

# OVERVIEW ON MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN LOW-ENERGY NUCLEAR PHYSICS

**NSAC TOWN HALL MEETING**  
ARGONNE NATIONAL LABORATORY  
15 NOVEMBER 2022

**MICHELLE KUCHERA**  
DAVIDSON COLLEGE

# NO MENTION OF MACHINE LEARNING OR ARTIFICIAL INTELLIGENCE IN 2015 LONG RANGE PLAN

three-family picture of the Standard Model. The fourth experiment, which lies at the heart of modern cosmology and particle physics, involves the search for the neutron electric dipole moment (nEDM). This experiment would improve sensitivity by two orders of magnitude over the best existing searches for CP violation beyond the Standard Model, as needed to account for the baryon asymmetry of the universe.

The ultracold neutron (UCN) facility at Los Alamos National Lab is the only currently operating UCN source in North America and provides UCN densities comparable to the world's other sources (located in Europe and Japan). Following the ongoing successful UCNA experiment on the neutron beta decay asymmetry, the facility will host the neutron lifetime measurement UCN $\tau$ , detector development for the Nab and UCNB experiments, the applied nuclear physics experiment UCNS, and neutron guide and storage cell development. A more precise determination of the neutron decay lifetime can be used to determine the CKM matrix element  $V_{ud}$  with high precision in a fashion that is relatively free of theoretical uncertainties. Complementary precision studies using decays of rare isotopes are being carried out at ANL using ion and atom traps.

The Fermilab Muon Campus is being developed to host two high-priority approved experiments that will challenge the Standard Model. While primary support comes from DOE-HEP, many nuclear physics groups and international partners are playing leading roles in these interdisciplinary experiments. The Muon g-2 Experiment will measure the anomalous magnetic moment of the muon to the unprecedented precision of 140 parts per billion. The result will either confirm or refute a long-standing discrepancy between the Standard Model and the previous measurement. The Mu2e Experiment will study the low-energy (essentially forbidden) process of coherent conversion of a muon to an electron from an atomically bound muonic atom. The goal is a four orders of magnitude improvement in the limit of this charged-lepton-violating process, with single event sensitivity approaching 1 part in  $10^{17}$ .

## ADVANCED TECHNOLOGIES

### Advanced Computing

Computation now plays an essential role in every area of nuclear physics research (Sidebar 7.3). Nuclear physicists

exploit available computational resources, ranging from leadership-class capability computing resources, such as Titan at OLCF and Mira at ALCF, through capacity (mid-scale) computing resources, such as Edison at the National Energy Research Scientific Computing Center (NERSC) and USQCD hardware at JLab, BNL, and Fermilab, as well as university clusters and small local clusters and workstations. The capability resources are allocated in programs such as INCITE and ALCC through peer-reviewed proposals in competition with other areas of science. Nuclear physics has obtained an approximately constant fraction (12%) of the national resources during the last several years. Access to capacity computing resources at NERSC and through the XSEDE program is also obtained through a proposal process. In addition, the USQCD project operates its own capacity computers, supported jointly by the DOE Offices of Nuclear Physics and High Energy Physics. In addition to the homogeneous machines it operates in the form of clusters and a Blue-Gene/Q, USQCD has invested in heterogeneous machines, primarily those accelerated with nVidia Graphics Processing Units (GPUs). GPU machines, through the development of very efficient software, have proven to be effective in many aspects of LQCD calculations.

Ten years ago, the capability, capacity, and local clusters were essentially of the same architecture, comprised of multiple homogeneous compute cores embedded in a fast communication fabric. Today, and into the future, the architectures are heterogeneous and diverse in nature. The limits of CMOS technology and the resulting failure to track Moore's Law, along with the power requirements of such technologies, make it necessary to embrace heterogeneous architectures. Two machine architectures are being pursued to deliver exascale computing resources within the next 10 years. One architecture is IBM Power-9 processors with Nvidia Volta GPUs being procured for Lawrence Livermore National Laboratory and Oak Ridge National Laboratory. The other is based on the evolution of Intel Xeon-Phi accelerators and will be deployed at Argonne National Laboratory as well as in the next NERSC machine.

Significant software development is required to exploit these two quite different architectures. Supported through the SciDAC program and in collaboration with the SciDAC Institutes, nuclear physicists collaborate to port and to optimize the performance of the code bases on these platforms. As an example, the Chroma



# NO MENTION OF MACHINE LEARNING OR ARTIFICIAL INTELLIGENCE IN 2015 LONG RANGE PLAN

## REVIEWS OF MODERN PHYSICS

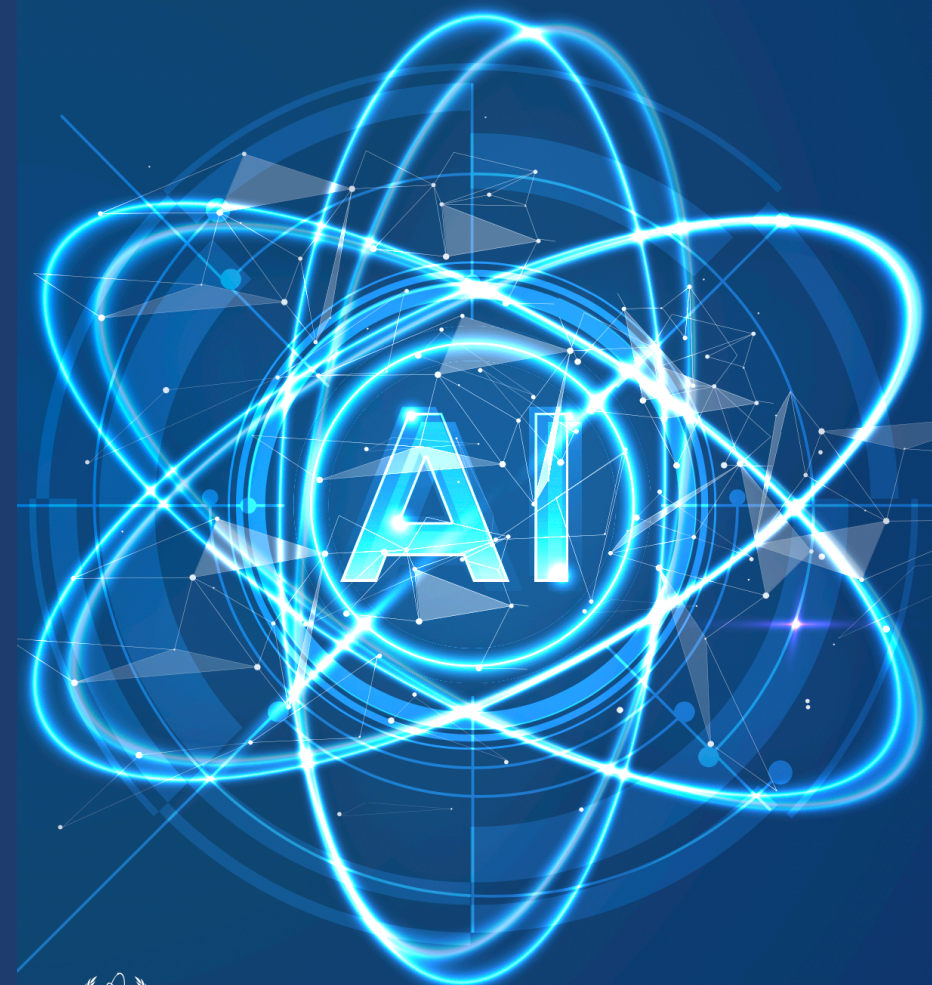
Recent Accepted Authors Referees Search Press About Editorial Team

Access by

### *Colloquium:* Machine learning in nuclear physics

Amber Boehnlein, Markus Diefenthaler, Nobuo Sato, Malachi Schram, Veronique Ziegler, Cristiano Fanelli, Morten Hjorth-Jensen, Tanja Horn, Michelle P. Kuchera, Dean Lee, Witold Nazarewicz, Peter Ostroumov, Kostas Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang  
Rev. Mod. Phys. **94**, 031003 – Published 8 September 2022

## Artificial Intelligence for Accelerating Nuclear Applications, Science and Technology



three-family picture of the Standard Model. The fourth experiment, which lies at the heart of modern cosmology and particle physics, involves the search for the neutron electric dipole moment (nEDM). This experiment would improve sensitivity by two orders of magnitude over the best existing searches for CP violation beyond the Standard Model, as needed to account for the baryon asymmetry of the universe.

The ultracold neutron (UCN) facility at Los Alamos National Lab is the only currently operating UCN source in North America and provides UCN densities comparable to the world's other sources (located in Europe and Japan). Following the ongoing successful UCNA experiment on the neutron beta decay asymmetry, the facility will host the neutron lifetime measurement UCN $\tau$ , detector development for the Nab and UCNB experiments, the applied nuclear physics experiment UCNS, and neutron guide and storage cell development. A more precise determination of the neutron decay lifetime can be used to determine the CKM matrix element  $V_{ud}$  with high precision in a fashion that is relatively free of theoretical uncertainties. Complementary precision studies using decays of rare isotopes are being carried out at ANL using ion and atom traps.

The Fermilab Muon Campus is being developed to host two high-priority approved experiments that will challenge the Standard Model. While primary support comes from DOE-HEP, many nuclear physics groups and international partners are playing leading roles in these interdisciplinary experiments. The Muon g-2 Experiment will measure the anomalous magnetic moment of the muon to the unprecedented precision of 140 parts per billion. The result will either confirm or refute a long-standing discrepancy between the Standard Model and the previous measurement. The Mu2e Experiment will study the low-energy (essentially forbidden) process of coherent conversion of a muon to an electron from an atomically bound muonic atom. The goal is a four orders of magnitude improvement in the limit of this charged-lepton-violating process, with single event sensitivity approaching 1 part in  $10^{17}$ .

## ADVANCED TECHNOLOGIES

### Advanced Computing

Computation now plays an essential role in every area of nuclear physics research (Sidebar 7.3). Nuclear physicists

exploit available computational resources, ranging from leadership-class capability computing resources, such as Titan at OLCF and Mira at ALCF, through capacity (mid-scale) computing resources, such as Edison at the National Energy Research Scientific Computing Center (NERSC) and USQCD hardware at JLab, BNL, and Fermilab, as well as university clusters and small local clusters and workstations. The capability resources are allocated in programs such as INCITE and ALCC through peer-reviewed proposals in competition with other areas of science. Nuclear physics has obtained an approximately constant fraction (12%) of the national resources during the last several years. Access to capacity computing resources at NERSC and through the XSEDE program is also obtained through a proposal process. In addition, the USQCD project operates its own capacity computers, supported jointly by the DOE Offices of Nuclear Physics and High Energy Physics. In addition to the homogeneous machines it operates in the form of clusters and a Blue-Gene/Q, USQCD has invested in heterogeneous machines, primarily those accelerated with nVidia Graphics Processing Units (GPUs). GPU machines, through the development of very efficient software, have proven to be effective in many aspects of LQCD calculations.

