

A short walk through machine learning in nuclear physics

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In this second lecture I will provide a **snapshot** of different applications of **Machine Learning techniques in Nuclear Physics**. Particularly, I will briefly go through some selected examples of **Machine Learning applications in Nuclear Theory and Experiments**

Most of what I will say is taken from these two very comprehensive recent reviews

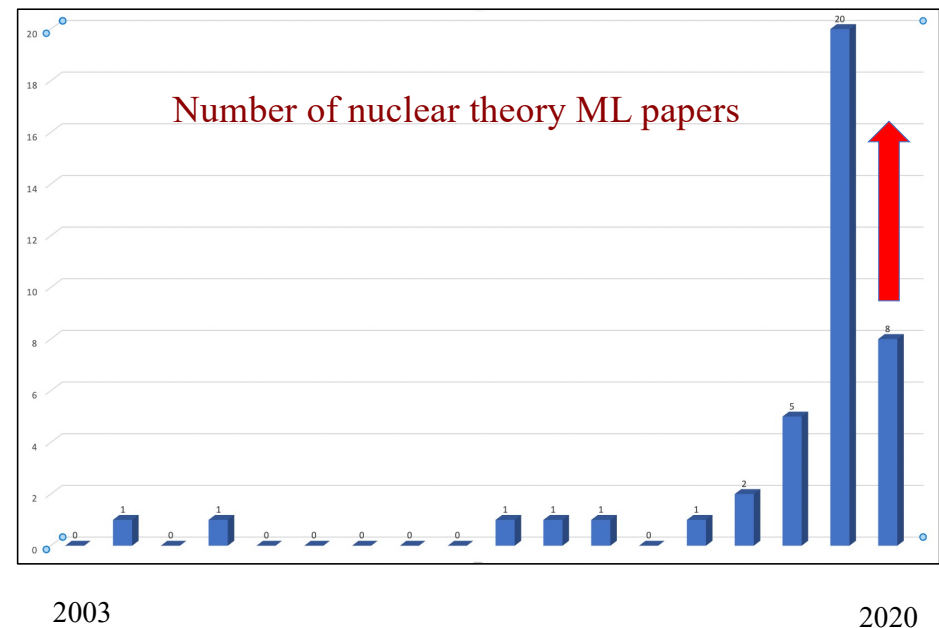
1. P. Bedaque et al, *A.I. for nuclear physics*, Eur. Phys. J. A (2021) 57:100
2. A. Boehnlein et al., *Machine Learning in Nuclear Physics*, Rev. Mod. Phys. 94, 031003 (2022)



Machine Learning Applications in Nuclear Theory

Since the pioneering work of *Gazula et al. Gazula et al., NPA 540 1 (1992)*, who employed a **feed forward neural network to study global nuclear properties across the nuclear landscape**, Machine Learning has been used to predict

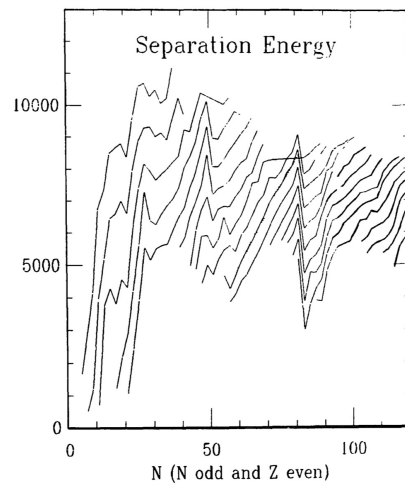
- Nuclear masses & charge radii
- α - & β -decay half-lives
- Fission yields
- Fusion reaction cross sections
- Isotropic cross-sections in proton-induced spallation reactions
- Ground and excited state energies
- Dripline locations
- The deuteron properties
- Proton radius
- Liquid-gas phase transition
- Nuclear energy density functionals
- Neutron star EoS
- The nucleon axial form factor from neutrino scattering
- Extrapolation of A-body results with ANN
- ...



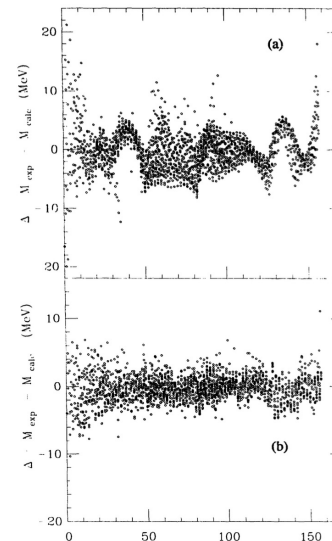
Early Applications of ML in Nuclear Physics

In a pioneering paper, *Gazula et al., NPA 540 1 (1992)*

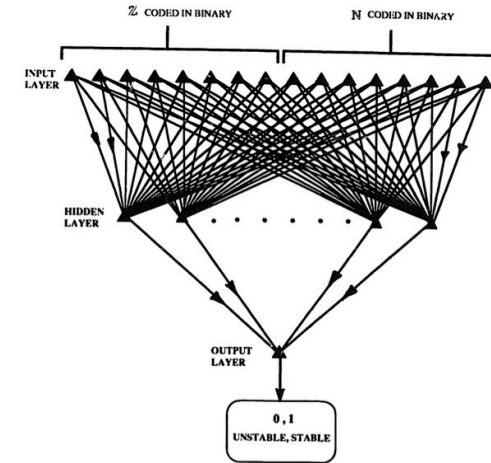
- Employed the backpropagation algorithm to **teach feedforward ANNs** the existing data on nuclear stability and atomic masses **to study global nuclear properties across the nuclear landscape**
- Particularly, they constructed networks that learn and predict: **stability of nuclides, dripline locations, atomic masses, separation energies**



Neutro separation energies Solid lines: training (experimental) data. Dotted line: prediction a the ANN with a 16+18+18+18+1 architecture



Deviation $\Delta(Z, N) = M_{exp} - M_{cal}$ between learned masses and the experimental ones



