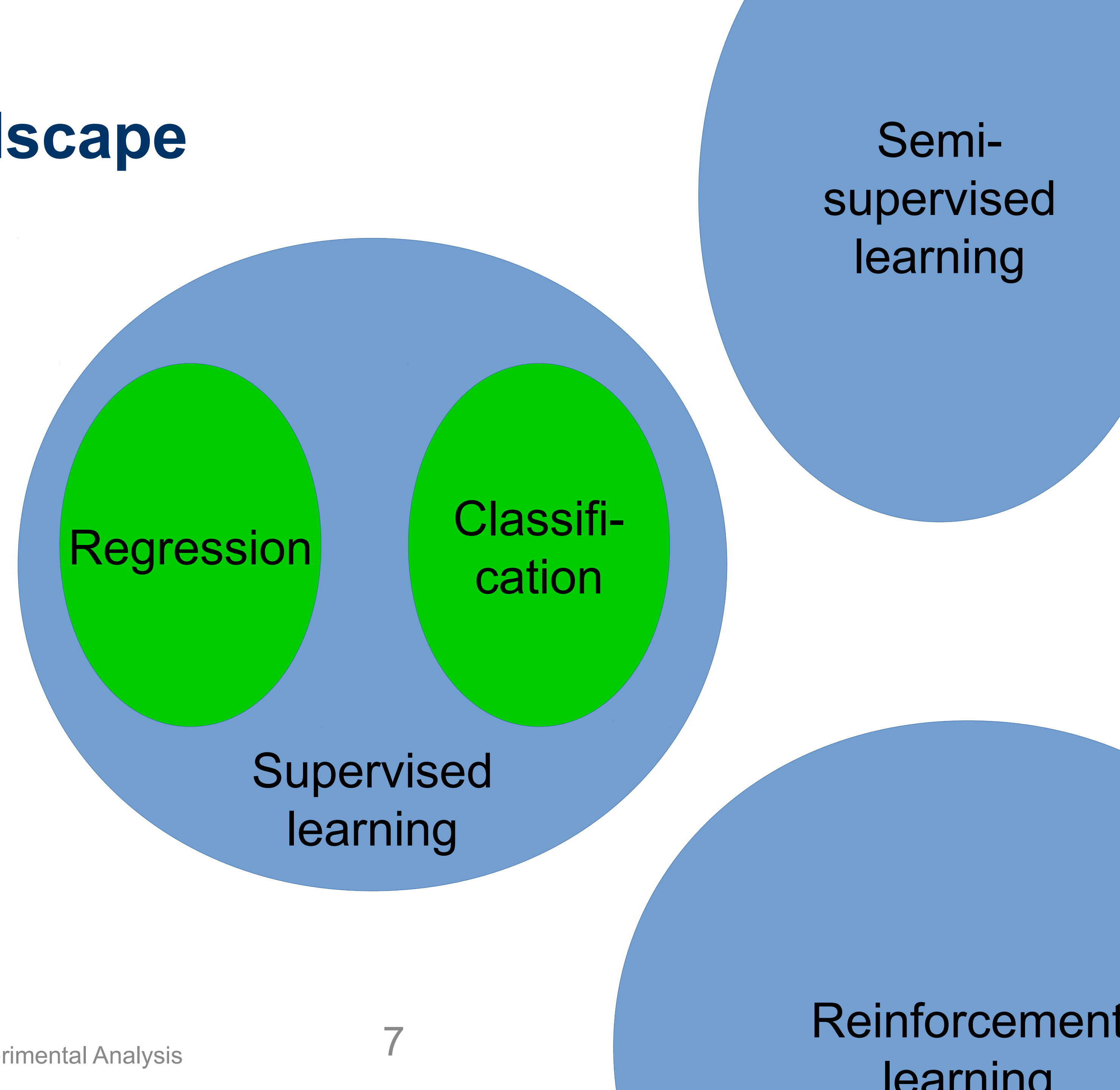
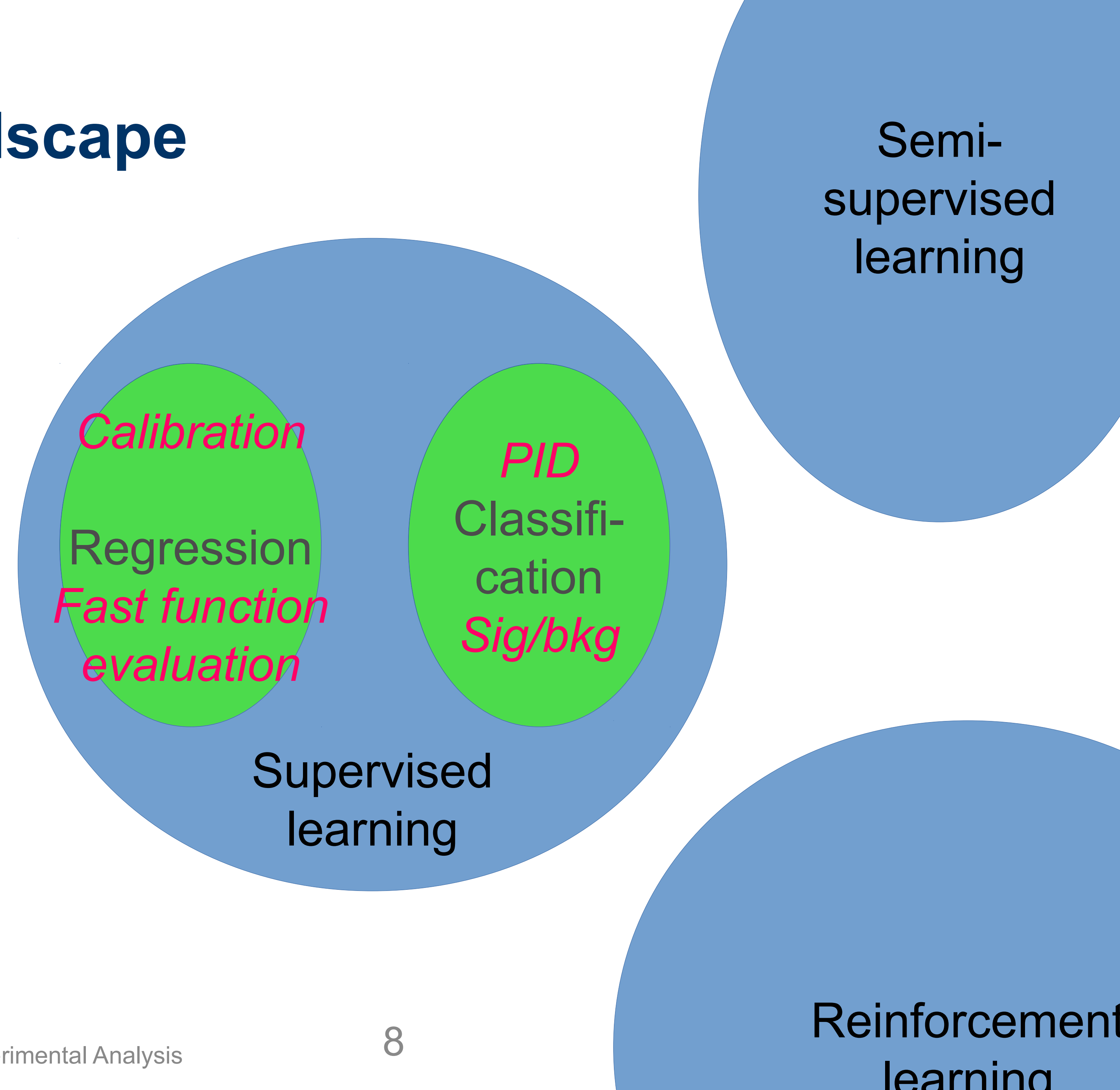
AI landscape