Ten years ago, the capability, capacity, and local clusters were essentially of the same architecture, comprised of multiple homogeneous compute cores embedded in a fast communication fabric. Today, and into the future, the architectures are heterogeneous and diverse in nature. The limits of CMOS technology and the resulting failure to track Moore's Law, along with the power requirements of such technologies, make it necessary to embrace heterogeneous architectures. Two machine architectures are being pursued to deliver exascale computing resources within the next 10 years. One architecture is IBM Power-9 processors with Nvidia Volta GPUs being procured for Lawrence Livermore National Laboratory and Oak Ridge National Laboratory. The other is based on the evolution of Intel Xeon-Phi accelerators and will be deployed at Argonne National Laboratory as well as in the next NERSC machine.

Significant software development is required to exploit these two quite different architectures. Supported through the SciDAC program and in collaboration with the SciDAC Institutes, nuclear physicists collaborate to port and to optimize the performance of the code bases on these platforms. As an example, the Chroma



## A Survey of Machine Learning-Based Physics Event Generation

**Yasir Alanazi<sup>1</sup>, Nobuo Sato<sup>2</sup>, Pawel Ambrozewicz<sup>2</sup>, Astrid Hiller-Blin<sup>2</sup>,  
Wally Melnitchouk<sup>2</sup>, Marco Battaglieri<sup>2</sup>, Tianbo Liu<sup>3</sup> and Yaohang Li<sup>1</sup>**

<sup>1</sup>Department of Computer Science, Old Dominion University, Norfolk, Virginia 23529, USA

<sup>2</sup>Jefferson Lab, Newport News, Virginia 23606, USA

<sup>3</sup>Key Laboratory of Particle Physics and Particle Irradiation (MOE). Institute of Frontier and Interdisciplinary Science, Shandong University, Jinan 250022, China  
yalan001@odu.edu, {nsato, pawel, ahblin, wlmelnitchouk, mbattaglieri, tliu, yaohang.li}

## Artificial Intelligence for Accelerating Nuclear Applications, Science and Technology

International Journal of Modern Physics A  
© World Scientific Publishing Company

### A Review on Machine Learning for Neutrino Experiments

Fernanda Psihas

*Neutrino Division, Fermi National Accelerator Laboratory  
Batavia, Illinois, United States of America  
psihas@fnal.gov*

Micah Groh

*Department of Physics, Indiana University  
Bloomington, IN, United States of America  
mcgroh@iu.edu*

Christopher Tunnell

*Department of Physics and Astronomy, RICE University  
Houston, Texas, United States of America  
tunnell@rice.edu*

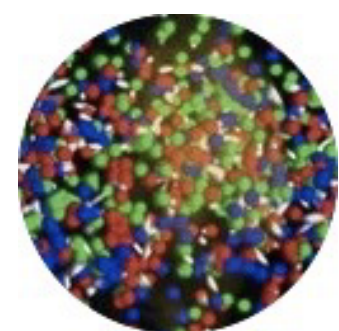
Karl Warburton

*Department of Physics and Astronomy, Iowa State University  
Ames, Iowa, United States of America  
karlwarb@iastate.edu*

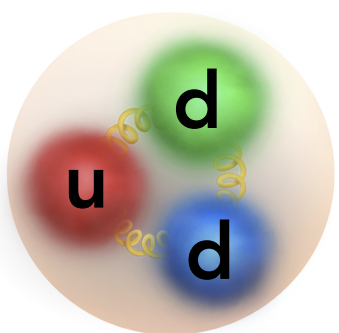
CONTENTS	
EXECUTIVE SUMMARY .....	1
CHAPTER 1. INTRODUCTION. ....	3
1.1. BACKGROUND .....	3
1.2. OBJECTIVE .....	4
1.3. SCOPE .....	4
1.4. STRUCTURE .....	4
CHAPTER 2. SUMMARY OF ARTIFICIAL INTELLIGENCE IN NUCLEAR APPLICATIONS, SCIENCE AND TECHNOLOGY .....	5
2.1. ETHICS .....	5
2.2. NUCLEAR APPLICATIONS .....	5
2.3. NUCLEAR SCIENCE .....	6
2.4. NUCLEAR POWER .....	7
2.5. RADIATION PROTECTION AND NUCLEAR SECURITY .....	7
2.6. SAFEGUARDS VERIFICATION .....	8
CHAPTER 3. ETHICS .....	9
3.1. STATE OF THE ART .....	9
3.1.1. Artificial intelligence ethics .....	9
3.1.2. Ethics of nuclear technology .....	10
3.2. NEXT STEPS .....	11
3.3. ACCELERATING PROGRESS—IAEA’S ROLE .....	13
3.3.1. Overarching concerns and way forward .....	14
3.4. EXPECTED OUTCOMES .....	14
3.5. ACKNOWLEDGMENTS .....	14
3.6. REFERENCES .....	15
CHAPTER 4. HUMAN HEALTH .....	19
4.1. STATE OF THE ART .....	19
4.1.1. Radiotherapy .....	19
4.1.2. Medical imaging and nuclear medicine .....	19
4.1.3. Nuclear nutrition assessments .....	20
4.1.4. Health education .....	20
4.2. NEXT STEPS .....	21
4.2.1. Radiotherapy .....	21
4.2.2. Medical imaging and nuclear medicine .....	21
4.2.3. Nuclear nutrition assessments .....	21
4.2.4. Health education .....	21
4.3. ACCELERATING PROGRESS—IAEA’S ROLE .....	22
4.3.1. Radiotherapy .....	22
4.3.2. Medical imaging and nuclear medicine .....	22
4.3.3. Nuclear nutrition assessments .....	23
4.3.4. Health education .....	23
4.4. EXPECTED OUTCOMES .....	23
4.5. ACKNOWLEDGMENTS .....	23
4.6. REFERENCES .....	24

5. FOOD AND AGRICULTURE .....	27
STATE OF THE ART .....	27
NEXT STEPS .....	27
ACCELERATING PROGRESS—IAEA’S ROLE .....	28
EXPECTED OUTCOMES .....	29
REFERENCES .....	29
CHAPTER 6. WATER AND ENVIRONMENT .....	31
6.1. STATE OF THE ART .....	31
6.2. NEXT STEPS .....	32
6.3. ACCELERATING PROGRESS—IAEA’S ROLE .....	33
6.3.1. Data hub .....	33
6.3.2. Connecting stakeholders .....	33
6.3.3. Providing training and guidelines .....	34
6.3.4. Making isotopes parts of earth science and climate models .....	35
6.4. EXPECTED OUTCOMES .....	35
6.4.1. Data hub .....	35
6.4.2. Connecting stakeholders .....	35
6.4.3. Providing training and guidelines .....	36
6.4.4. Making isotopes parts of earth science and climate models .....	36
6.5. ACKNOWLEDGMENTS .....	36
6.6. REFERENCES .....	36
CHAPTER 7. NUCLEAR DATA .....	39
7.1. STATE OF THE ART .....	39
7.2. NEXT STEPS .....	41
7.3. ACCELERATING PROGRESS—IAEA’S ROLE .....	42
7.4. EXPECTED OUTCOMES .....	42
7.5. REFERENCES .....	43
CHAPTER 8. NUCLEAR PHYSICS .....	45
8.1. STATE OF THE ART .....	45
8.1.1. Data analysis and modelling .....	45
8.1.2. Data processing and management .....	45
8.1.3. Experimental design and optimization .....	46
8.1.4. Facility operation .....	46
8.2. NEXT STEPS .....	46
8.2.1. Nuclear physics drivers .....	46
8.2.2. Education efforts .....	47
8.2.3. Interdisciplinary funding .....	47
8.3. ACCELERATING PROGRESS—IAEA’S ROLE .....	47
8.3.1. Hosting and curating central resources .....	47
8.3.2. Sponsorships and community efforts .....	48
8.3.3. Workforce development and providing funding opportunities .....	48
8.3.4. Interdisciplinary coordination .....	48
8.4. EXPECTED OUTCOMES .....	49
8.5. ACKNOWLEDGMENTS .....	49
8.6. REFERENCES .....	49