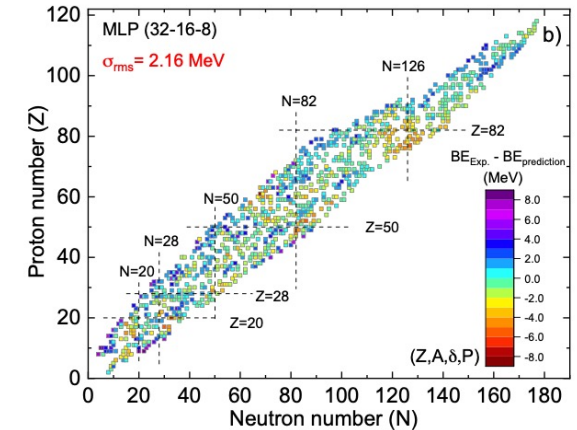
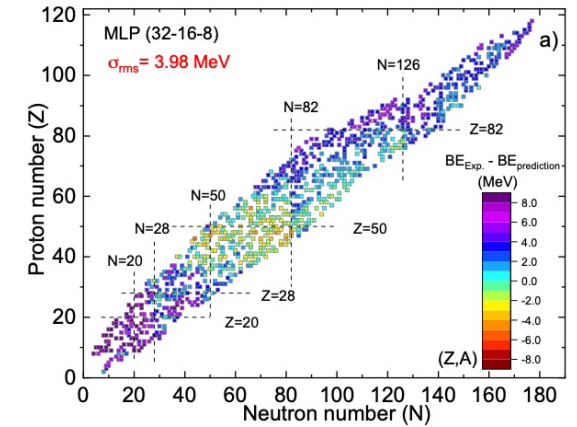
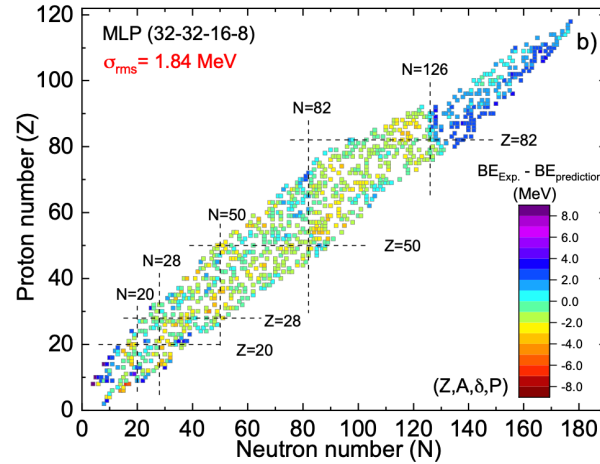
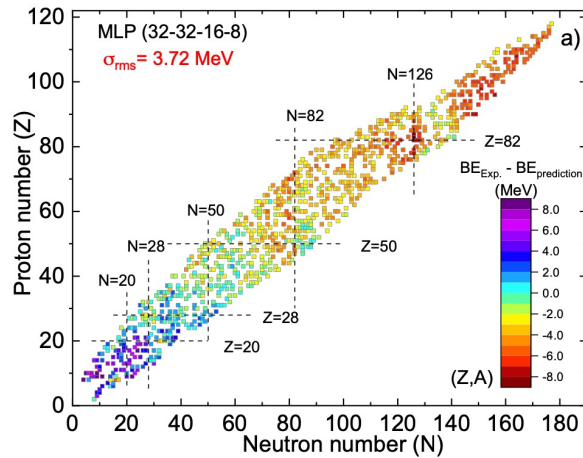
Feedforward ANN taught to distinguish between stable & unstable nuclides.

- Architecture: 16+H+1. Several values of the number H of neurons in the hidden layer were considered
- Training set: 2226 entries from the General Electric Chart of the Nuclides

Nuclear Masses

Recently, *Yüskel et al., arXiv:2101.12117v2*

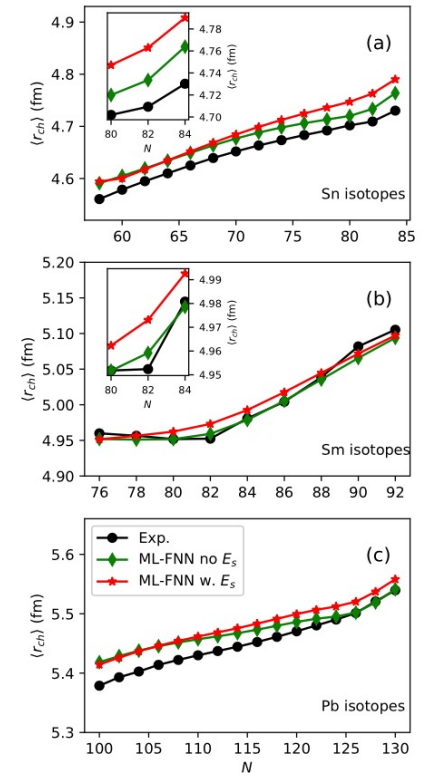
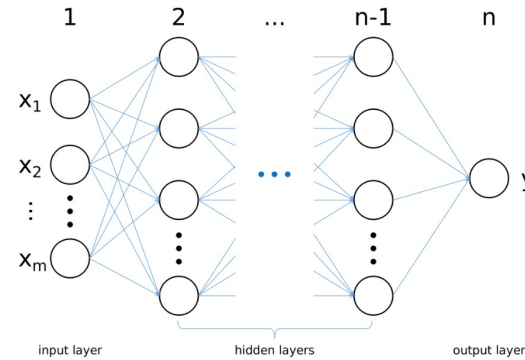
- Have implemented a **Multilayer Perceptron (MLP)**, to predict **ground-state binding energies of atomic nuclei**.
- They use two different MLP architectures with **three** and **four hidden layers** to study their effects on the predictions
- In the first one, they use as input the **proton and mass numbers** of nuclei whereas in the second they added **pairing** as additional input
- They show that using **appropriate MLP architectures** and putting more physical information in the input channels, **MLP can make fast and reliable predictions for binding energies of atomic nuclei**