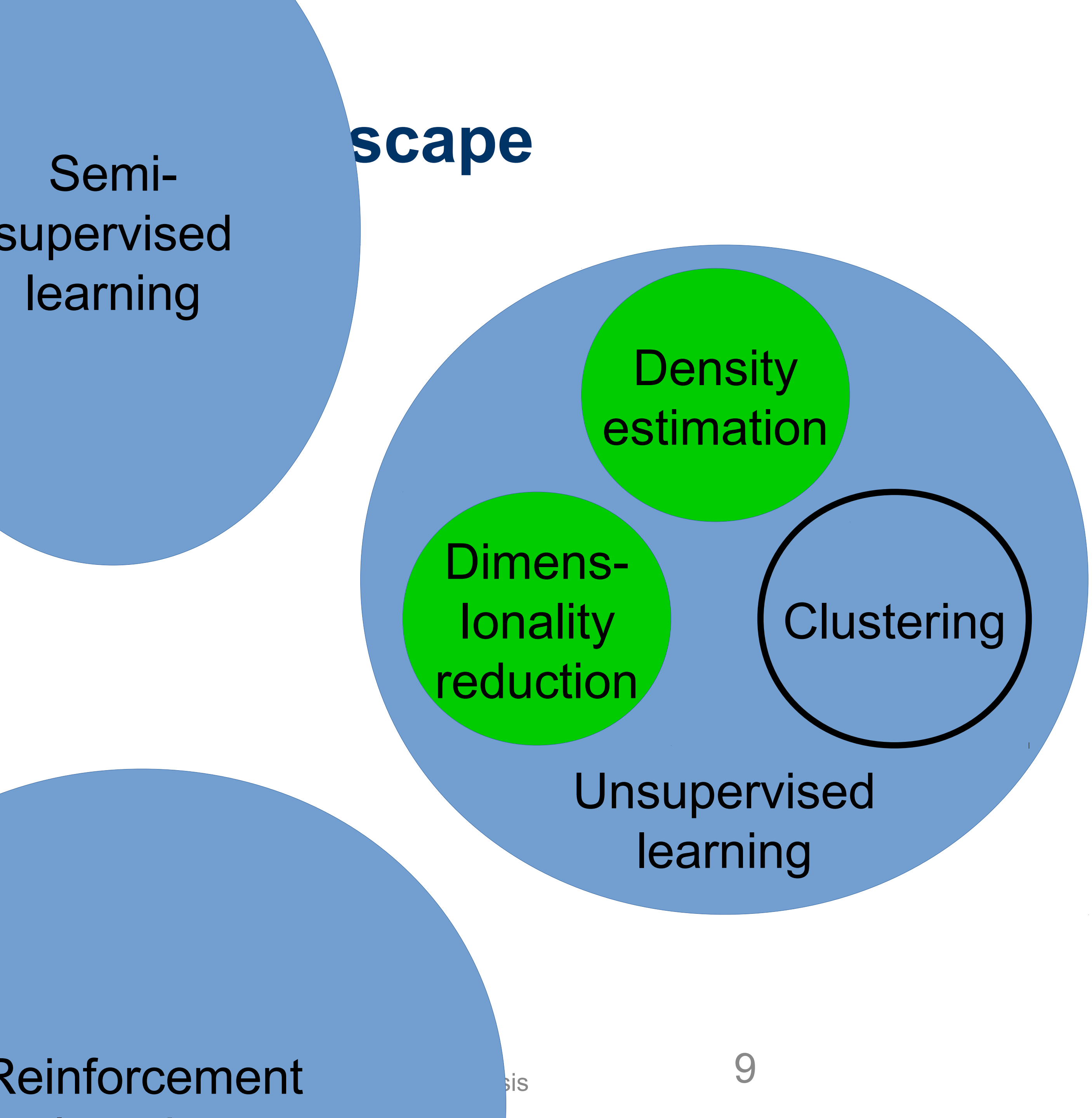
AI landscape



AI landscape



scape


Semi-
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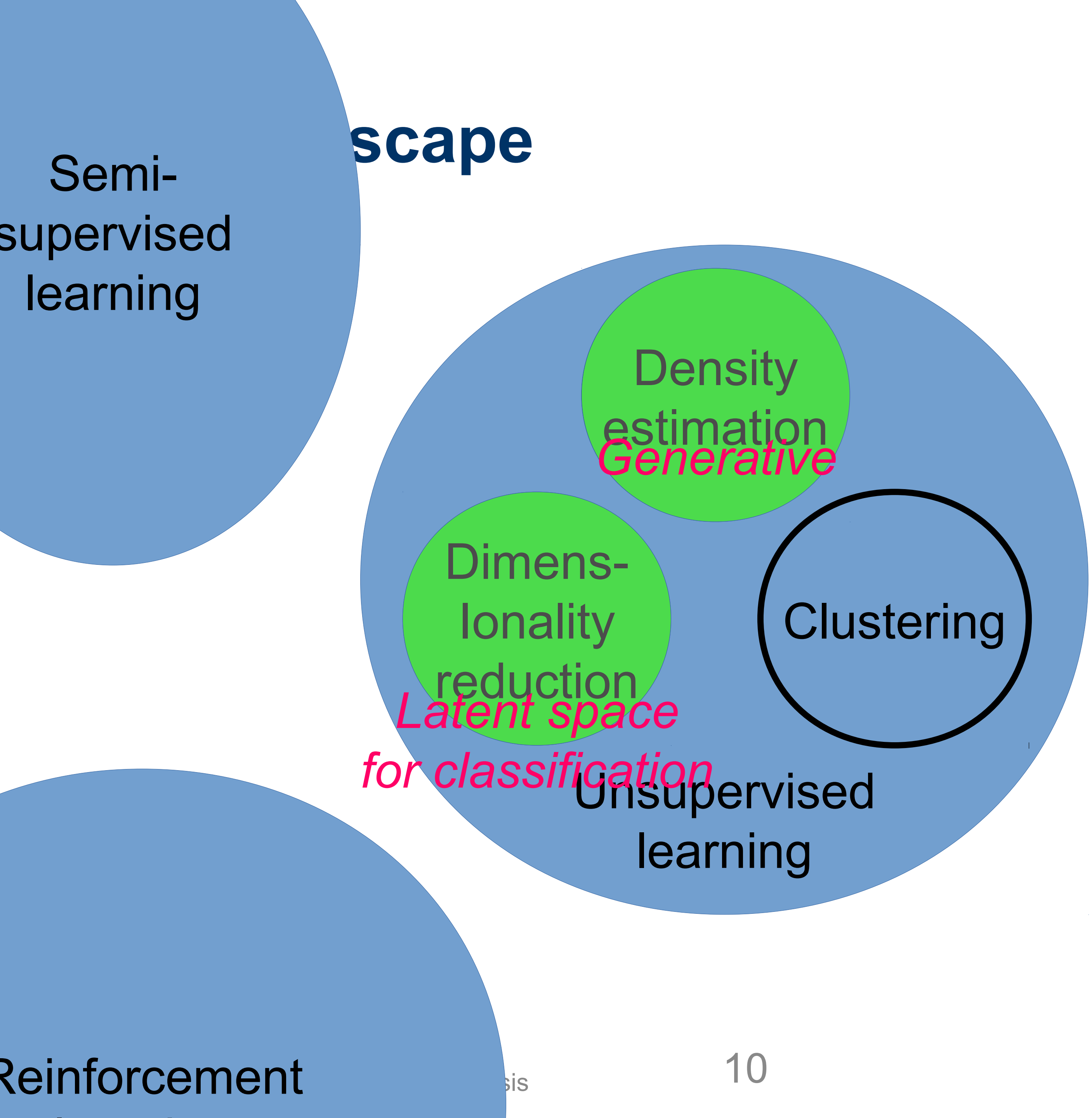
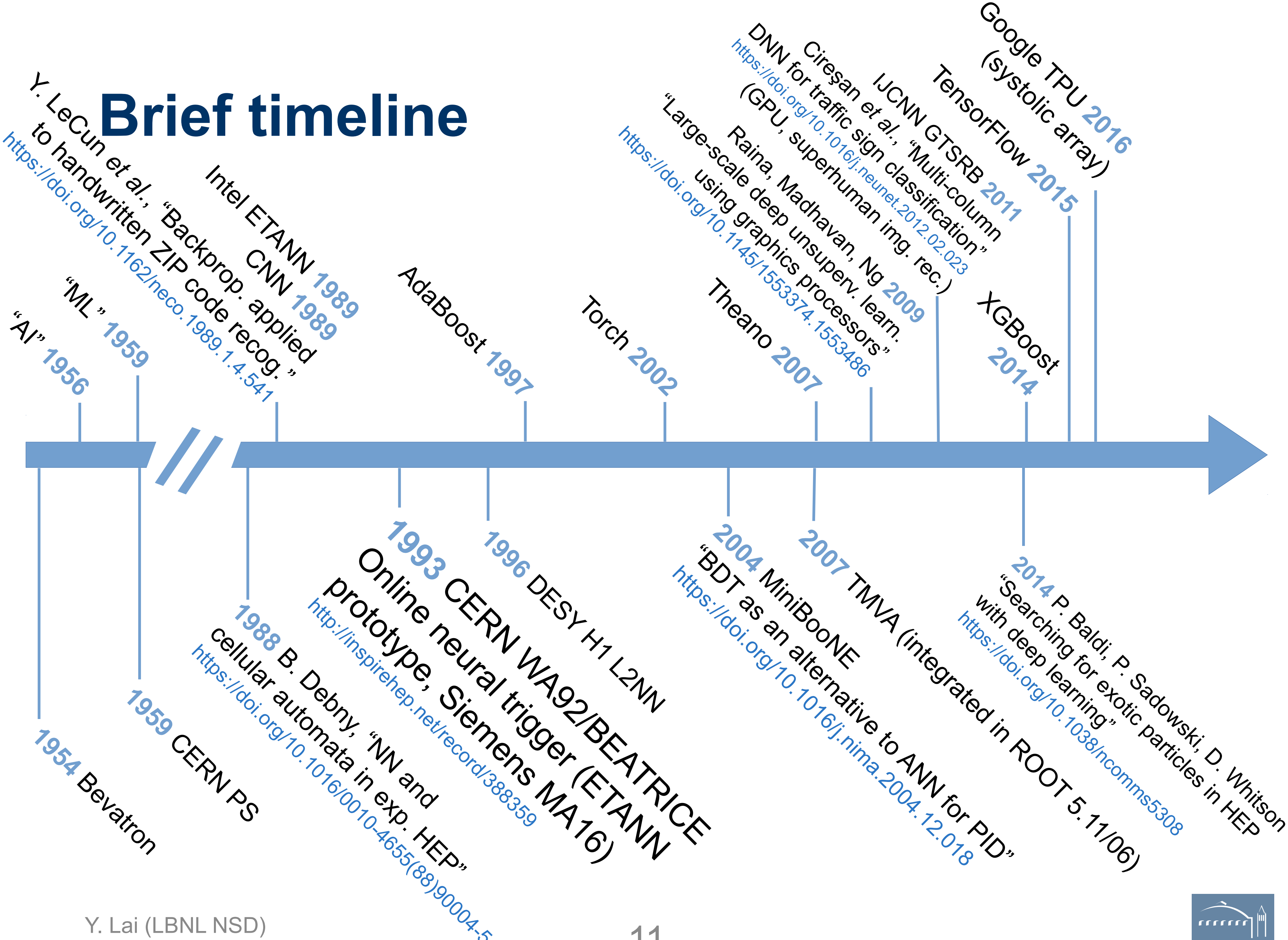
learning
Density
estimation
Dimens-
Ionality
reduction
Clustering
Unsupervised
learning
Reinforcement

scape



Semi-
supervised
learning
Density
estimation
Generative
Dimens-
Ionality
reduction
Latent space
for classification
Clustering
Unsupervised
learning
Reinforcement