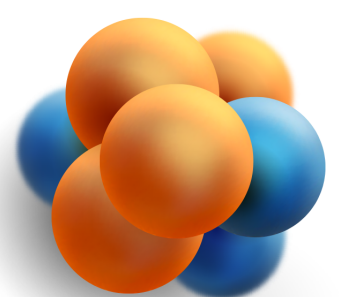




Hot and Dense Nuclear Matter



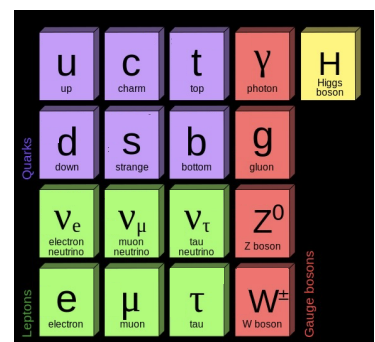
Hadrons



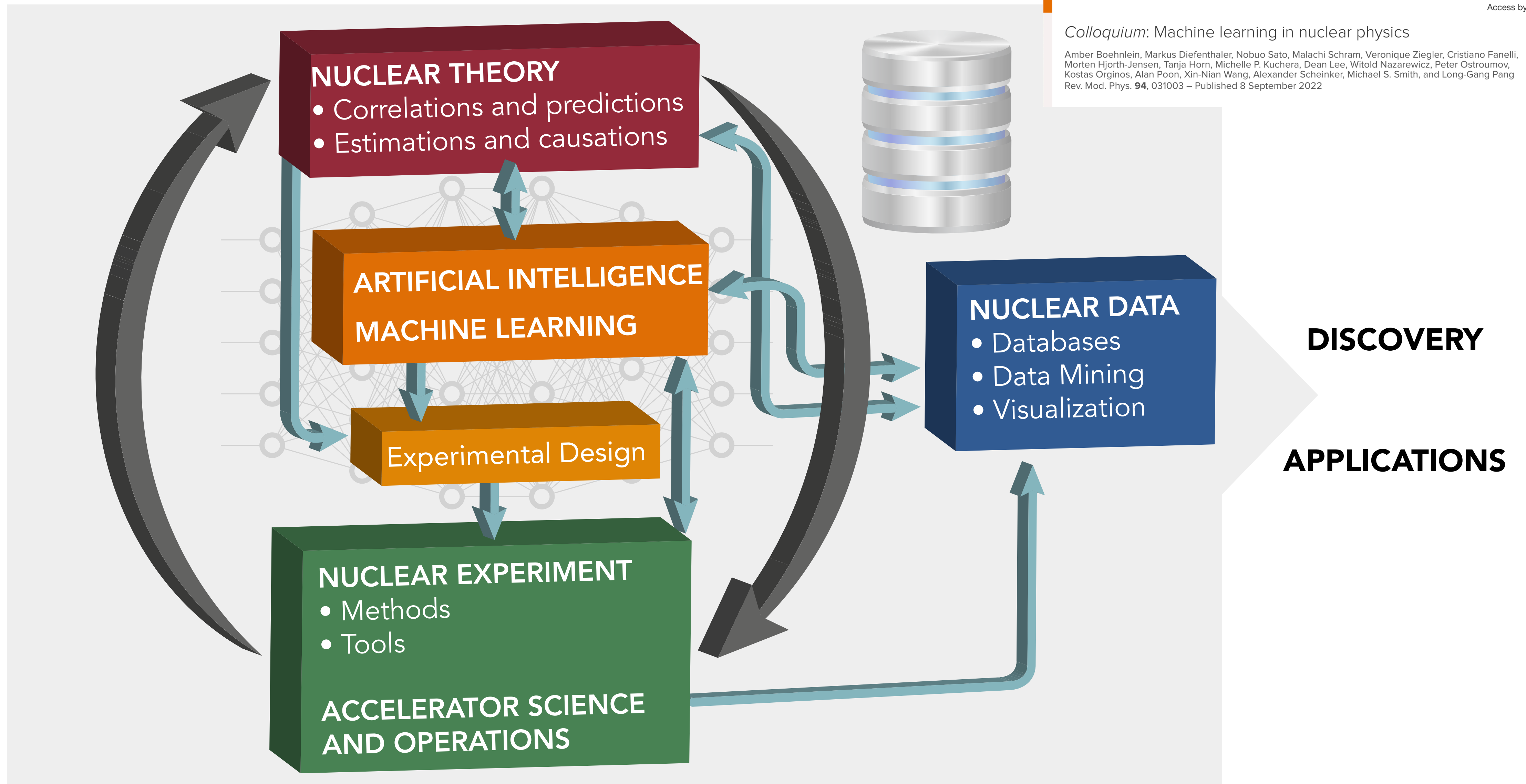
Atomic Nucleus



Nuclei in the Cosmos



Fundamental Interactions



Colloquium: Machine learning in nuclear physics

Amber Boehnlein, Markus Diefenthaler, Nobuo Sato, Malachi Schram, Veronique Ziegler, Cristiano Fanelli, Morten Hjorth-Jensen, Tanja Horn, Michelle P. Kuchera, Dean Lee, Witold Nazarewicz, Peter Ostroumov, Kostas Orginos, Alan Poon, Xin-Nian Wang, Alexander Scheinker, Michael S. Smith, and Long-Gang Pang  
Rev. Mod. Phys. **94**, 031003 – Published 8 September 2022



# OUTLINE

## **Research Highlights**

- low-energy uses underrepresented in this meeting

## **Looking forward**

- promising research avenues
- research needs in our field

## **Enabling advancement**

- educational efforts
- interdisciplinary collaboration



# HIGHLIGHTS



<b>Day 1 (Monday, November 14, 2022)</b> Registration and coffee/refreshments will be available from 7:30 (APS Conference Center)			
<b>Plenary Session 1</b> Chair: Rebecca Surman (Notre Dame) Held in the APS Conference Center (Bldg. 402) Auditorium			
Time (CST)	Presentation	Speaker	Duration
08:05-08:15	Welcome and logistics	Rebecca Surman (Notre Dame)	10
08:15-08:30	Charge and LRP process	Gail Dodge (ODU)	15
08:30-09:00	Predictive theory of nuclei and their interactions	Thomas Papenbrock (UTK)	30
09:00-09:30	Experimental studies of nuclei - Structure and reactions	Heather Crawford (LBNL)	30
09:30-10:00	Theory for nuclear astrophysics	Gail McLaughlin (NSCU)	30
10:00-10:30	Nuclear astrophysics experiments	Kelly Chipps (ORNL)	30

<b>Plenary Session 3</b> Chair: Grigory Rogachev (TAMU) Held in the APS Conference Center (Bldg. 402) Auditorium			
13:30-13:55	Fostering a culture of belonging in the low-energy nuclear physics community	Warren Rogers (IWU)	25
13:55-14:20	Training the next generation of nuclear scientists	Shelly Leshner (UW-La Crosse)	25
14:20-14:45	Quantum computing and simulations for nuclear physics	Dean Lee (FRIB)	25
14:45-15:10	Challenges, opportunities, and priorities for nuclear data	Libby McCutchan (BNL)	25
15:10-15:35	Broader applications of nuclear science and technology (remotely from London)	Graham Peaslee (ND)	25
15:35-16:00	Isotope production and harvesting	Sherry Yennello (TAMU)	25



# Active learning:

Generate first subset of training data

Train model

Identify new training examples

Repeat

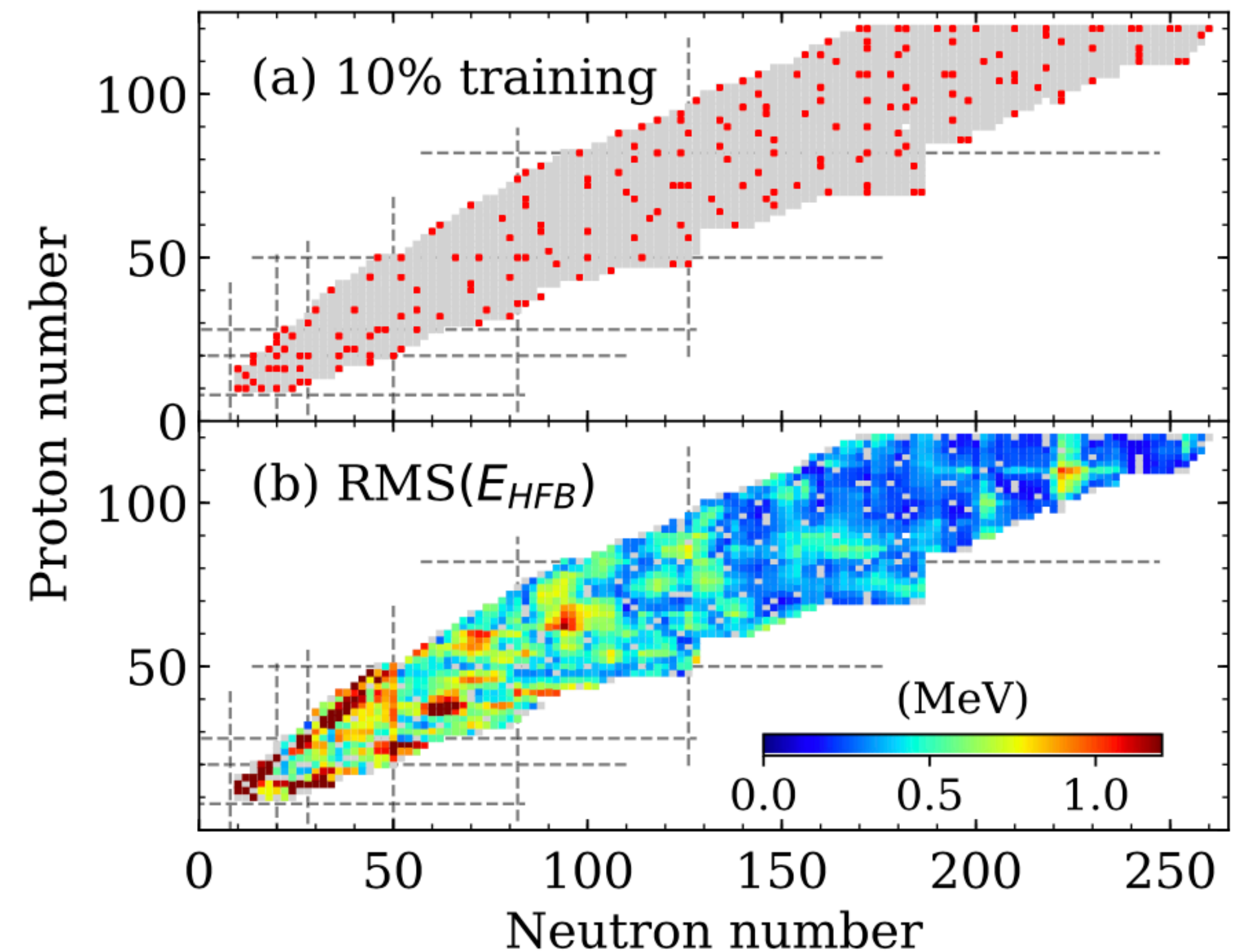
## PHYSICAL REVIEW LETTERS

Highlights Recent Accepted Collections Authors Referees Search Press About Edit

Editors' Suggestion

### Taming Nuclear Complexity with a Committee of Multilayer Neural Networks

Raphaël-David Lasserri, David Regnier, Jean-Paul Ebran, and Antonin Penon  
Phys. Rev. Lett. **124**, 162502 – Published 20 April 2020





Find articles with these terms

machine learning

Q

Journal or book title: Nuclear Instruments and Methods in Physics Research ... ✕

📄 Advanced search

346 results

sorted by *relevance* | [dat](#)

Research article

Comparative pulse shape discrimination study for Ca(Br, I)<sub>2</sub> scintillators using machine learning and conventional methods

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 23 October 2022, ...

M. Yoshino, T. Iida, ... A. Yoshikawa

Research article

Experimental tests of Gamma-ray Localization Aided with Machine-learning (GLAM) capabilities

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 3 June 2022, ...

Matthew Durbin, Ryan Sheatsley, ... Azaree Lintereur

Research article

Implementation of a machine learning technique for estimating gamma direction using a coaxial High Purity Germanium detector

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 30 June 2022, ...

R. W. Gladen, T. J. Harvey, ... V. A. Chirayath

Estimation of uranium concentration in ore samples with machine learning methods on HPGe gamma-ray spectra

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 16 March 2022, ...

P. G. Allinei, N. Pérot, ... R. Goupillou

Research article

Machine learning based event classification for the energy-differential measurement of the <sup>nat</sup>C(n,p) and <sup>nat</sup>C(n,d) reactions

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 6 April 2022, ...

P. Žugec, M. Barbagallo, ... E. Chiaveri

Research article ● *Open access*

Machine learning for beam dynamics studies at the CERN Large Hadron Collider

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 16 September 2020, ...

P. Arpaia, G. Azzopardi, ... J. Wenninger

 [View PDF](#)

Research article

Fast muon tracking with machine learning implemented in FPGA

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 10 October 2022, ...

Chang Sun, Takumi Nakajima, ... Makoto Tomoto

Research article

Classical and machine learning methods for event reconstruction in NeuLAND

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 19 July 2021, ...