Nuclear Charge Radii

In 2020, *Wu et al., PLB 809 135743 (2020)*

- Trained a **feed-forward neural network** model to calculate the nuclear charge radii
- The model was trained with the **input data** set of proton and neutron number Z , N , the electric quadrupole transition strength $B(E2)$ from the first excited $2+$ state to the ground state, together with the symmetry energy
- Their model reproduced well not only the isotope dependence of charge radii, but also the kinks of charge radii at the neutron magic numbers $N = 82$ for Sn and Sm isotopes, and also $N = 126$ for Pb isotopes

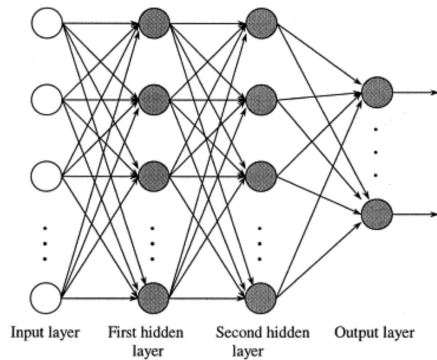


- Activation function:** hyperbolic tangent
- Cost function:** mean squared error
- Optimization algorithm:** RMSProp method

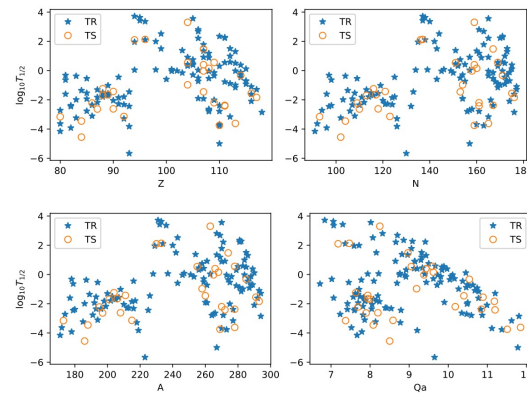
α -decay half-lives

Freitas & Clark, arXiv:1910.12345 have trained ANNS by a standard backpropagation learning algorithm to model and predict the systematics of α -decay of heavy and superheavy nuclei. They employ **two kinds of network models**:

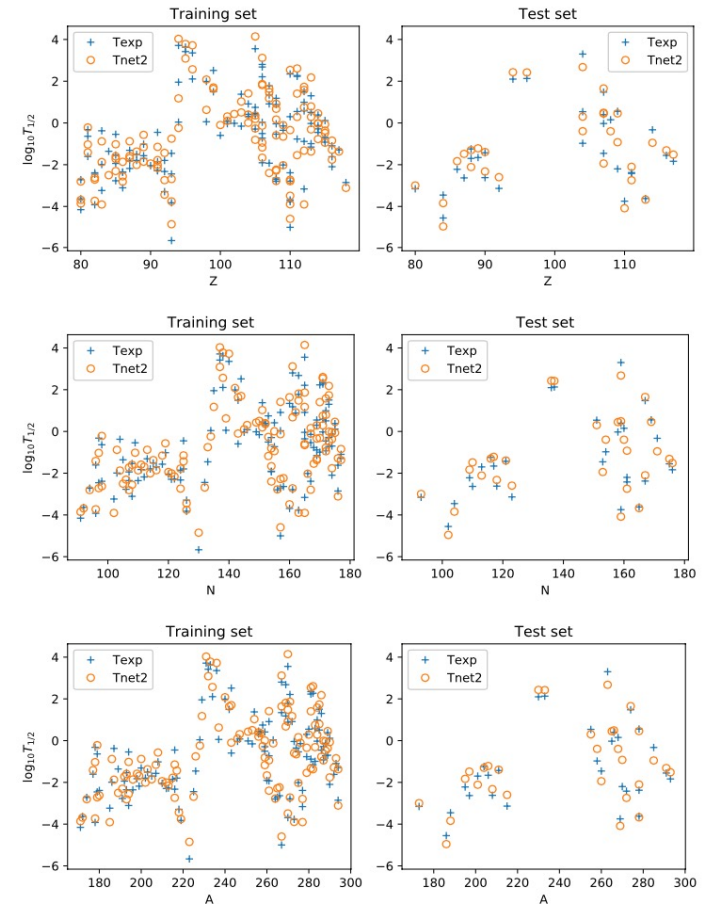
- **Net1**: Trained on the experimental half-life data for the selected 150 nuclear examples, yielding a purely statistical model of α decay
- **Net2**: Trained on the data set consisting of the differences between the predictions of a given theoretical model of α decay (specifically, effective liquid drop model), providing statistically derived corrections to this model



Net1 results



Net2 results

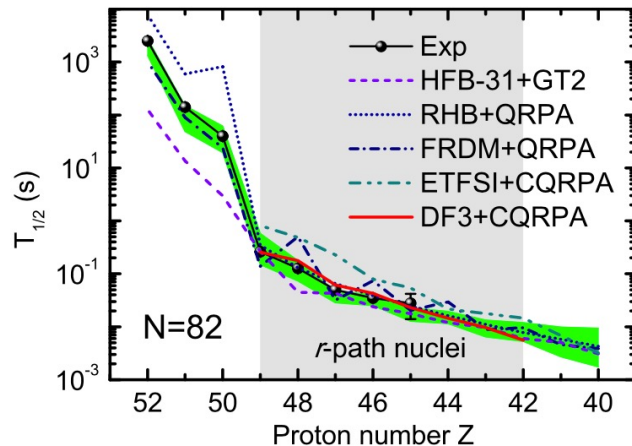


β -decay half-lives

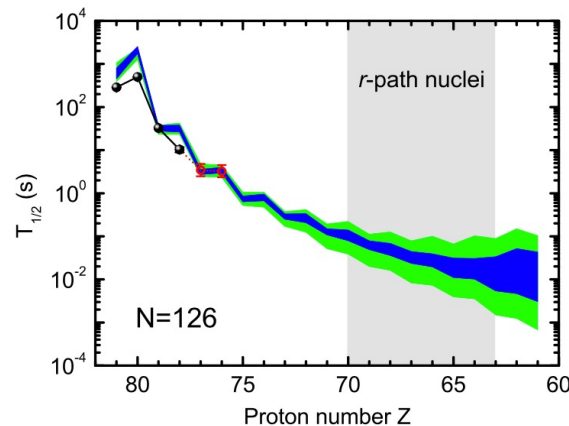
Recently, *Niu et al., PRC 99, 064307 (2019)*