Brief timeline



Use of AI in NP analyses

Exp → ↓ Method	Heavy-ion ALICE, STAR, EIC, LBNL ALICE (+LEP) LDRD	$0\nu\beta\beta$/neutrinos EXO, NEXT, DUNE/THEIA	Photoproduction GlueX	γ-ray tracking GRETA
Calib.	✔ (TPC, jets, kin.)		✔ (RICH)	
Multiv. Cut	✔ (HF)	✔ (PID)		
CNN (superv.)		✔ (PID)		
Graph convol.				✔ (tracking)
RNN		✔ (PID)		
Semi-sup.				
Generative	✔ (jets)			
Dimens. red.			✔ (PID)	

AI tools in NP analyses

NN

Keras/TensorFlow
PyTorch
SparseConvNet
Scikit-Learn

BDT

TMVA
XGBoost

Infrastructure

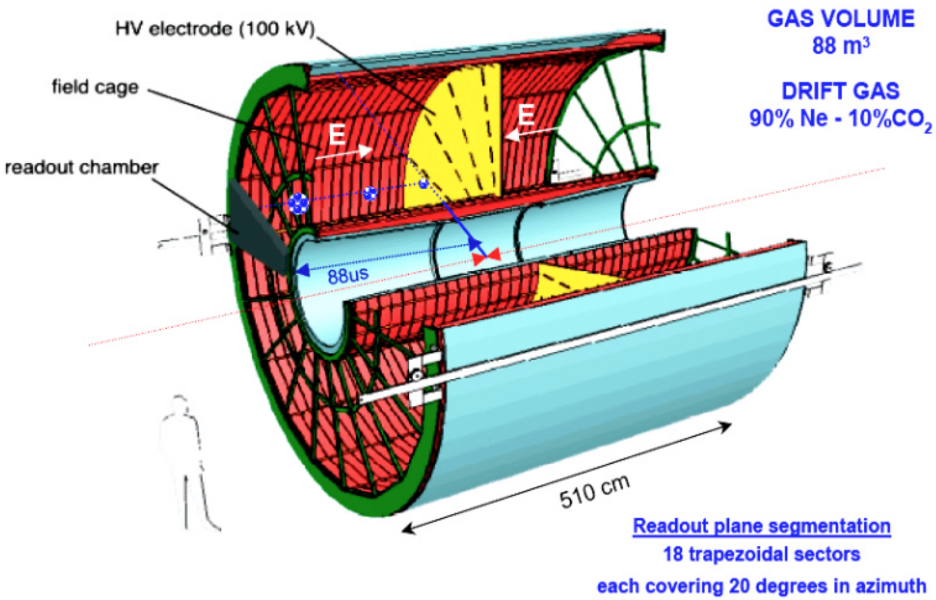
Horovod

Supervised: Calibration

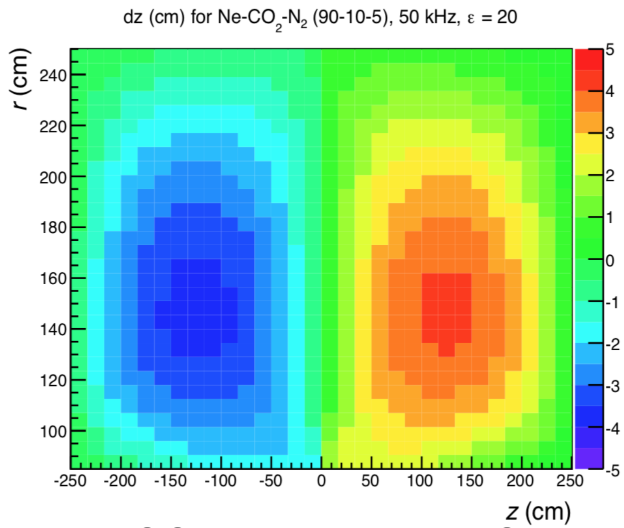
ALICE, TPC charge distortion

Large distortions are expected in LHC Run-3 due to the presence of a intense flux of ions produced un-ionization processes:

- very slow ion drift speed (~0.16s compared to ~92μs for electrons)
- not uniform electric fields cause deviations from the expected field lines



distortion along the z axis



CERN-LHCC-2013-020 / ALICE-TDR-016

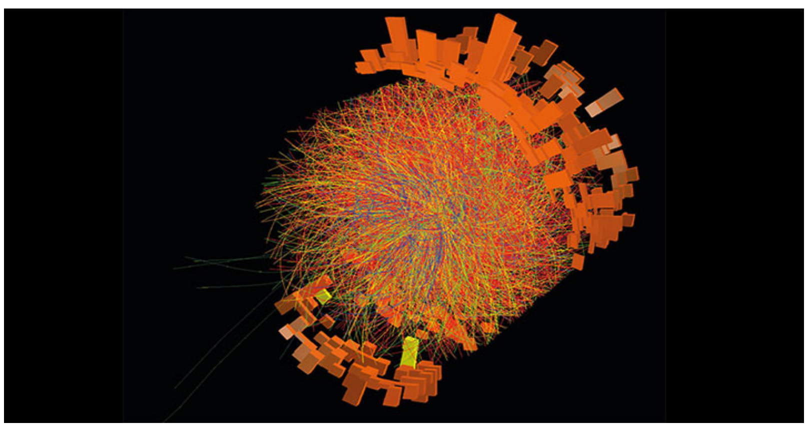
Deep neural network algorithms being studied to perform **fast calculation** of the distortion maps based on the expected digital current measured by TPC readout

Supervised: Calibration

Subtraction of underlying-event energy for jets at low p_T very challenging in heavy-ion collisions:

- large region-to-region fluctuations

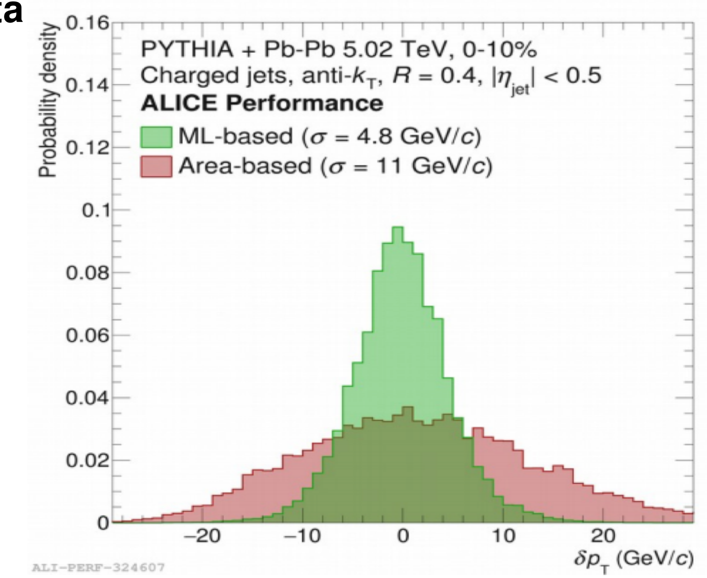
Traditional techniques: event-by-event subtraction of the average energy density + unfolding



ML techniques for jet-by-jet background subtraction:

- exploit the different properties of particles belonging to the event background and those belonging to the jet (jet constituents)
- Regression algorithms based on shallow neural networks, random forest and linear regression