Jan Mayer, Konstanze Boretzky, ... Andreas Zilges

Research article

Particle identification and analysis in the SciCRT using machine learning tools

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 8 April 2021, ...

R. Garcia, M. Anzorena, ... Y. Nakamura

Research article

Machine Learning aided 3D-position reconstruction in large LaCl3 crystals

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 16 March 2021, ...

J. Balibrea-Correa, J. Lerendegui-Marco, ... C. Domingo-Pardo

Short communication

Imaging particle collision data for event classification using machine learning

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 9 April 2019, ...

S. V. Chekanov

Research article

Improvement of machine learning enhanced genetic algorithm for nonlinear beam dynamics optimization

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 5 September 2019, ...

Jinyu Wan, Paul Chu, ... Yongjun Li

Research article

Machine learning methods for track classification in the AT-TPC

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 14 June 2019, ...

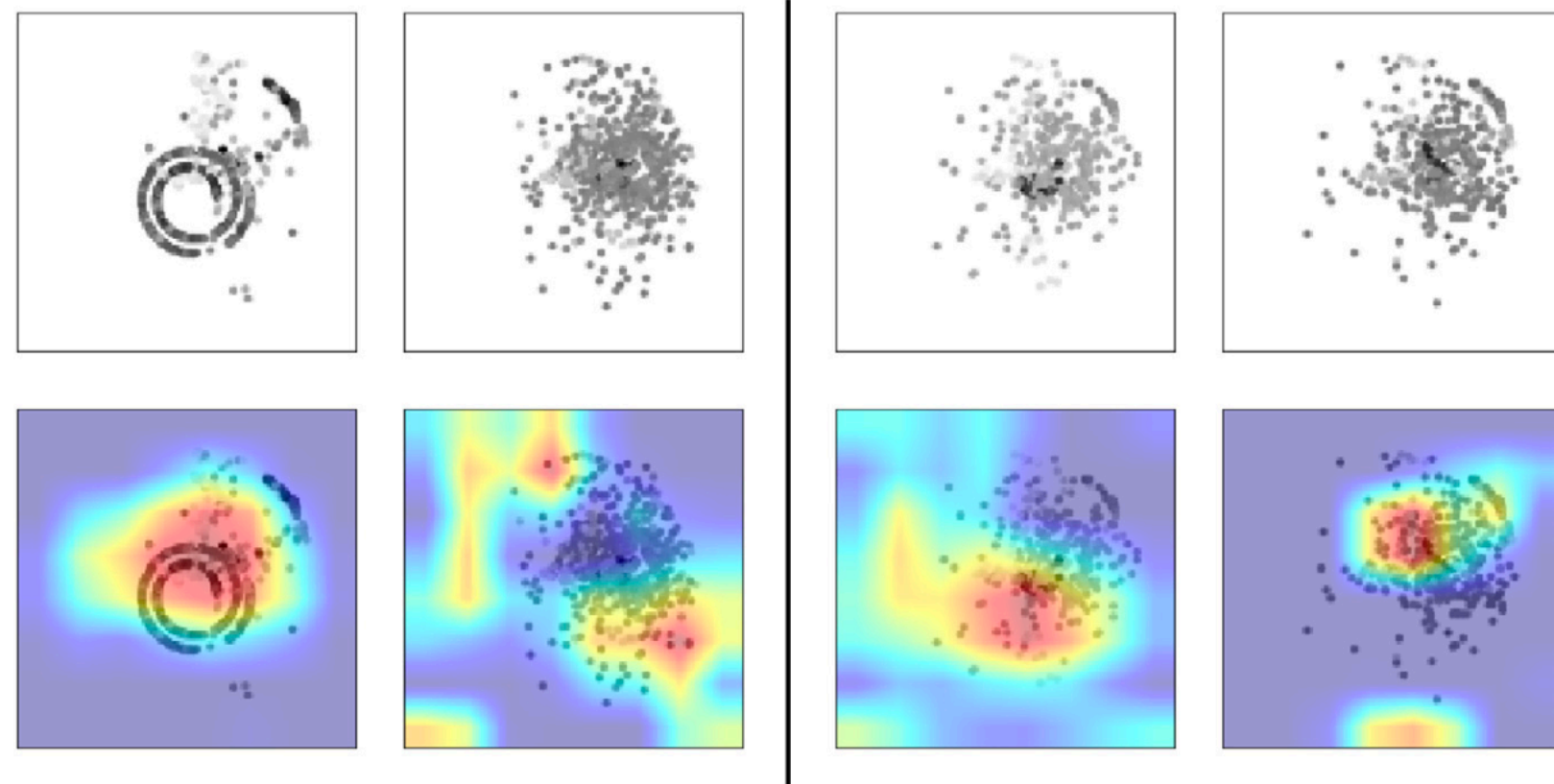
M. P. Kuchera, R. Ramanujan, ... Ruiming Chen



# ML IN LOW-ENERGY EXPERIMENTS

M.P. Kuchera, R. Ramanujan, J.Z. Taylor et al.

Nuclear Inst. and Methods in Physics Research, A 940 (2019) 156–167



**Fig. 12.** Sample visual explanations of the CNN's classification decisions on experimental data. The top row shows the input images. The heatmaps on the bottom row indicate the regions of the respective images that the model paid particular attention to when making its classification decisions. Areas shaded in red correspond to pixels that were weighted more heavily in the decision, while areas shaded in blue were weighted less. From left-to-right, these examples constitute cases where the model correctly labeled a proton event, correctly labeled a non-proton event, mistook a proton event for a non-proton event, and mistook a non-proton event for a proton event. We note that the model focuses on regions of the point cloud that display structure when correctly identifying proton events. Its “attention” is more diffuse in the other scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



Nuclear Instruments and Methods in Physics  
Research Section A: Accelerators, Spectrometers,  
Detectors and Associated Equipment

Volume 1010, 11 September 2021, 165461



## Unsupervised learning for identifying events in active target experiments

R. Solli <sup>a, b, c, d, e</sup>, D. Bazin <sup>c</sup>, M. Hjorth-Jensen <sup>c, d</sup>, M.P. Kuchera <sup>e</sup>, R.R. Strauss <sup>f, g</sup>

Show more

Share Cite

<https://doi.org/10.1016/j.nima.2021.165461>

Get rights and content

Nuclear Inst. and Methods in Physics Research, A 940 (2019) 156–167



Contents lists available at ScienceDirect

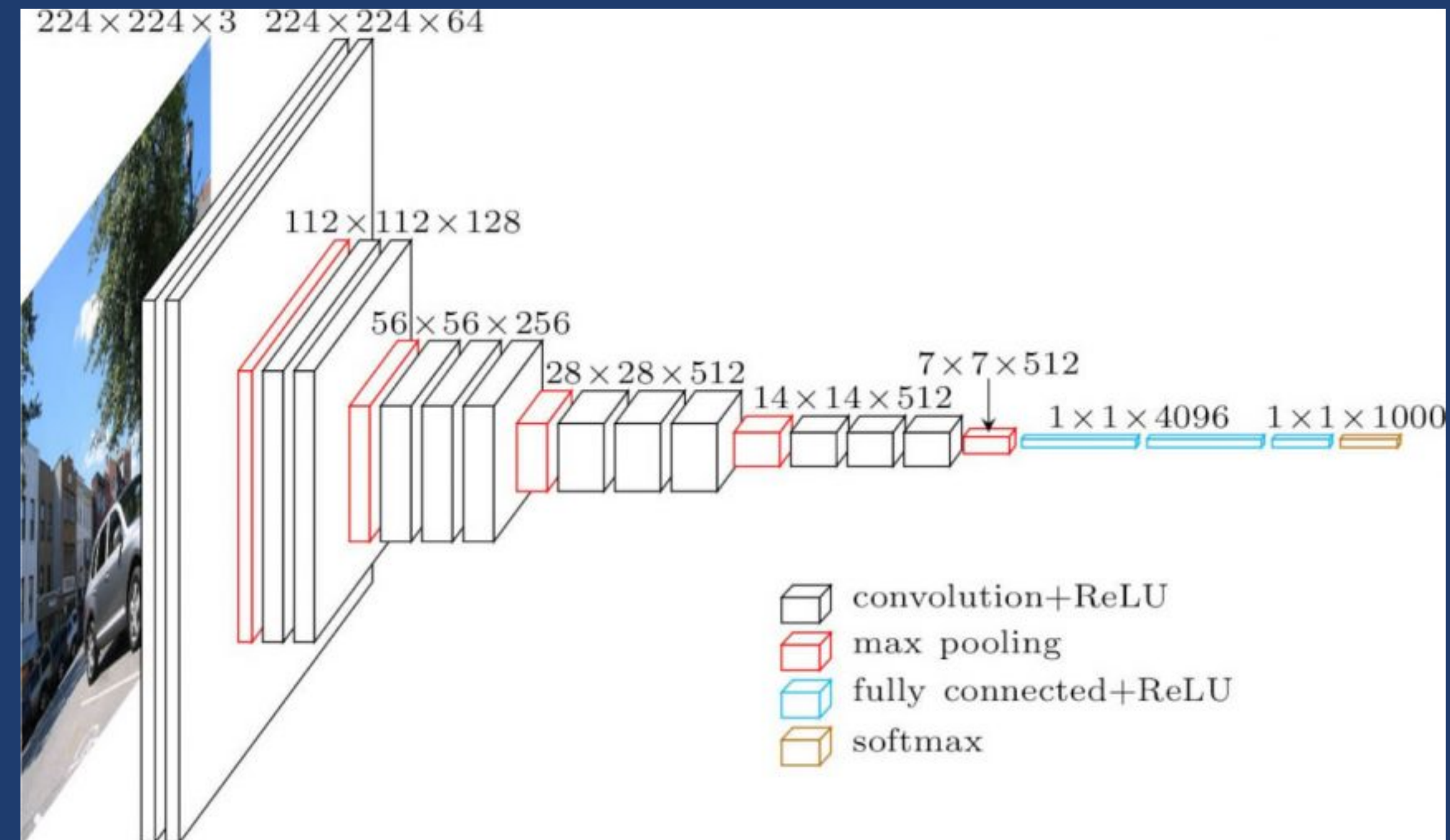
Nuclear Inst. and Methods in Physics Research, A

journal homepage: [www.elsevier.com/locate/nima](http://www.elsevier.com/locate/nima)



## Machine learning methods for track classification in the AT-TPC

M.P. Kuchera <sup>a, \*</sup>, R. Ramanujan <sup>b</sup>, J.Z. Taylor <sup>a</sup>, R.R. Strauss <sup>b</sup>, D. Bazin <sup>c</sup>, J. Bradt <sup>c</sup>,  
Ruiming Chen <sup>a</sup>