- Have employed a **Bayesian Neural Network** (BNN) to predict nuclear β -decay half-lives accurately and give reasonable uncertainty evaluations.
- Known physics was explicitly embedded, including the ones described by the Fermi theory of β decay, and the dependence of half-lives on pairing correlations and decay energies.
- Potential physics, which is not clear or even missing in nuclear models nowadays, is learned by the BNN

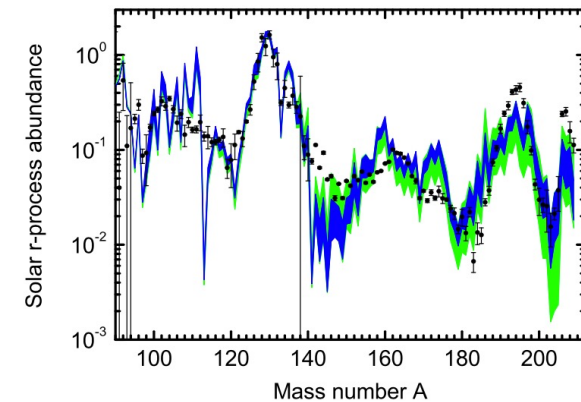
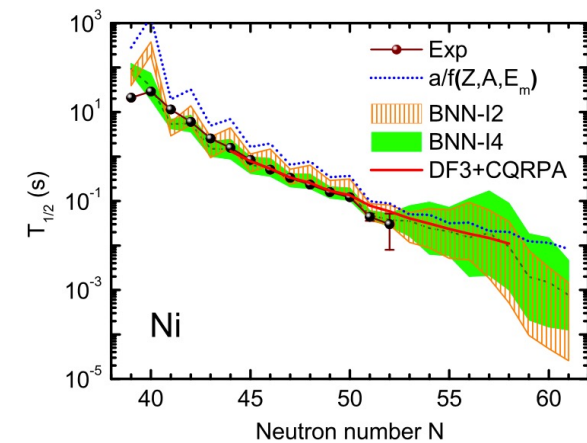
β -decay half-lives of N=82 isotopes



β -decay half-lives of N=126 isotopes



β -decay half-lives of Ni isotopes

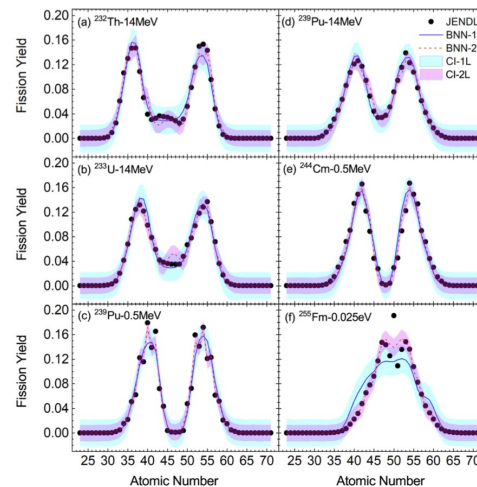


Impact of β -decay half-lives on solar r-processes abundances

Fission Yields

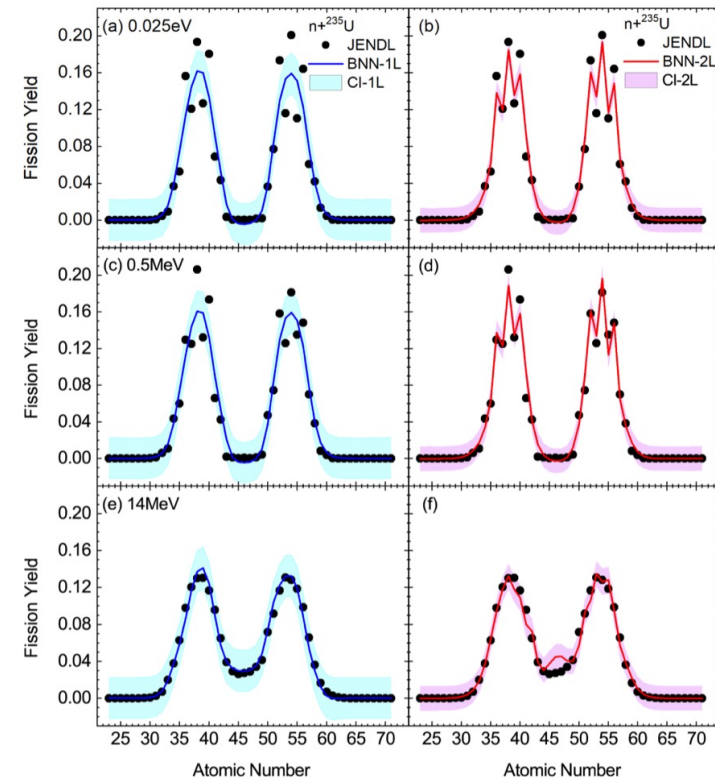
Last year, *Qiao et al., PRC 103, 034621 (2021)*

- Applied a **Bayesian neural network (BNN)** approach to learn existing evaluated **charge yields** and infer the incomplete charge yields of ^{239}U .
- They found that a two-hidden-layer BNN is improved the results compared to a single- hidden-layer BNN for overall performance.
- Their results support the normal charge yields of ^{239}U around Sn and Mo isotopes.
- The BNN evaluation results are quite satisfactory on distribution positions and energy dependencies of fission yields