→ **push jet measurements in heavy-ion down to lower momenta**



https://arxiv.org/pdf/1810.06324.pdf

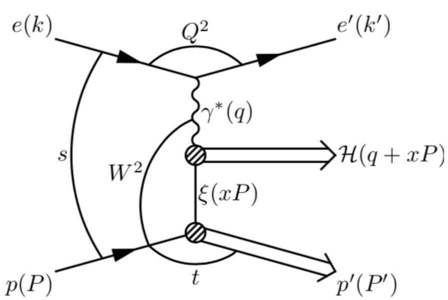
Rüdiger Haake, Constantin Loizides

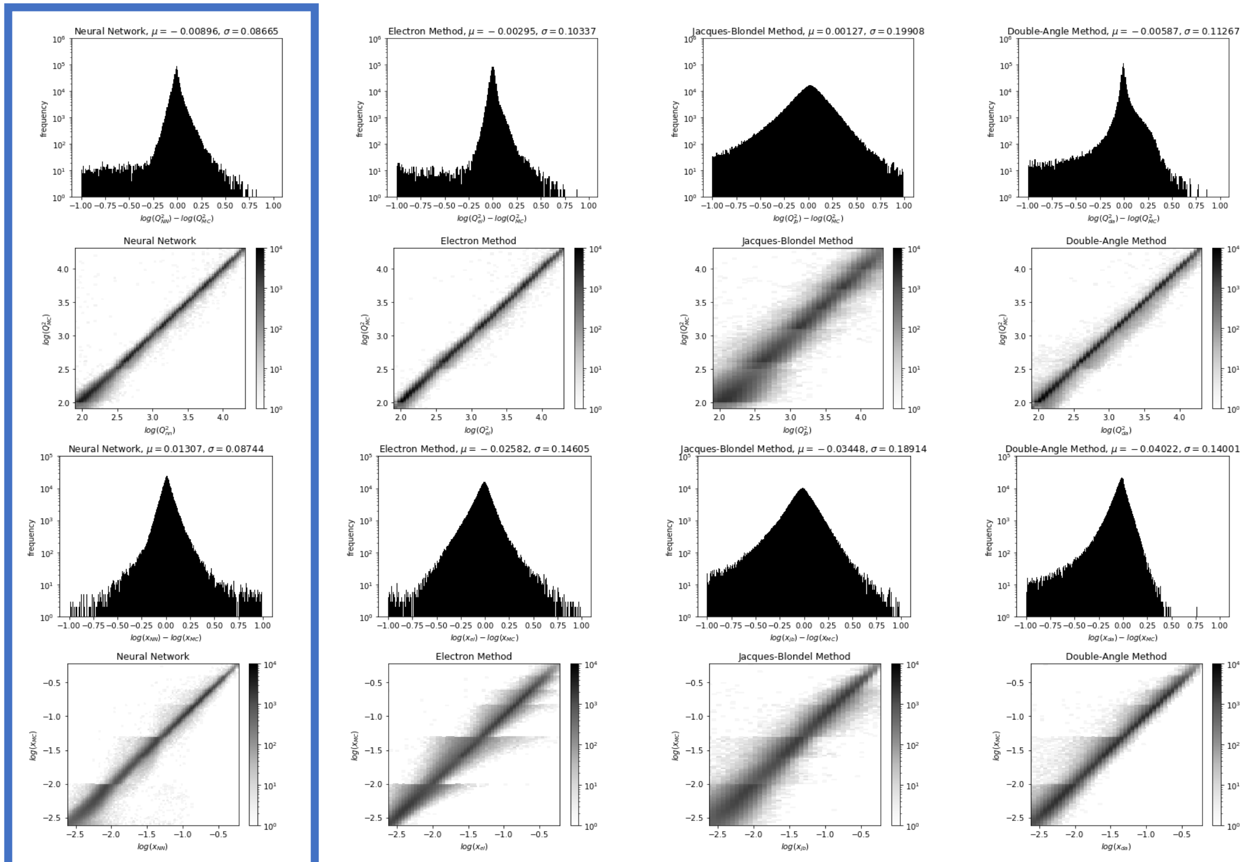
Supervised: Calibration

EIC

Use both electron and hadronic final state (overdetermined)

Optimally determine ep collision kinematics

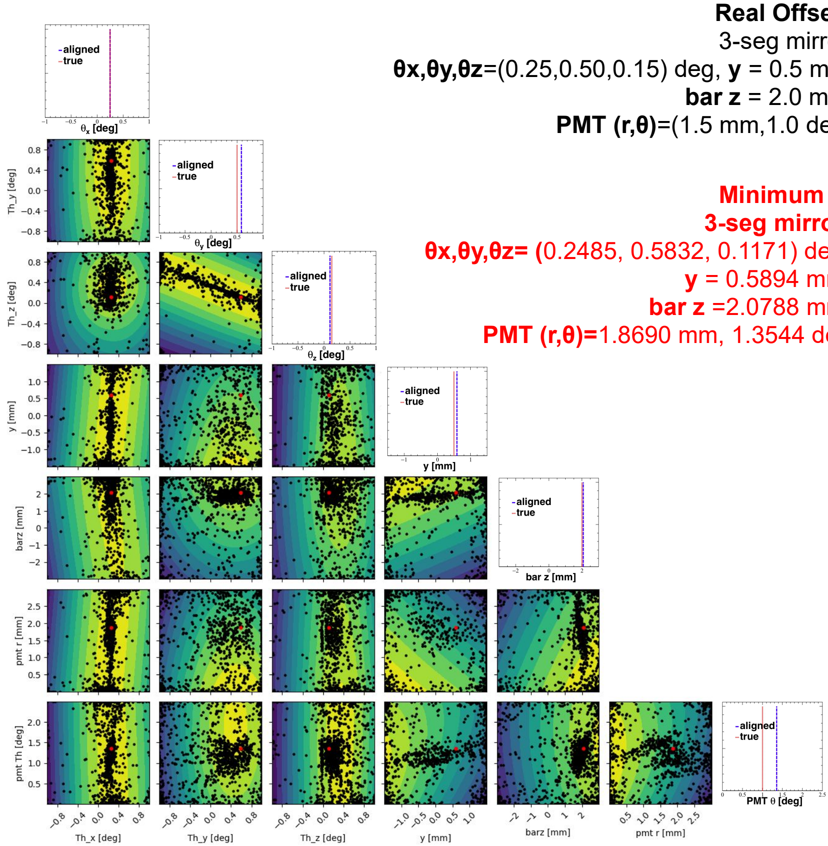




Abdullah Farhat, Yuesheng Xu (Department of Mathematics, Old Dominion University)
Markus Diefenthaler, Dmitry Romanov, Douglas Higinbotham (EIC Center, Jefferson Lab)
Andrii Verbytskyi (Max-Planck-Institut für Physik)

Bayesian optimization: Calibration

GlueX, Cristiano Fanelli



Real Offsets
3-seg mirror:
θx,θy,θz=(0.25,0.50,0.15) deg, **y** = 0.5 mm;
bar z = 2.0 mm;
PMT (r,θ)=(1.5 mm,1.0 deg)

Minimum at
3-seg mirror:
θx,θy,θz= (0.2485, 0.5832, 0.1171) deg,
y = 0.5894 mm;
bar z =2.0788 mm;
PMT (r,θ)=1.8690 mm, 1.3544 deg

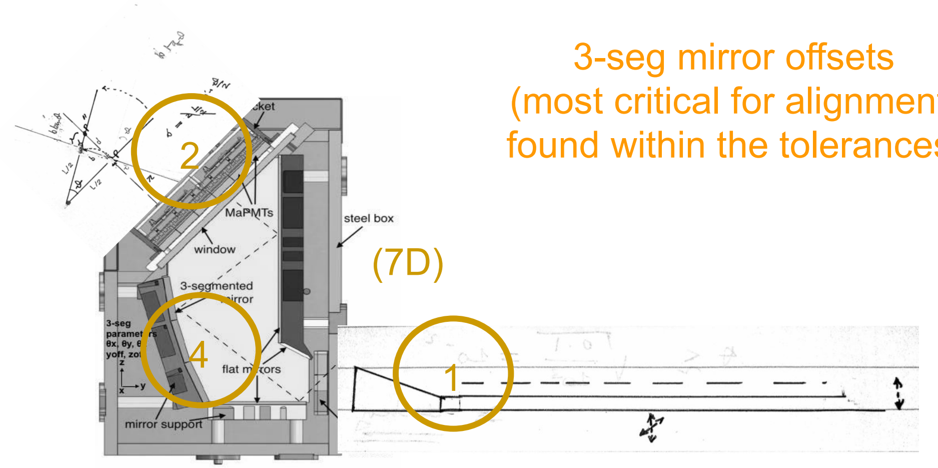
Recipe: For each call of the optimizer, M offset points are explored using N different particles (for each call). The total number of calls is T

T=120 M=10 N=125

Particles used = 15000

Points explored = 1200

FoM = LogL normalized to a default alignment

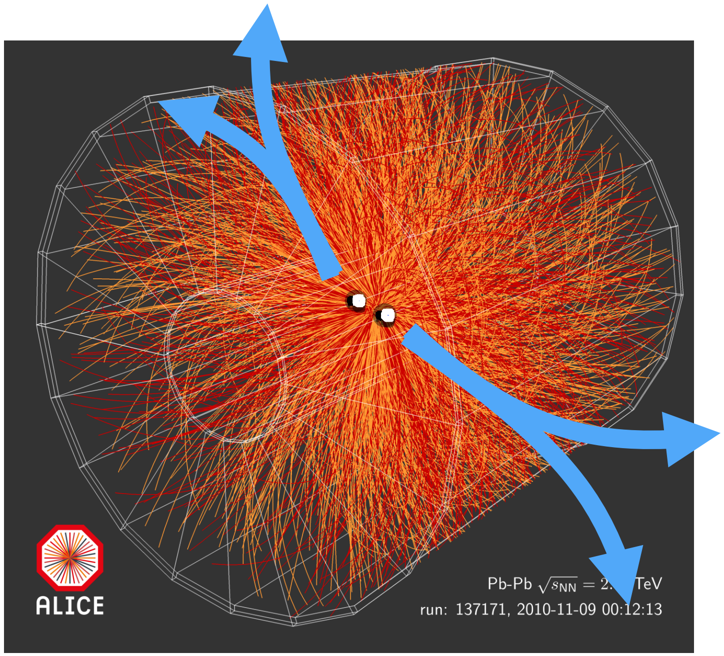


3-seg mirror offsets (most critical for alignment) found within the tolerances.