# LOOKING FORWARD:

- NUCLEAR DATA
- UNCERTAINTY QUANTIFICATION
- UNIQUELY STRUCTURED DATA
- REALTIME SYSTEMS



# IMPACT OF AI FOR NUCLEAR SCIENCE

MORE HIGH-QUALITY DATA

IMPROVED BEAM QUALITY

DATA STANDARDS

ACCELERATION OF SCIENTIFIC  
DISCOVERY

REPRODUCIBILITY

INCREASED BEAMTIME / MORE  
EXPERIMENTS

WORKFORCE DEVELOPMENT

IAEA TECHNICAL MEETING ON AI



# CROSS-CUTTING NEEDS

## Nuclear Science Drivers

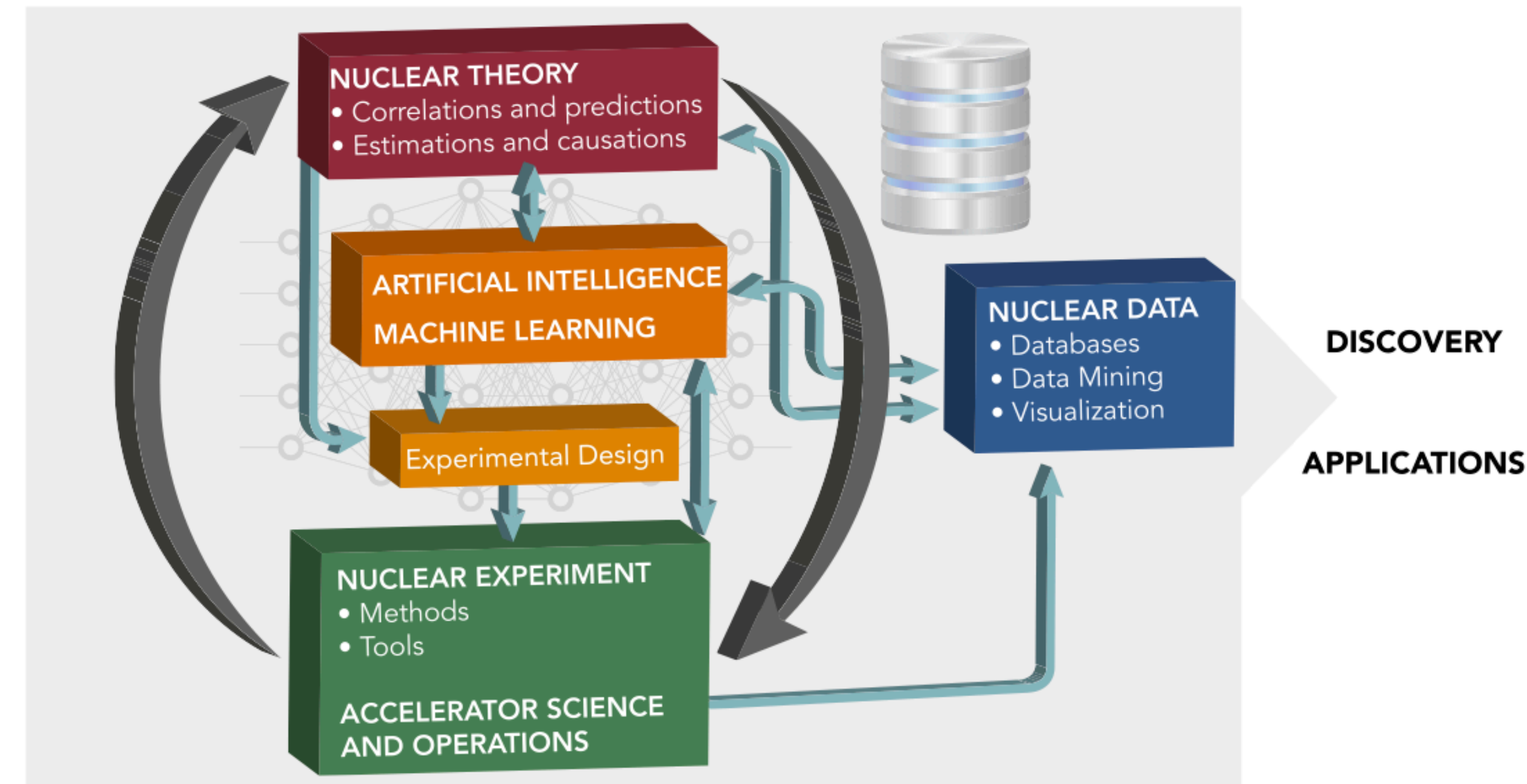
- Realtime systems
- Uncertainty quantification in AI

## Education Efforts

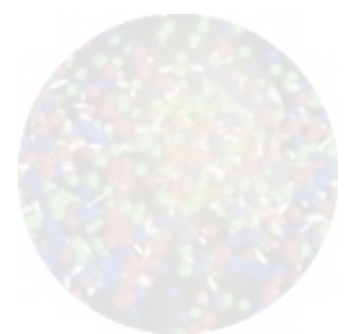
- AI focused summer schools and workshops

## Interdisciplinary collaboration and funding

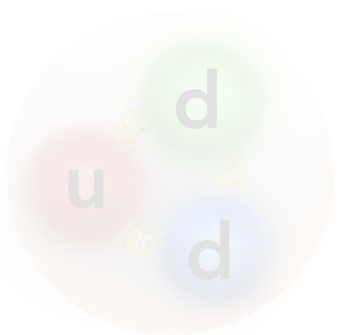
- Interdisciplinary positions
- Research and development
- Production and deployment



IAEA TECHNICAL MEETING ON AI



Hot and Dense Nuclear Matter



Hadrons



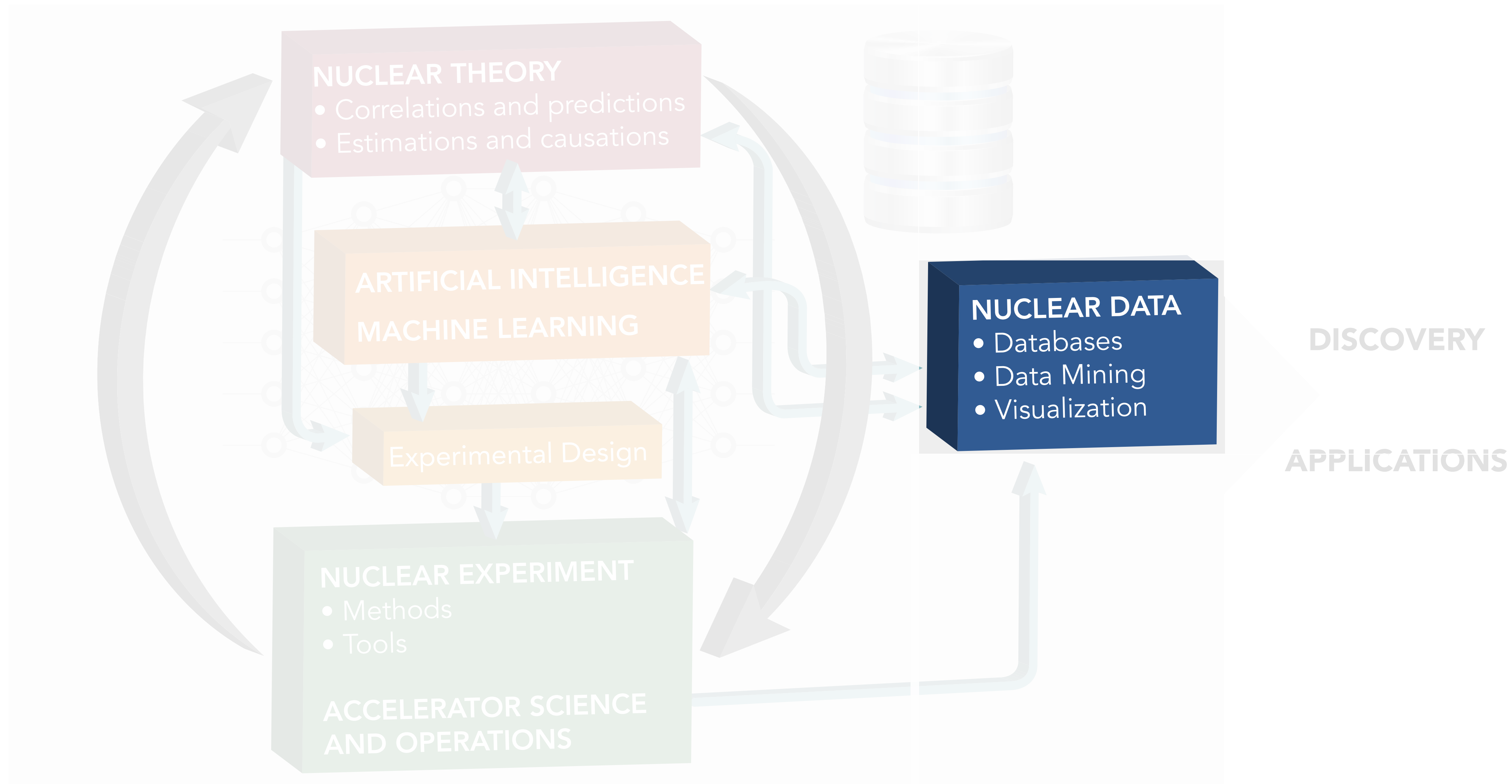
Atomic Nucleus



Nuceli in the Cosmos



Fundamental Interactions





# NUCLEAR DATA

COURTESY C. MORSE, BNL (DNP 2022)

## NNDC: new database format

- 2023 release for ENSDF
- JSON based
- python API
- enables ML



```
# Initialize API
api = ensdfAPI(ipAddress="127.0.0.1", port=5001)

# Get all ground state halflives
values_dict = api.filterByGroundStateHalfLife()

# Create dataframe and add log scale column
dataframe = plot.createViewDataFrame(values_dict)
dataframe["halflife_log"] = np.log2(dataframe["halfLife"])

# Label plot
plot.configuration.setAxisTitle("x", "log<sub>10</sub>(t<sub>1/2</sub> [s])")
plot.configuration.setAxisTitle("y", "Counts")

# Plot as a histogram
figure=plot.createHistogram(dataframe, "halflife_log")

plot.showFigure(figure)
```