BNN learning results of charge distributions of six nuclei

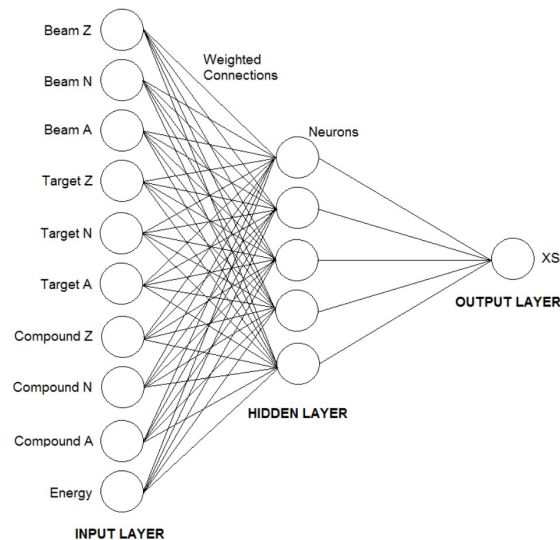
BNN predicted fission charge yields of $n + ^{235}\text{U}$



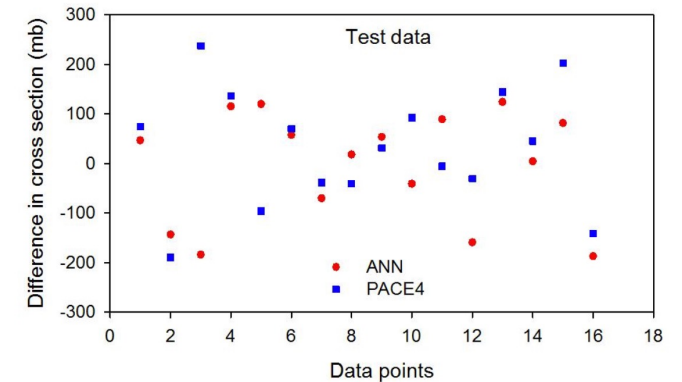
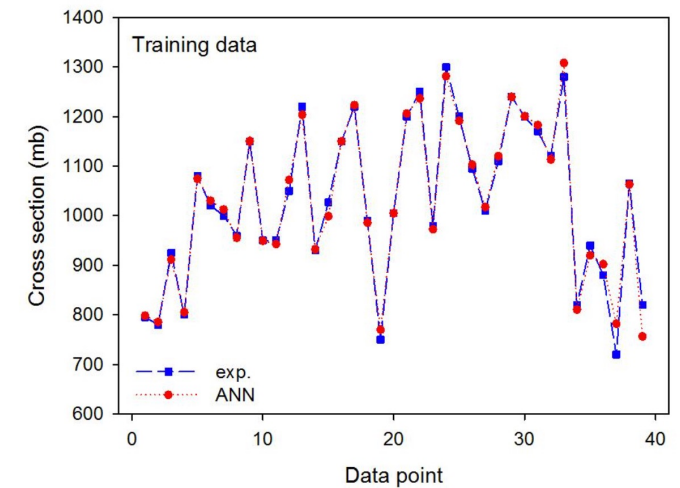
Fusion Reaction Cross Sections

ANN have been used recently (*Akkoyun, NIM B 461, 51 (2020)*) to estimate the **fusion-evaporation cross section** values for different reactions.

- Deviations of 1.8% and 10.5% for the training and test data from the experimental values are obtained, respectively
- This order of deviations is lower than the cross section value from most common theoretical calculations indicating that ANNs are **capable for the estimation of cross section values of fusion-evaporation reactions**



Beam			Target			Compound			Energy (MeV)	Cross section(mb)		
Z	N	A	Z	N	A	Z	N	A		Exp.	ANN	PACE
3	4	7	6	6	12	9	10	19	16.3	975	928.48	901
4	5	9	14	14	28	18	19	37	23.8	950	1093.56	1140
5	5	10	7	7	14	12	12	24	35.2	1045	1229.09	808
6	7	13	6	6	12	12	13	25	18	960	840.48	1056
6	6	12	12	12	24	18	18	36	33.7	1200	1085.32	1064
6	6	12	12	14	26	18	20	38	37	1300	1218.63	1098
6	6	12	14	14	28	20	20	40	34.5	960	1147.62	1102
7	8	15	13	14	27	20	22	42	45	1200	1142.80	1130
8	8	16	6	6	12	14	14	28	20.8	1060	1055.91	1015
8	8	16	14	14	28	22	22	44	38.8	1050	1032.30	1091
8	8	16	14	15	29	22	23	45	39	1260	1136.27	1116
9	10	19	14	16	30	23	26	49	44.5	1235	1181.68	1204
12	12	24	12	12	24	24	24	48	39.3	1050	1091.32	958
14	14	28	14	16	30	28	30	58	42.8	820	731.23	826
14	14	28	12	12	24	26	26	52	38	760	919.29	791