Supervised: Cut-based reco./analyses

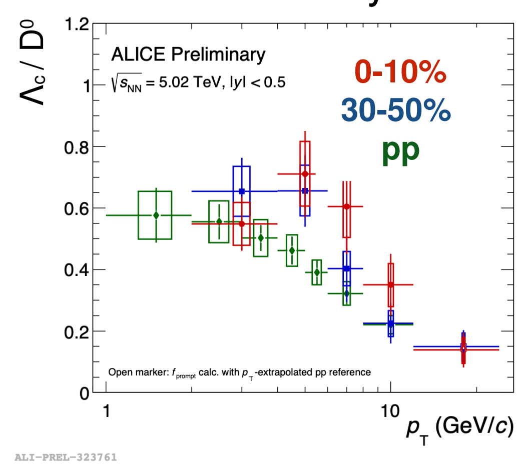
ALICE, Heavy Flavor (Λ_c)

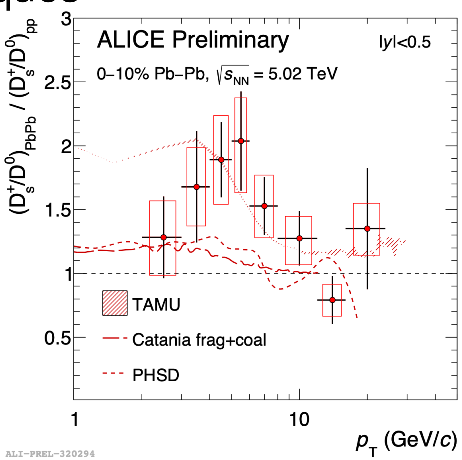
Gian Michele Innocenti



BDT techniques (XGBoost) have been exploited to select heavy-flavor decays in central PbPb collisions:

- E.g. Λ_c selection ($c\tau$~50μm)
  - TOF and TPC variables used in the training to exploit correlations with topological selections
  - increase in significance up to 3-4 at low p_T with respect to standard analysis techniques

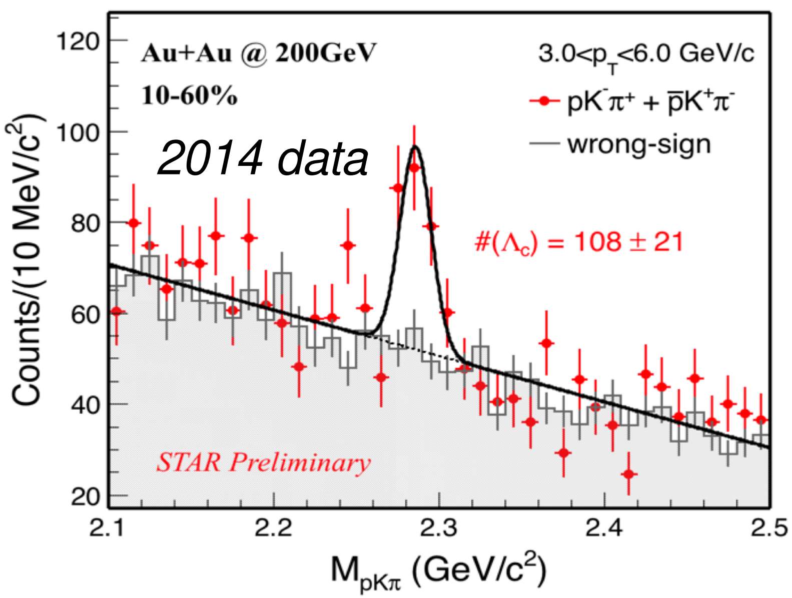




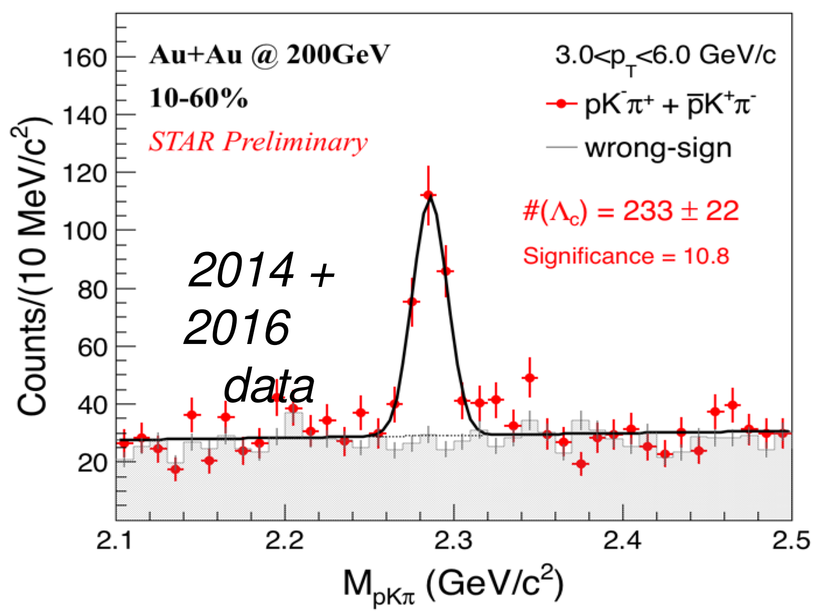
Supervised: Cut-based reco./analyses

STAR, also HF/Λ_c, Nu Xu

Rectangular Cuts (QM 2017)



Using Boosted Decision Trees (QM 2018)



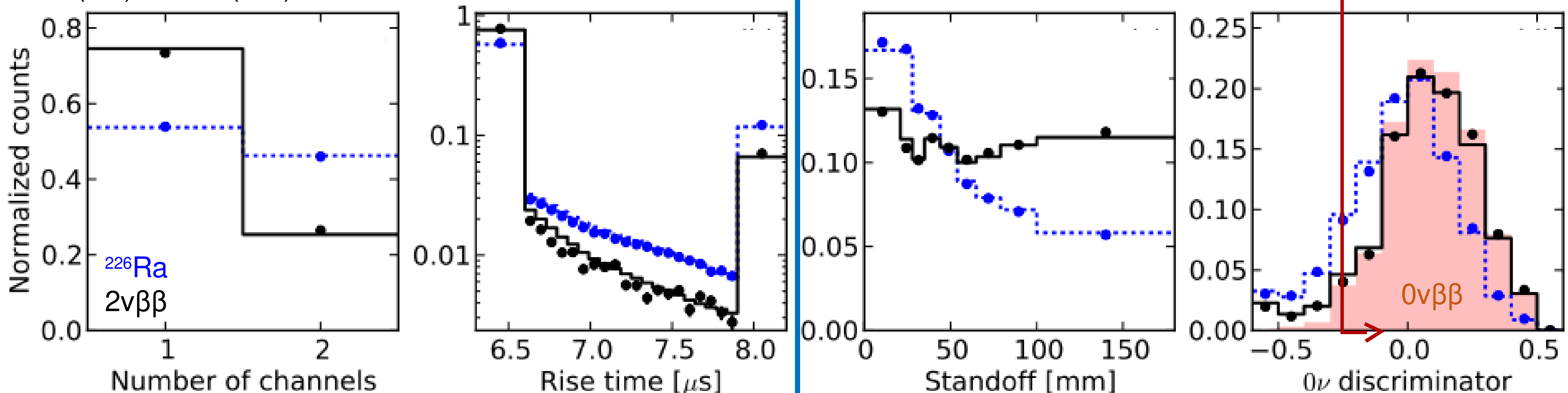
<u>QM 2017 —> QM 2018:</u>

- Total statistics doubled with combined 2014+2016 data
- More than 50% improvement in signal significance using Boosted Decision Trees! Effectively providing 2x additional data!

Supervised: Cut-based reco./analyses

~35% γ-rejection
~90% signal efficiency

Data (dot) vs MC (line)



EXO-200

0νββ with background from detector material

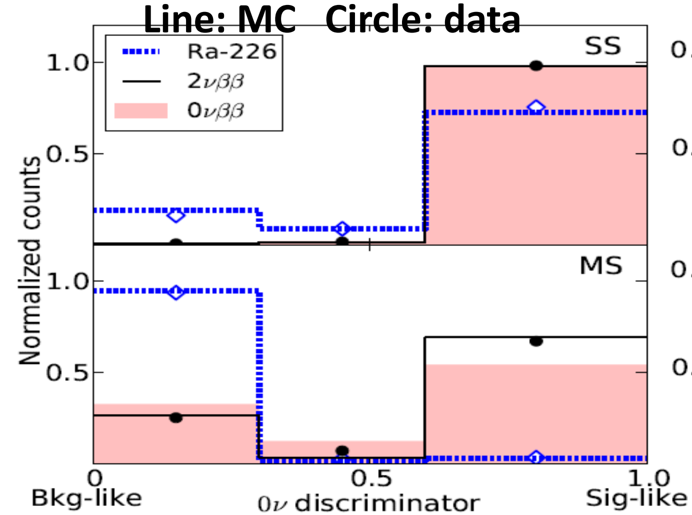
2018 result using BDT: 15% better than energy-only