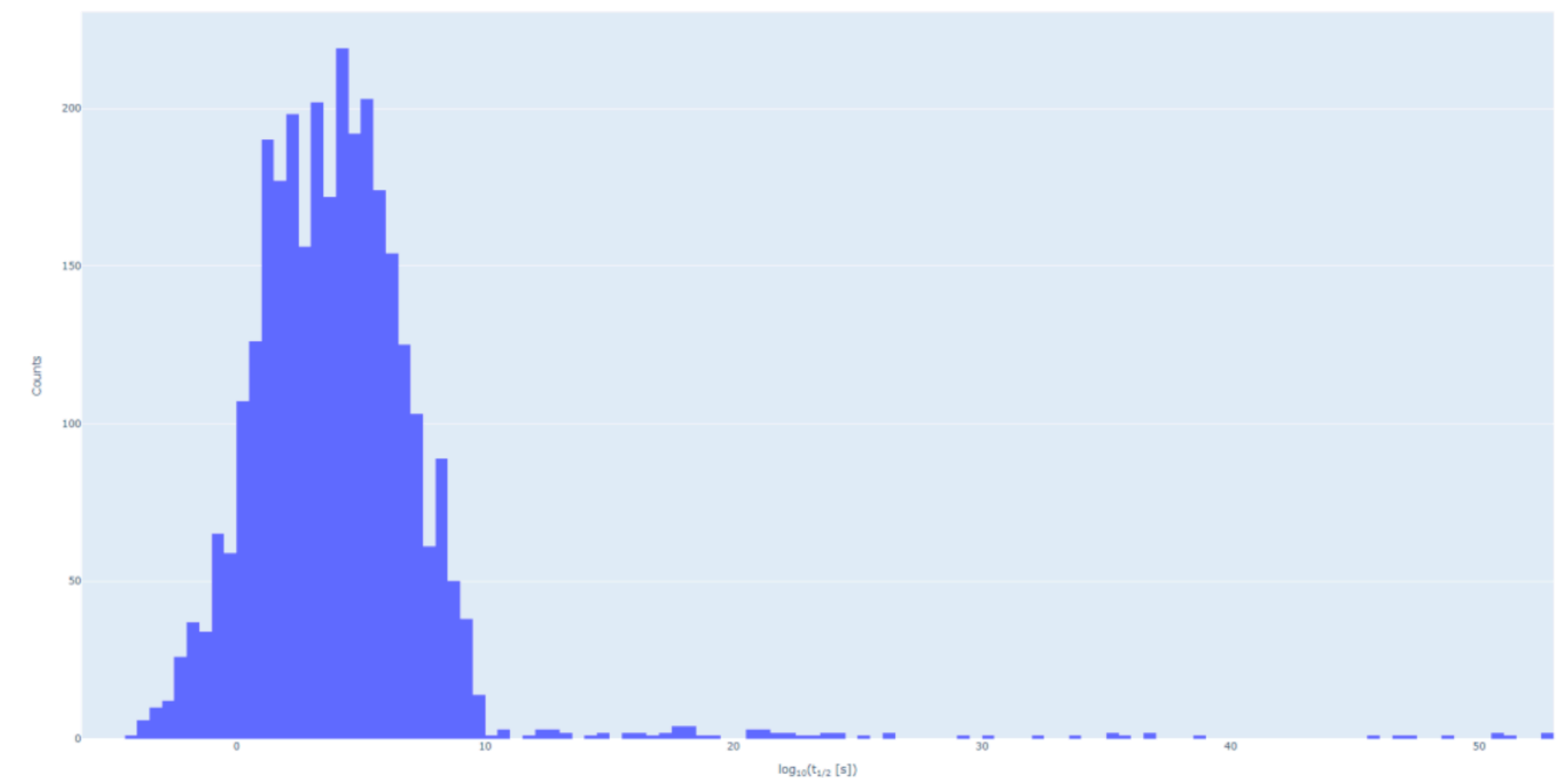
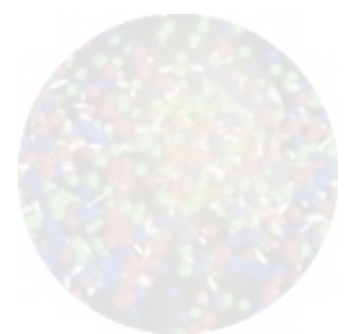
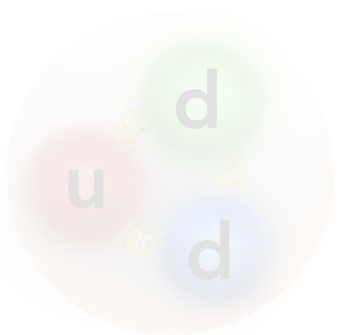


Image courtesy of Donnie Mason



Hot and Dense  
Nuclear Matter



Hadrons



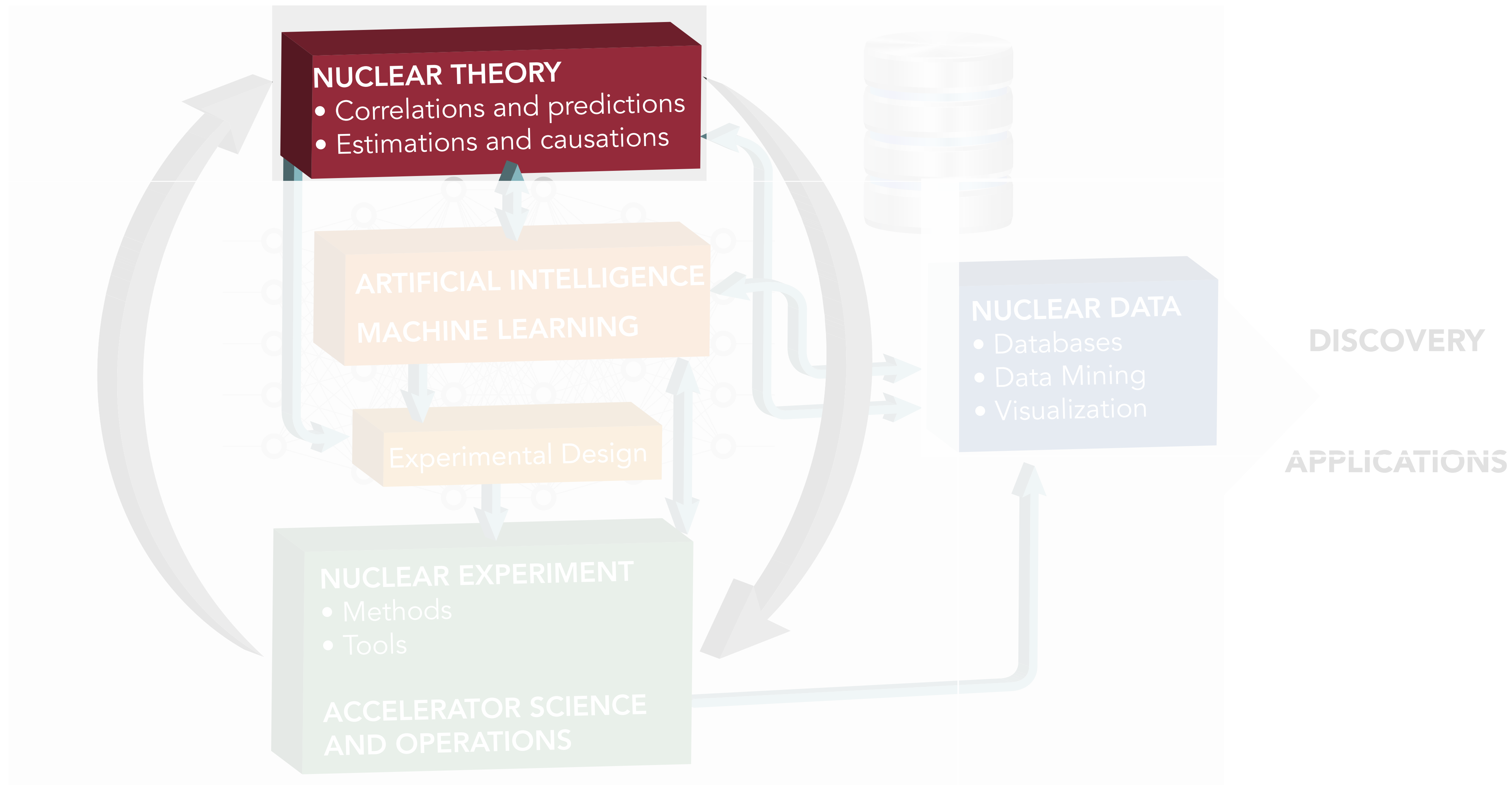
Atomic Nucleus



Nuceli in the Cosmos



Fundamental Interactions





# NUCLEAR THEORY: UNCERTAINTY QUANTIFICATION

Mach. Learn.: Sci. Technol. 2 (2021) 015002 <https://doi.org/10.1088/2632-2153/aba6f3>

MACHINE  
LEARNING  
Science and Technology

PAPER

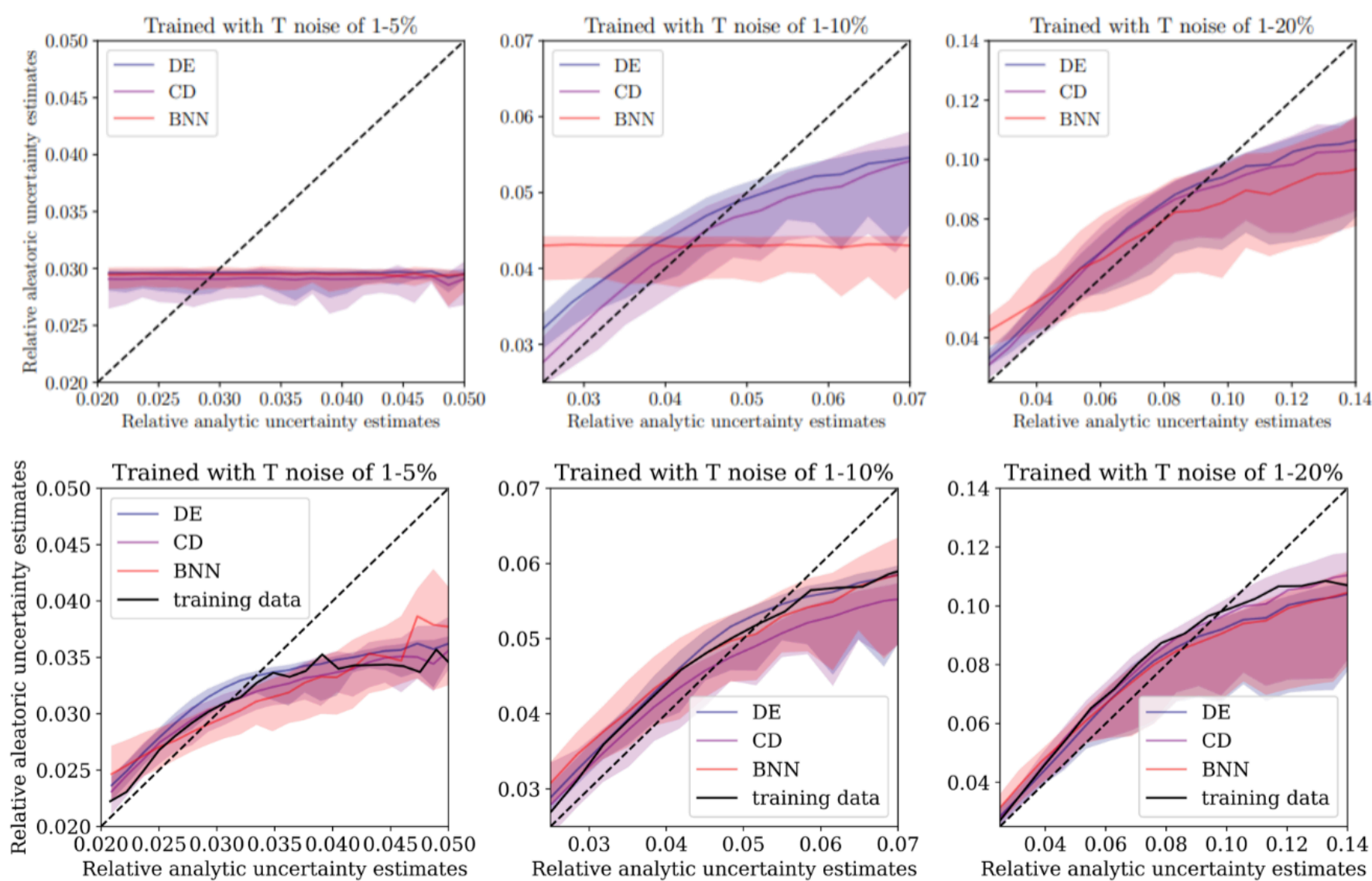
Deeply uncertain: comparing methods of uncertainty quantification in deep learning algorithms