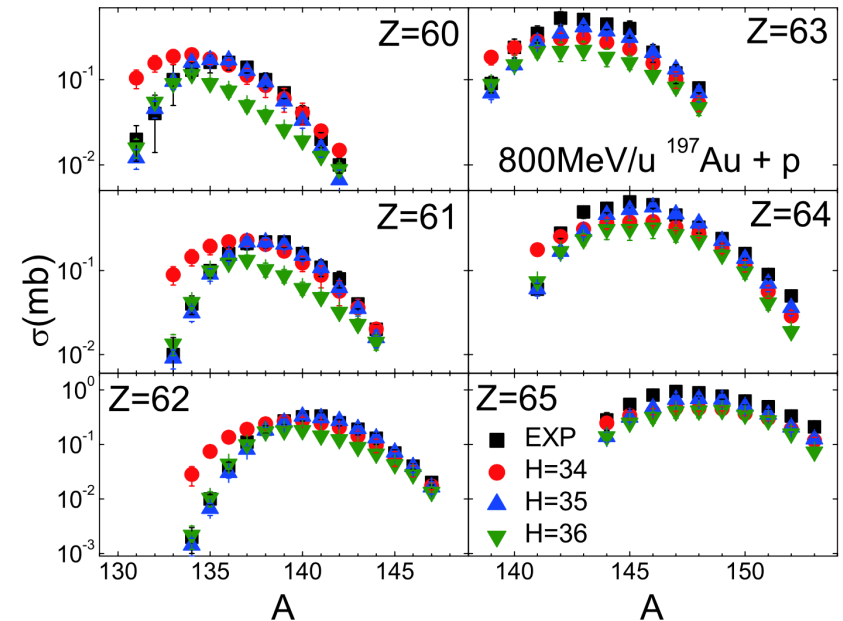
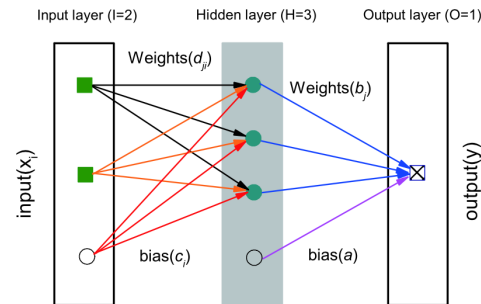


Isotropic Cross Sections in Proton-induced Spallation Reactions

A few years ago *Ma et al., CPC 44, 014104 (2020)*

- Proposed the **Bayesian neural network (BNN) method** to predict the **isotropic cross-sections in proton induced spallation reactions**.
- Learning from more than 4000 data sets of isotopic cross-sections from 19 experimental measurements and 5 theoretical predictions with the SPACS parametrization, in which the mass of the spallation system ranges from 36 to 238, and the incident energy from 200 MeV/u to 1500 MeV/u, they demonstrated that the **BNN method can provide good predictions of the residue fragment cross-sections in spallation reactions**

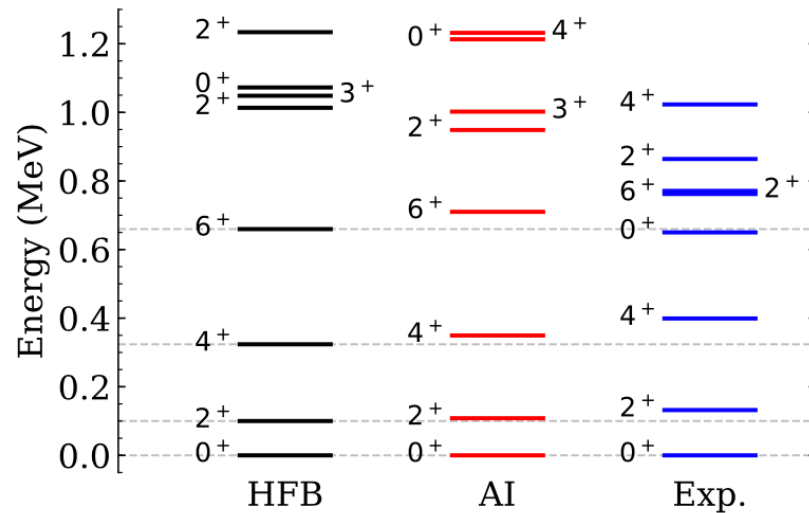
Input: incident energy, the mass and charge numbers of the projectile nucleus, the mass and charge numbers of the fragment, the neutron-excess and the pairing effect in the fragment



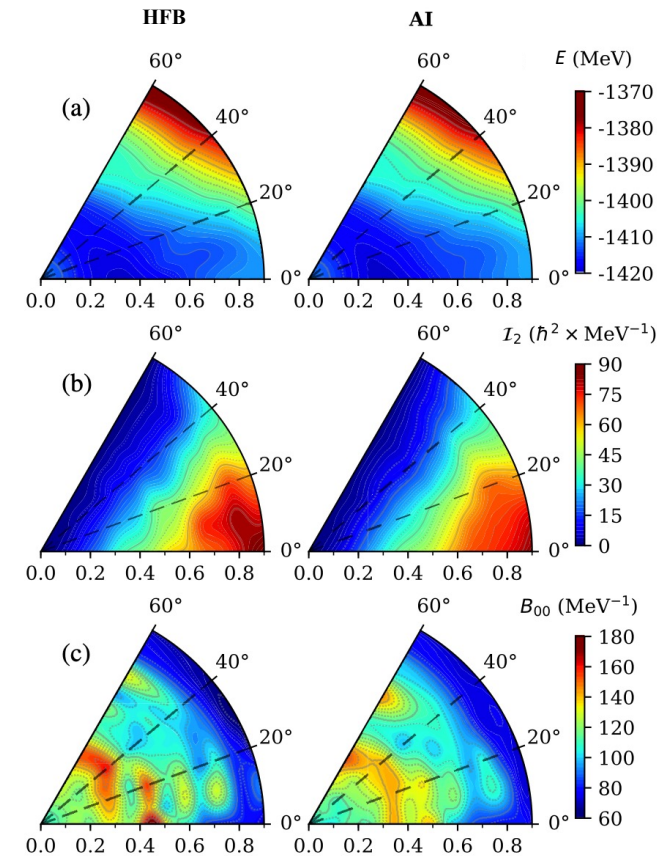
BNN predictions for selected residue fragments with $Z=60$ to 65 in the $800\text{ MeV/u } ^{197}\text{Au} + p$ spallation reaction. Three different numbers of hidden nodes are tested, $H = 34$ (circles), 35 (triangles), 36 (triangles)

Ground and Excited State Energies

Lasseri et al., PRL 124, 162502 (2020) showed that **deep neural networks are capable of predicting the ground-state and excited energies of more than 1800 atomic nuclei** with an accuracy similar to the one achieved by state-of-the-art nuclear energy density functionals (EDFs) and with significantly less computational cost



Excitation spectrum of ^{178}Os obtained from both artificial intelligence (AI) and HFB calculations