https://doi.org/10.1103/PhysRevLett.120.072701

2019 result using BDT: 25% better than energy-only

https://doi.org/10.1103/PhysRevLett.123.161802

Liang Yang, Gaosong Li



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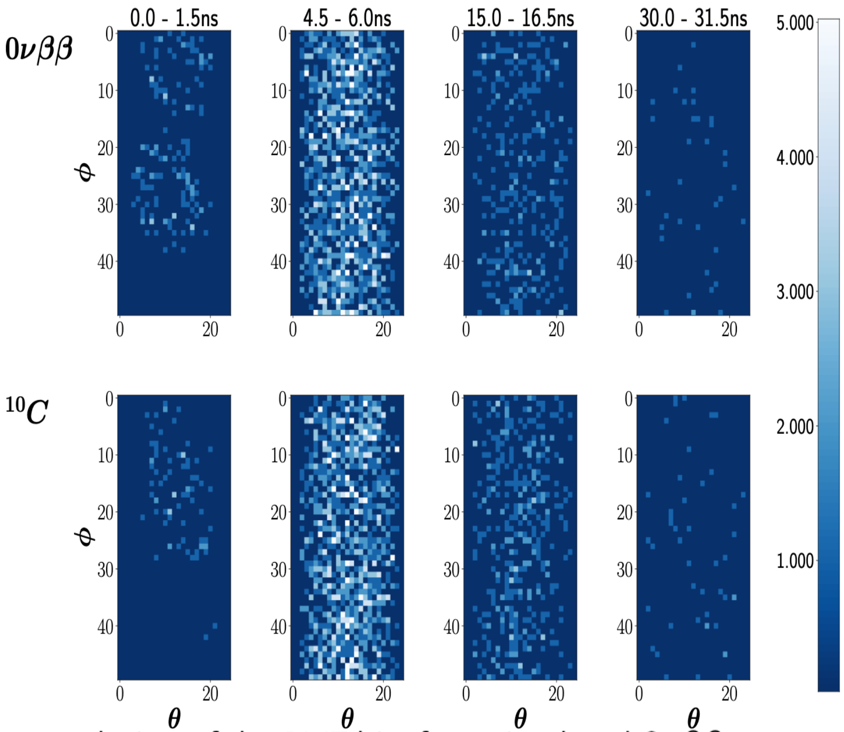
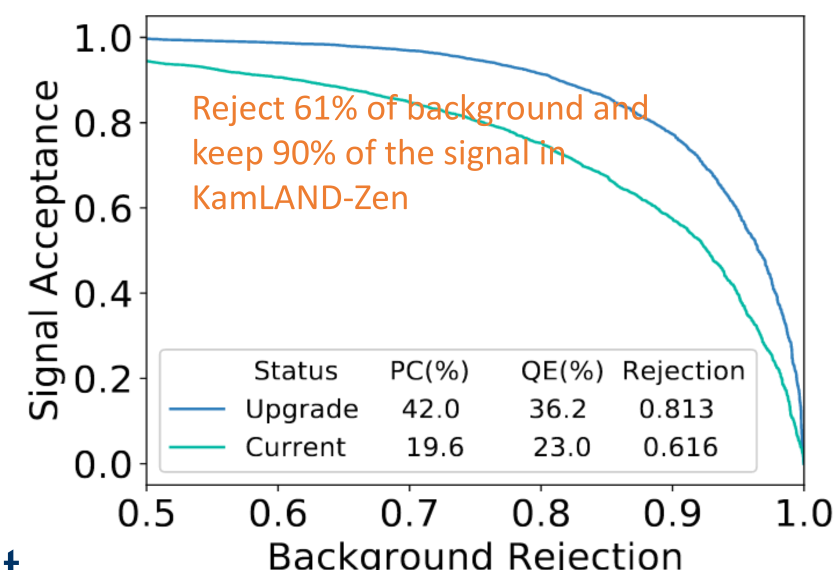
Supervised: Image-based (CNN)

A. Li et al. NIM A 947 (2019) 162604



Time evolution of the PMT hits for a simulated $0\nu\beta\beta$ event and ^{10}C background event at the center of the KamLAND-Zen detector

- **Greatly improved background rejection** when used on simulated events
- **A. Li and C. Grant (Boston University)** are implementing this network model and ***a more sophisticated spherical CNN*** on the KamLAND-Zen and SNO+ experiments



KamiLAND-Zen, Christopher Grant

Supervised: Image-based (CNN)

NEXT

2D CNN classification of Xe TPC

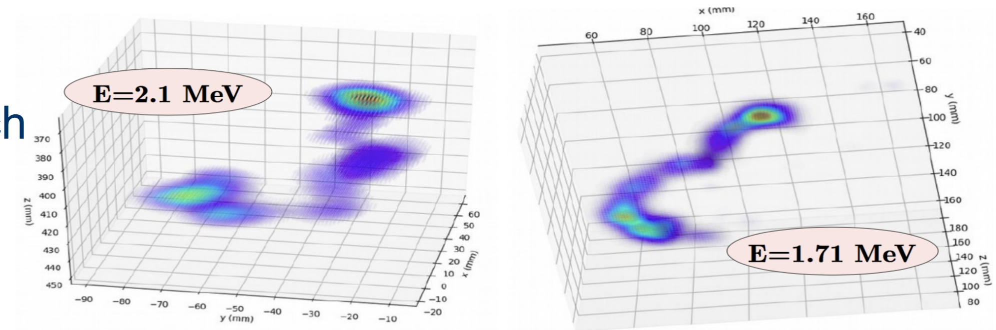
Planned semantic segmentation of decay candidates

Runs on OLCF Summit with PyTorch + SparseConvNet and Horovod

Eric Church

NEXT's 3D images – lend themselves naturally to DNNs

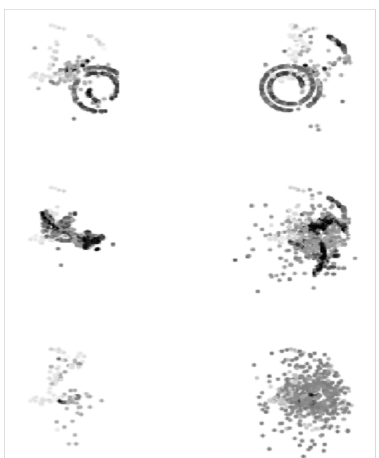
Two-neutrino double beta decay candidates



NEXT-White data
Topologically identified and energy-separated from double escape peaks
JHEP 1910 (2019) 230. JHEP 10 (12019) 51.

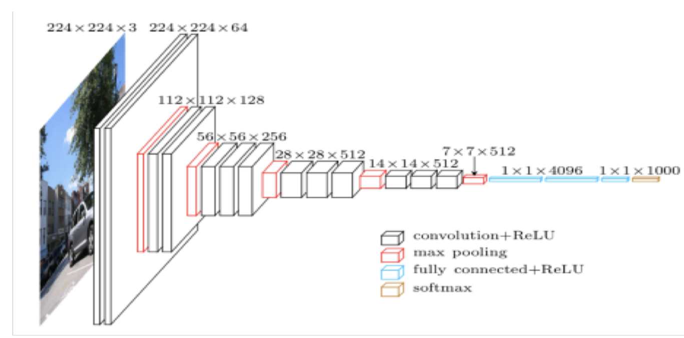
FRIB Hall B

Michelle Kouchera



AT-TPC

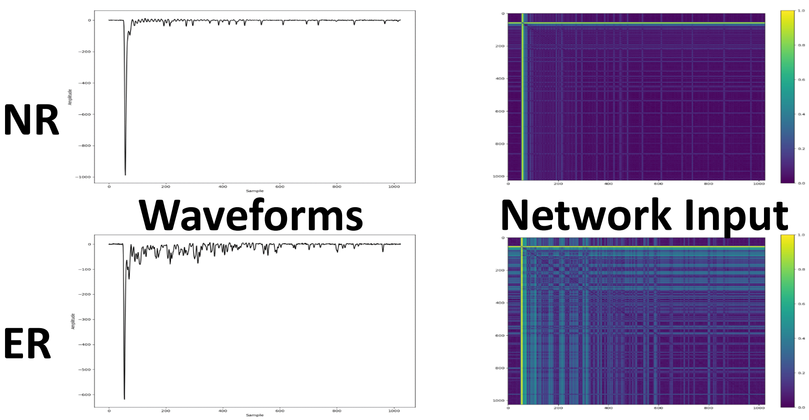
HALL B

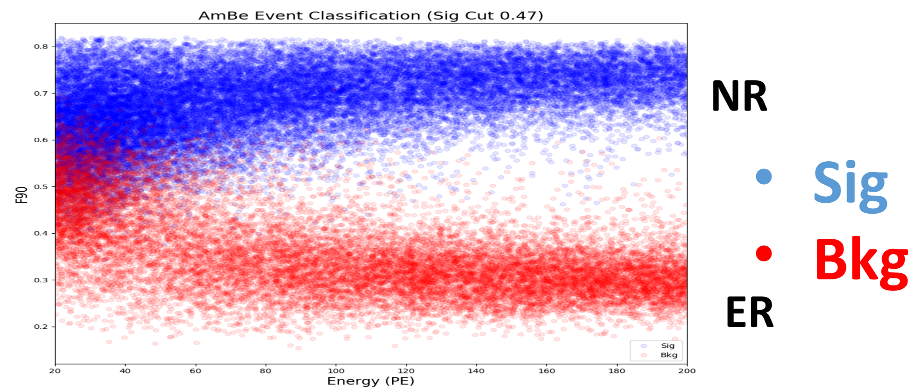


PRE-TRAINED ON IMAGENET DATA!