João Caldeira<sup>1</sup> and Brian Nord<sup>1,2,3</sup>

- <sup>1</sup> Fermi National Accelerator Laboratory, P.O. Box 500, Batavia, IL 60510, United States of America
- <sup>2</sup> Kavli Institute for Cosmological Physics, University of Chicago, Chicago, IL 60637, United States of America
- <sup>3</sup> Department of Astronomy and Astrophysics, University of Chicago, Chicago, IL 60637, United States of America

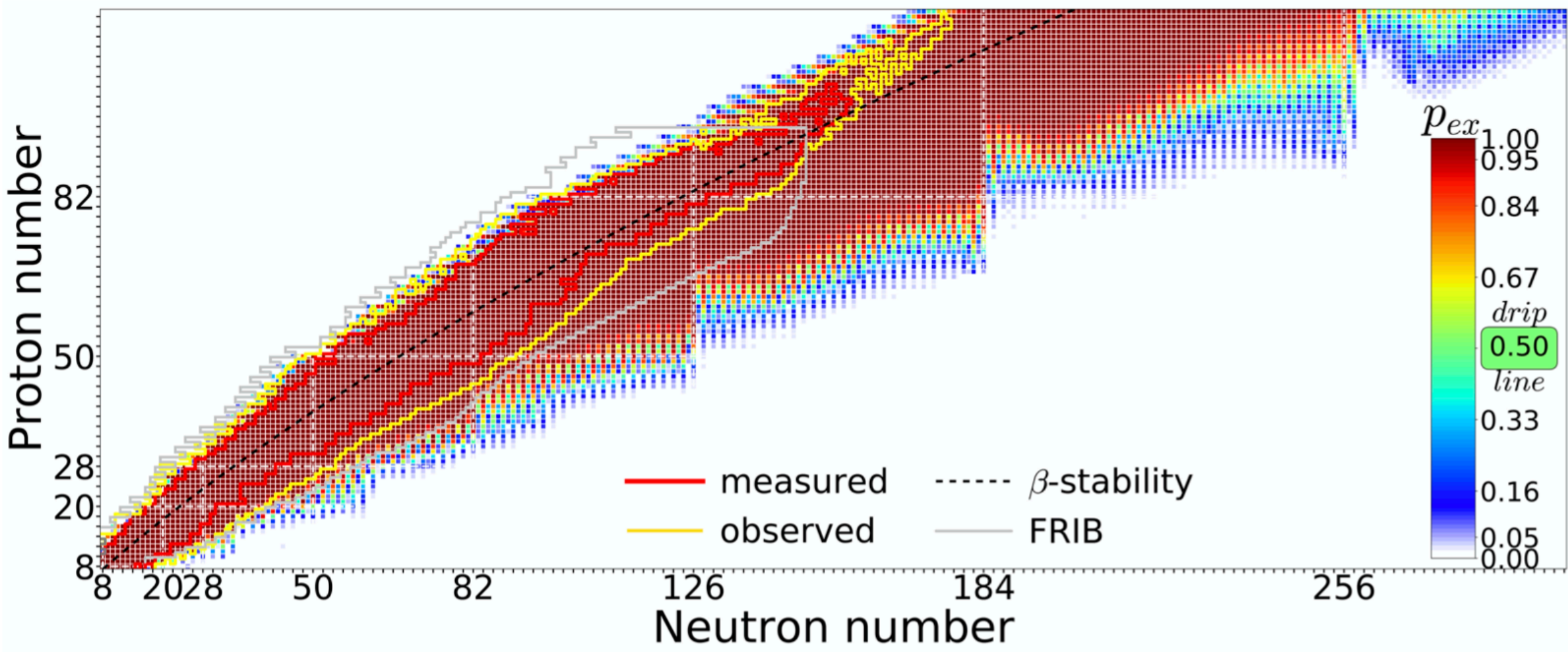
E-mail: [caldeira@fnal.gov](mailto:caldeira@fnal.gov)

Keywords: uncertainty quantification, neural networks, Bayesian inference, ensemble of neural networks

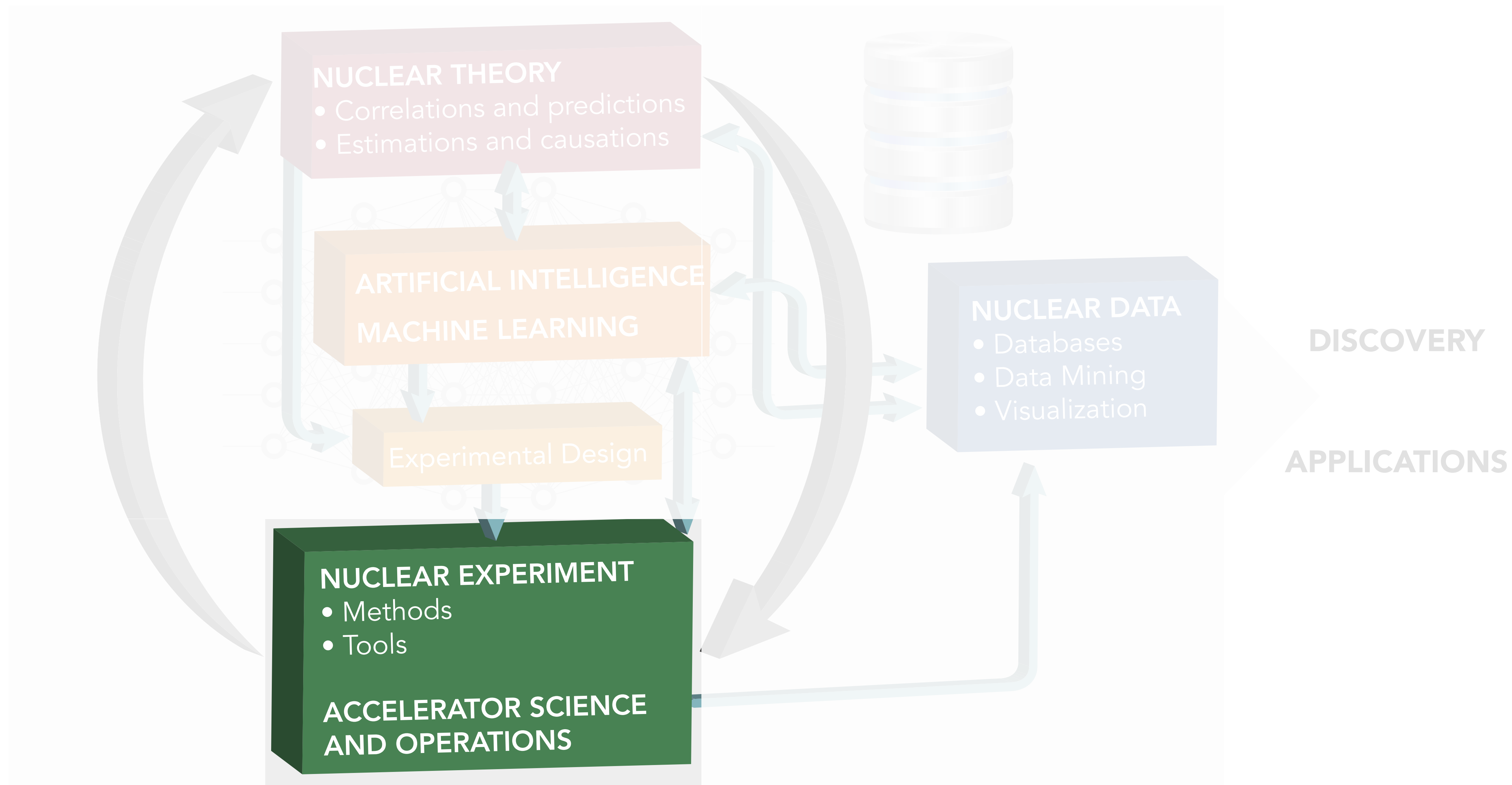


Neufcourt et al., Phys. Rev. C 101, 044307 (2020)

probability of existence



PLOTS COURTESY B. KRONHEIM, UMD





# UNIQUE CHALLENGES / OPPORTUNITIES IN LE-NP

- uniquely structured data
- “multimessenger” data sources
- distributed systems

# STEPS TOWARDS WIDESPREAD CAPABILITIES

- data standards
- open source code
- following best practices
  - + standards
  - + documentation
  - + fully-working examples
- collaboration with AI scientists



# BIG-PICTURE ADVANCEMENTS IN AI

## Large models trained on massive amounts of data

- large language models
- image-based models
- image-text pairs
- transformer models

RECENT DISRUPTORS  
IN AI RESEARCH

## Would require:

- (more) open access, data sharing
- computational resources (GPUs)
- easy interface with packages
- collaboration

# ENABLING ADVANCEMENT OF OUR SCIENCE WITH AI/ML

- EDUCATION EFFORTS
- INTERDISCIPLINARY COLLABORATIONS



# EDUCATION EFFORTS

Pipeline: students enter graduate school with strong computational skills



"Both graduates and their employers report that preparation for positions available to those with physics training could be significantly improved. Studies of physics graduates conclude that their technical skills should be expanded to address a wider and deeper knowledge of computational analysis tools..."