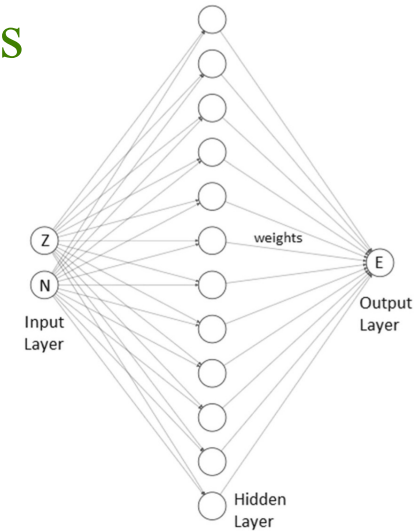


Energy (a), rotational inertial along the principal axis (b) and vibrational inertia related to elongation (c) of ^{178}Os

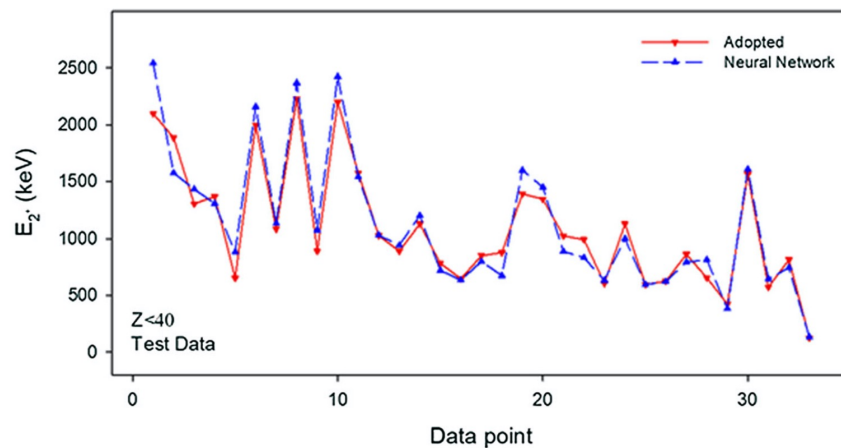
Ground and Excited State Energies

The first excited 2^+ energy states of nuclei give much substantial information related to the nuclear structure. In the even–even nuclei, the first excited state is generally 2^+ , and the energy values of them increase as the closed shells are approached. The nuclei's excited levels can be investigated using theoretical nuclear models, such as the nuclear shell model.

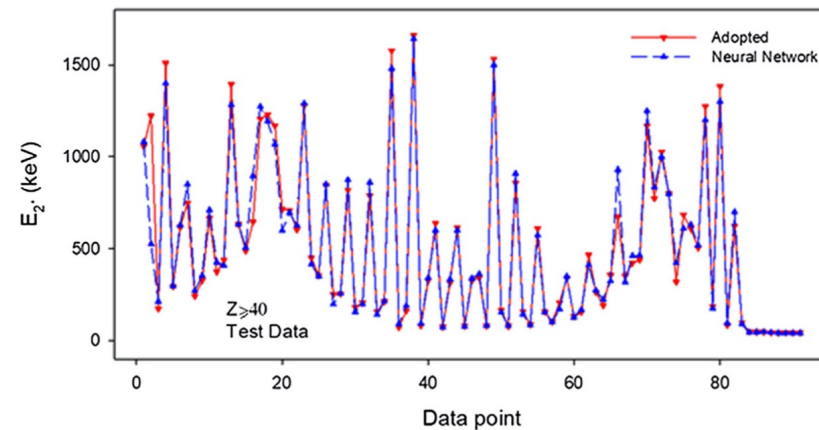
Very recently, *Akkoyun et al., IJP 96, 1791 (2022)* have used **ANNS to determine the energies of the first 2^+ states in the even–even nuclei** in the nuclidic chart as a function of Z and N numbers for the first time.



$Z < 40$ even – even nuclei



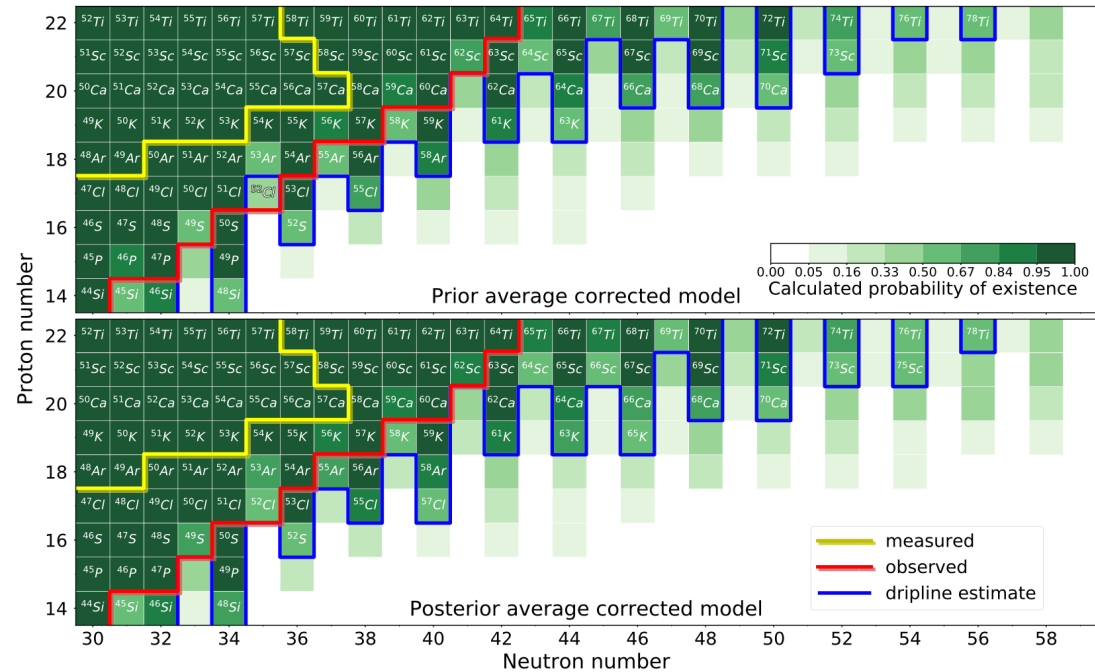
$Z \geq 40$ even – even nuclei



Dripline Locations

Neufcourt et al., PRL 122, 062502 (2019) have used global mass models and statistical machine learning to make predictions, with quantified levels of certainty, for **bound nuclides between Si and Ti**.