Supervised: Image-based (CNN)

COHERENT, Kate Scholberg





- Searching for rare events in liquid noble gas detectors requires excellent background rejection.
- Backgrounds (gamma rays and betas) produce differently shaped waveforms than CEvNS signals (nuclear recoils).
- **Convolutional Neural Network** can be trained on waveform images to provide classification.
- Provides a tool to discriminate event types at detector-thresholds where conventional analysis fails.

Jacob Daughhetee, U. of Tennessee, Knoxville

Supervised: Graph convolution

GRETA

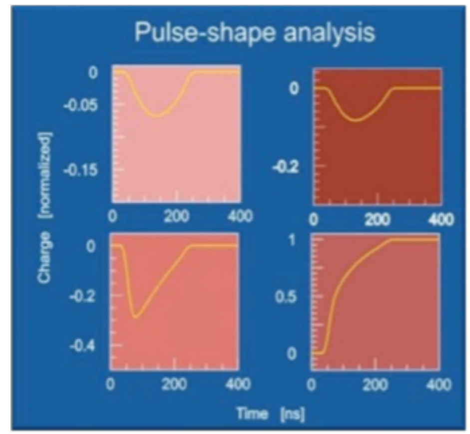
Gamma-ray tracking

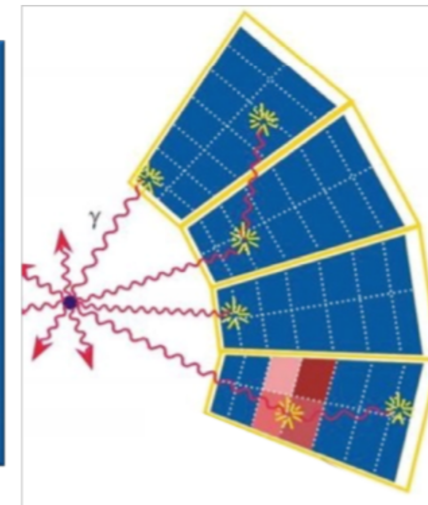
Tracks from multiple-scattering

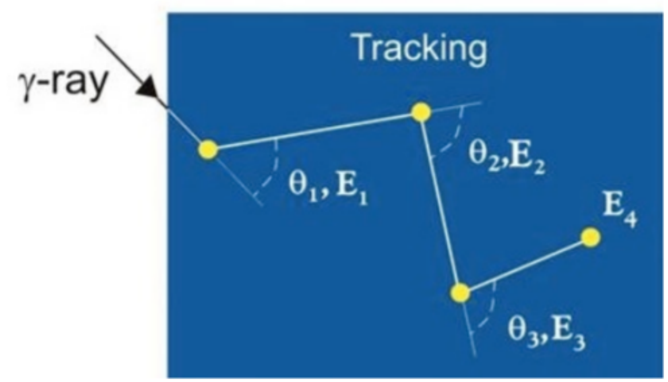
Several recent technologies considered:

Bayesian search for Ge-transport + CNN (for interaction point)

Graph convolution (for tracking)







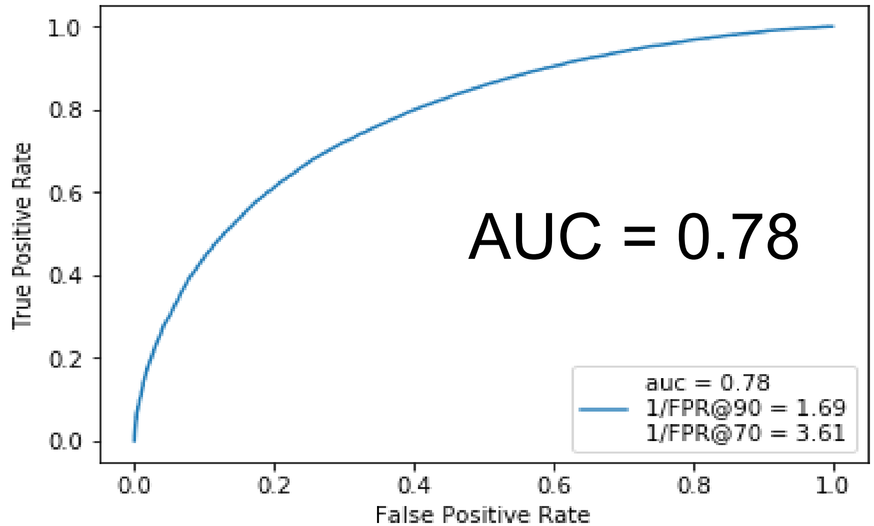
Supervised: RNN

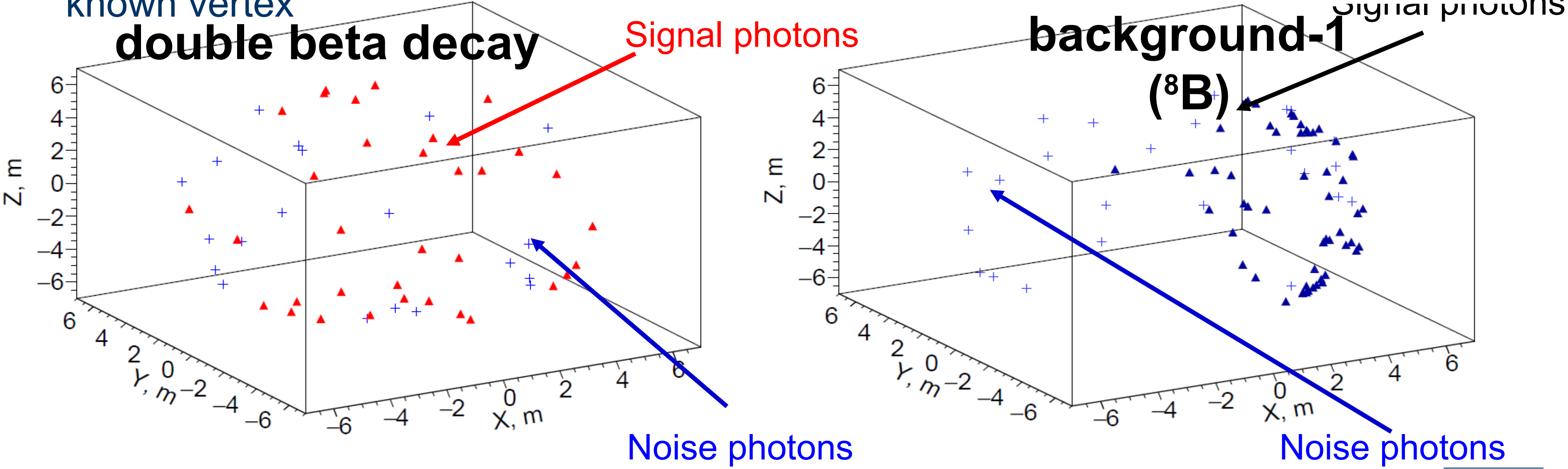
LAPPD for THEIA 0νββ, Andrey Elagin

Performance for accepting 0νββ (positive) and rejecting ^{8}B background (negative)

LSTM used due to high sparsity/mostly empty pixels

Traditional rejection only works with known vertex



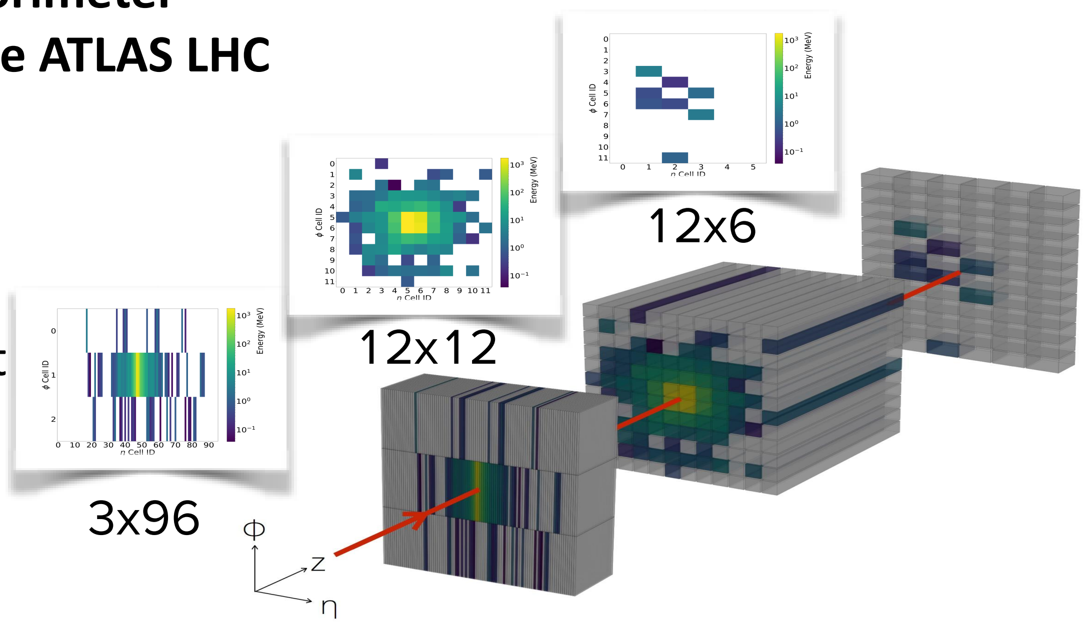


Generative: Simulation

LHC ATLAS, Wahid Bhimji (NERSC)

- Particle physics uses detailed micro-physics detector simulations (e.g. with Geant4)
  - >~50% LHC computing budget (10^9 CPU hours)
  - Much of this compute time in calorimeter 'shower'
- **CaloGAN models a 3-layer calorimeter detector inspired by that of the ATLAS LHC experiment**
- **Custom NN design**
  - sparsity
  - high dynamic range
  - highly location-dependent features

Application for EIC?