[J-TUPP Report: "Preparing Physics Students for the 21st Century Careers"](#)



PARTNERSHIP FOR INTEGRATION OF COMPUTATION INTO UNDERGRADUATE PHYSICS

## 2023 Excellence in Physics Education Award Recipient

### Citation:

*"For developing an active, inclusive, and supportive community of physics educators dedicated to integrating computation into their instruction; creating, reviewing, and disseminating instructional materials; and generating knowledge of computation in physics curricula and of effective practices."*



# EDUCATION EFFORTS

Establish annual education efforts to build an AI literate workforce





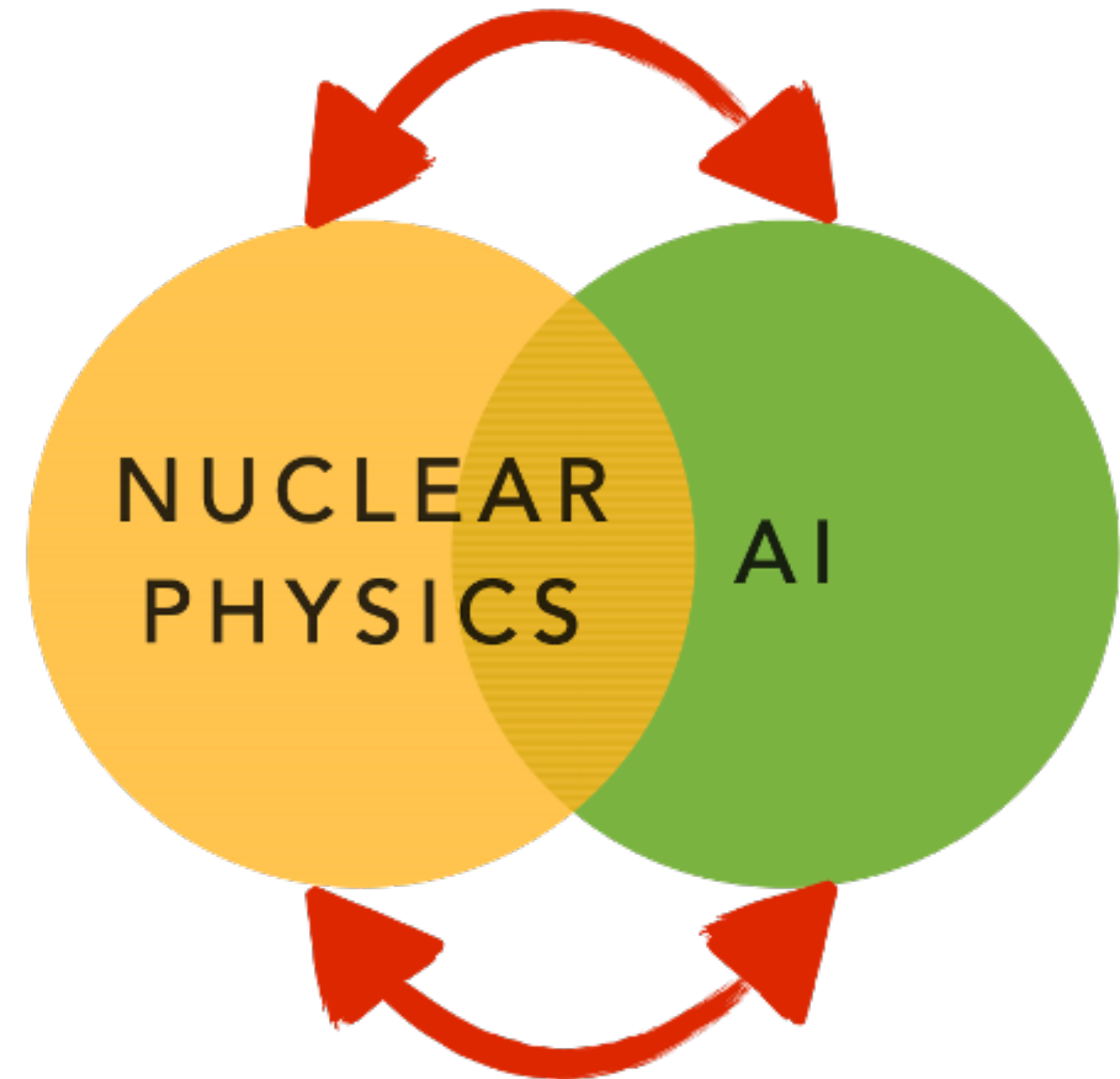
# INTERDISCIPLINARY COLLABORATION AND FUNDING

## Collaboration

- AI scientists
- Experts in adjacent fields

## Funding

- Interdisciplinary positions
- Research and development
- Production and deployment



# INTERDISCIPLINARY COLLABORATION

Engage meaningfully with the AI research community



---

PHYSICAL REVIEW LETTERS **125**, 121601 (2020)

## **Equivariant Flow-Based Sampling for Lattice Gauge Theory**

Gurtej Kanwar<sup>1</sup>, Michael S. Albergo<sup>2</sup>, Denis Boyda<sup>1</sup>, Kyle Cranmer<sup>2</sup>, Daniel C. Hackett<sup>1</sup>,  
Sébastien Racanière<sup>3</sup>, Danilo Jimenez Rezende<sup>3</sup>, and Phiala E. Shanahan<sup>1</sup>

<sup>1</sup>Center for Theoretical Physics, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA

<sup>2</sup>Center for Cosmology and Particle Physics, New York University, New York, New York 10003, USA

<sup>3</sup>DeepMind Technologies Limited, 5 New Street Square, London EC4A 3TW, United Kingdom





# INTERDISCIPLINARY COLLABORATION

Engage meaningfully with the AI research community



Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence (IJCAI-21)  
Survey Track

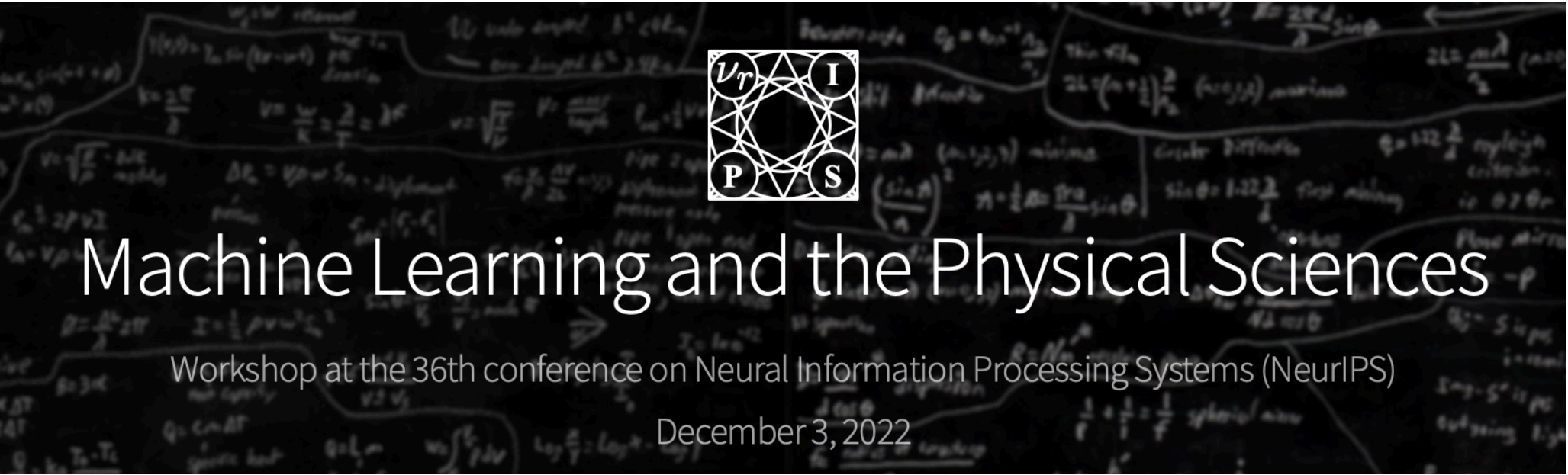
### A Survey of Machine Learning-Based Physics Event Generation

**Yasir Alanazi<sup>1</sup>, Nobuo Sato<sup>2</sup>, Pawel Ambrozewicz<sup>2</sup>, Astrid Hiller-Blin<sup>2</sup>,  
Wally Melnitchouk<sup>2</sup>, Marco Battaglieri<sup>2</sup>, Tianbo Liu<sup>3</sup> and Yaohang Li<sup>1</sup>**

<sup>1</sup>Department of Computer Science, Old Dominion University, Norfolk, Virginia 23529, USA

<sup>2</sup>Jefferson Lab, Newport News, Virginia 23606, USA

<sup>3</sup>Key Laboratory of Particle Physics and Particle Irradiation (MOE), Institute of Frontier and Interdisciplinary Science, Shandong University, Qingdao, Shandong 266237, China  
yalan001@odu.edu, {nsato, pawel, ahblin, wmelnitc, battagli}@jlab.org, liutb@sdu.edu.cn, yaohang@cs.odu.edu



Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence (IJCAI-21)

### Simulation of Electron-Proton Scattering Events by a Feature-Augmented and Transformed Generative Adversarial Network (FAT-GAN)

**Yasir Alanazi<sup>1</sup>, Nobuo Sato<sup>2</sup>, Tianbo Liu<sup>2</sup>, Wally Melnitchouk<sup>2</sup>, Pawel Ambrozewicz<sup>2</sup>,  
Florian Hauenstein<sup>3</sup>, Michelle P. Kuchera<sup>4</sup>, Evan Pritchard<sup>4</sup>, Michael Robertson<sup>5</sup>,  
Ryan Strauss<sup>5</sup>, Luisa Velasco<sup>6</sup> and Yaohang Li<sup>1</sup>**

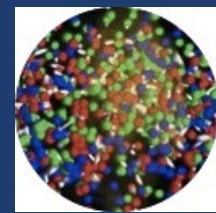


IJCAI

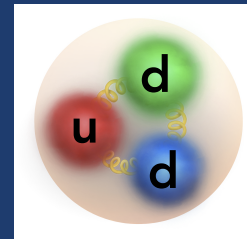


**ICML**  
International Conference  
On Machine Learning

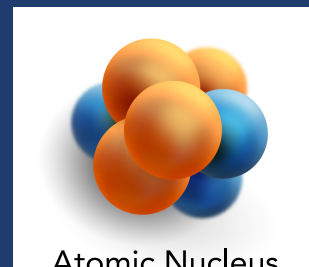
# THANK YOU!



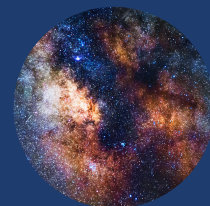
Hot and Dense  
Nuclear Matter



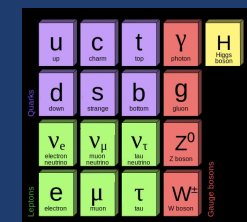
Hadrons



Atomic Nucleus



Nuceli in the Cosmos



Fundamental Interactions