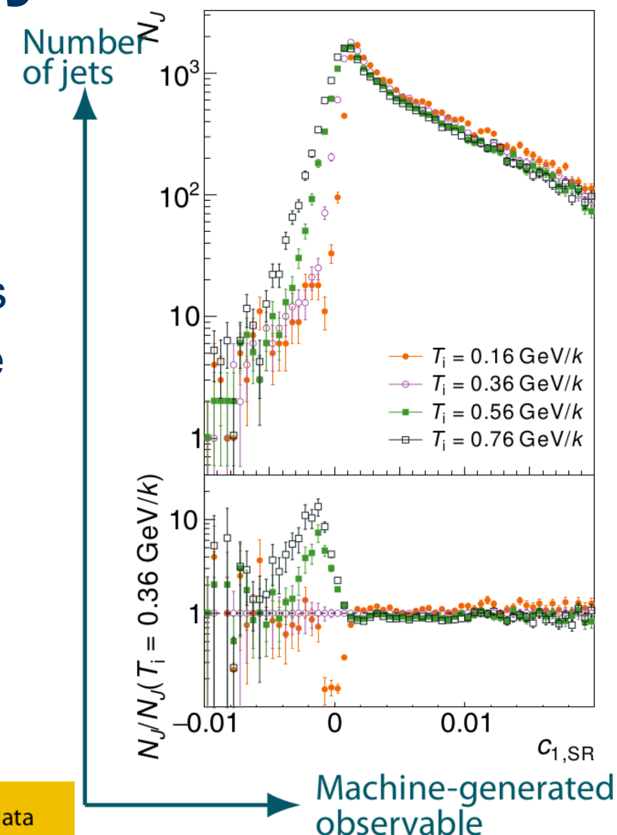


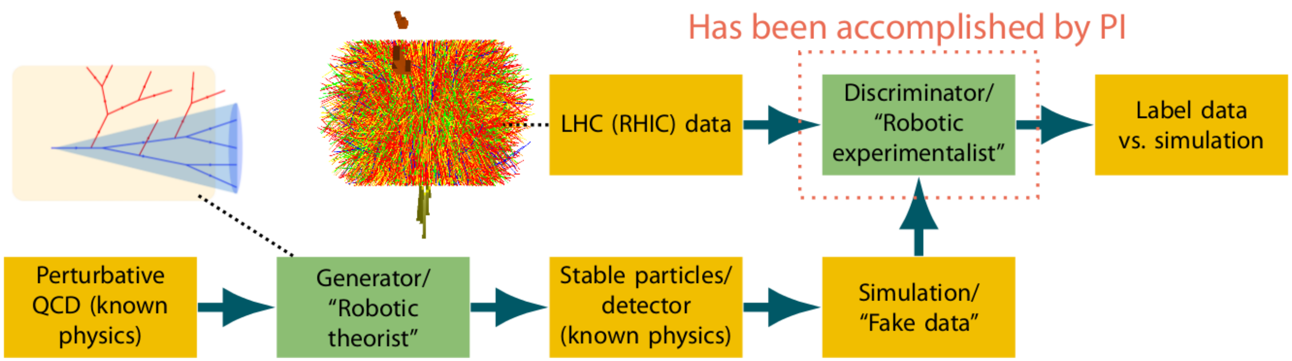
M. Paganini, L. de Oliveira, and B. Nachman, Phys. Rev. Lett. 120 (2018) 042003.

Generative: Automated analysis

LBNL LDRD, YSL, Mateusz Ploskon, Felix Ringer

- Discovery of new observables by NN (arXiv:1810.00835)
- Discovery of theoretical models via automated analysis
  - A generator that mimicks the quark/gluon passing the plasma, and learns data-driven from experiment how to parton-shower and hadronize
  - A discriminator looks at both the output of the generator, and real measurement data, and decide if this was simulated or is the reality/reference





Experimentalist NN learning how to measure plasma with Jewel

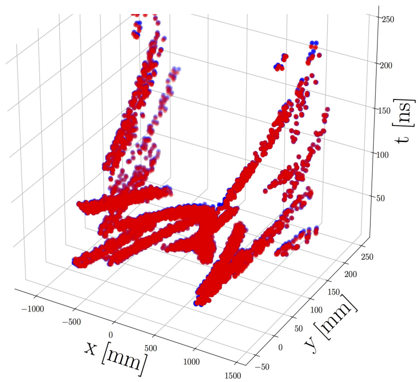
NN reduced to 13 algebraic terms

Dimensionality reduction

PID GlueX DIRC

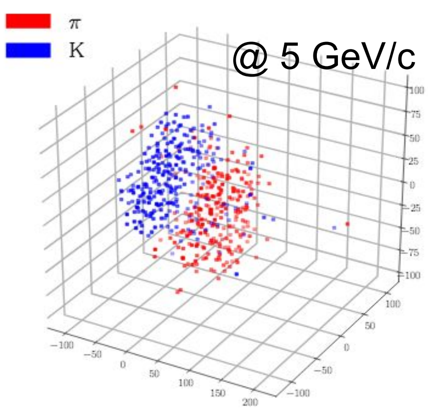
C. Fanelli and J. Pomponi. "*DeepRICH: Learning Deeply Cherenkov Detectors*." arXiv:1911.11717 (2019), C. Fanelli, "*Machine learning for imaging Cherenkov detectors*", JINST 15 C02012 (2020)

injected π
reconstructed π

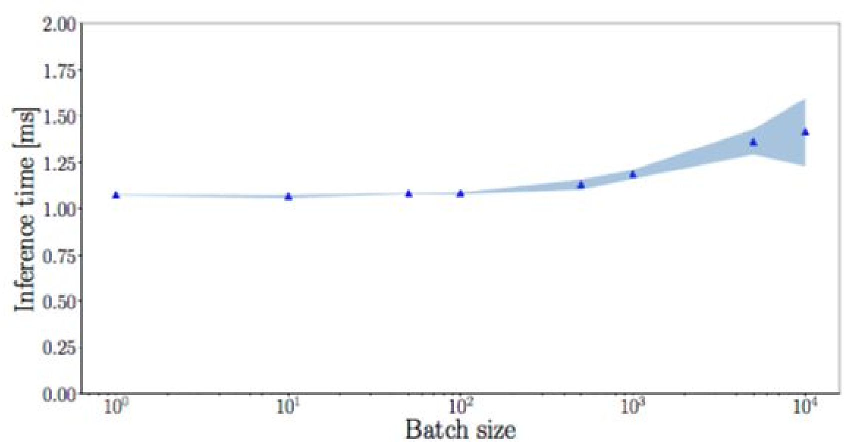


Fanelli & Pomponi proved that deepRICH can reach the PID performance of established algorithms. This depends only on the available resources for

	DeepRICH			FastDIRC		
Kinematics	AUC	ϵ_S	ϵ_B	AUC	ϵ_S	ϵ_B
4 GeV/c	99.74	98.18	98.16	99.88	98.98	98.85
4.5 GeV/c	98.78	95.21	95.21	99.22	96.33	96.32
5 GeV/c	96.64	91.13	91.23	97.41	92.40	92.47



Improvement by ~4 orders of magnitude the reconstruction time.



Cristiano Fanelli

Challenges

Methodological challenges using current AI techniques:

- How to find the least complex model that fits the job description? “Model parameter efficiency”
- Uncertainty quantification (UQ): Reliability data vs. MC and how to avoid rare, but catastrophically wrong results

Infrastructure challenges:

- Lack of GPU at high-throughput computing (HTC) facilities, HTC projects require separate high-performance computing (HPC) allocation for GPU training

Opportunities for NP

Area where NP benefits greatly from AI application:

- Fast turn-around using simulation, and without investing in many person-years of custom algorithm development
- Performance that are difficult/humanly impossible to achieve with manually crafted algorithms
- Fast reconstruction without manually tuned GPU/FPGA code
- Many experiments already benefit from off-the-shelf methods

Opportunities beyond NP

Some of the projects/goals are unique to NP and solves challenges that are cross-cutting to other fields

- Large (measurement) sample size allowing generative models, automated learning of underlying physics principles.
- Some of the data sets are not first-principles calculable: strong interaction physics, many-body physics
- Problems demanding innovative reconstruction algorithms

Cross-cutting goals where collaboration with wider AI field would be beneficial:

- Study of physics behavior: NN with built-in known symmetries/conservation laws
  - Interpretability
  - Data efficiency

Summary

- There is already wide adoption of AI techniques in NP
- AI for NP promises:
  - Fast development cycle
  - Efficient utilization of commercial hardware
- It comes with a few pitfalls
- There is uniqueness of NP and the dataset we are dealing with, for AI application
  - Potential synergies and collaboration with the wider AI field for cross-cutting questions

Thanks

Wahid Bhimji, Eric Church, Mario Cromaz, Jacob Daughhetee, Markus Diefenthaler, Andrey Elagin, Cristiano Fanelli, Gian Michele Innocenti, Gaosong Li, Kate Scholberg, Nu Xu, Liang Yang

ALICE, COHERENT, EXO, GlueX, GRETA, KamiLAND-Zen, NEXT, STAR