- Using a **Bayesian model averaging analysis based on Gaussian-process-based extrapolations** they introduce the posterior probability p_{ex} for each nucleus to be bound to neutron emission
- They found that extrapolations for drip-line locations are consistent across the global mass models used
- In particular, considering the current experimental information and current global mass models, they predicted that ^{68}Ca has an average posterior probability $p_{ex} \approx 76\%$ to be bound to two-neutron emission while the nucleus ^{61}Ca is likely to decay by emitting a neutron ($p_{ex} \approx 46\%$)

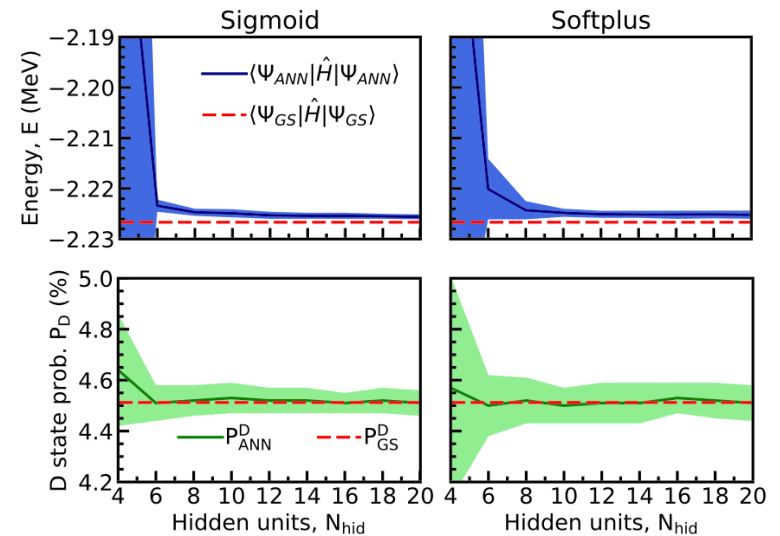
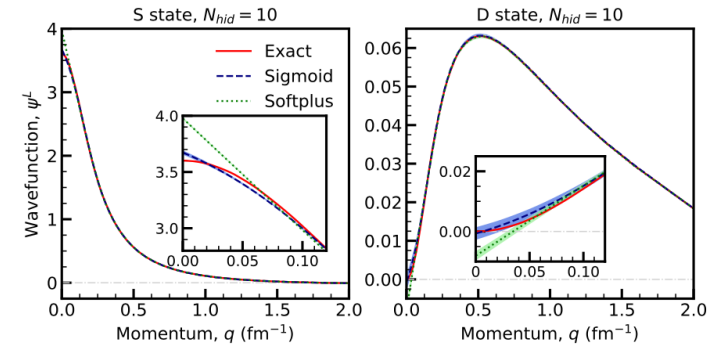


Posterior probability of existence of neutron-rich nuclei in the Ca region

Deuteron Properties

Keeble & Rios, PLB 809 135743 (2020) have used machine learning techniques to solve the **nuclear two-body bound state problem, the deuteron**.

- They used a minimal one-layer, feed-forward neural network to represent the deuteron S - and D -state wavefunction in momentum space, and solve the problem variationally using ready-made machine learning tools
- They found that **a network with 6 hidden nodes can provide a faithful representation of the ground state wavefunction, with a binding energy that is within 0.1% of exact results**

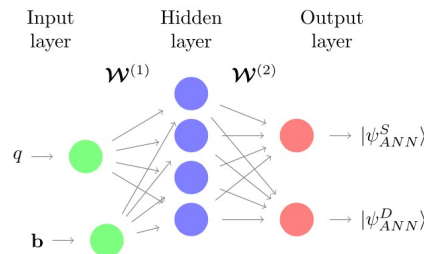


- Input data:** neutron-proton relative momentum q

- Target wavefunctions for training:**

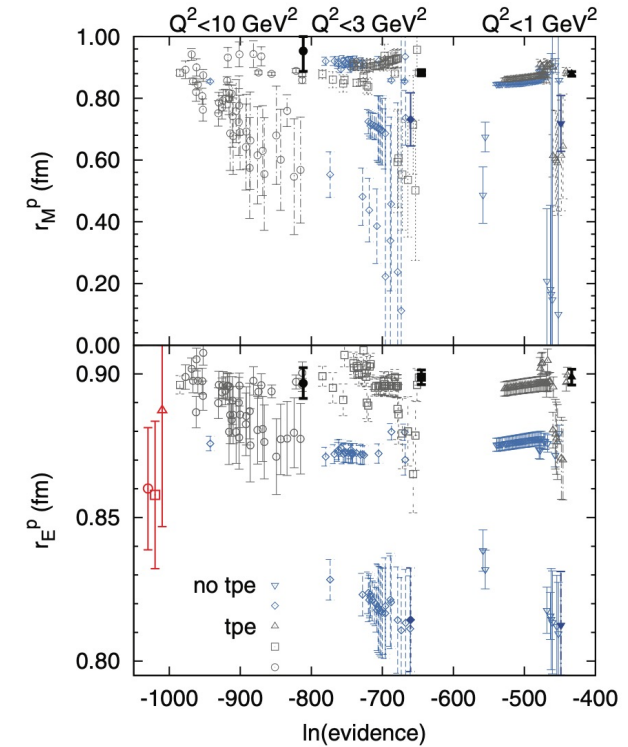
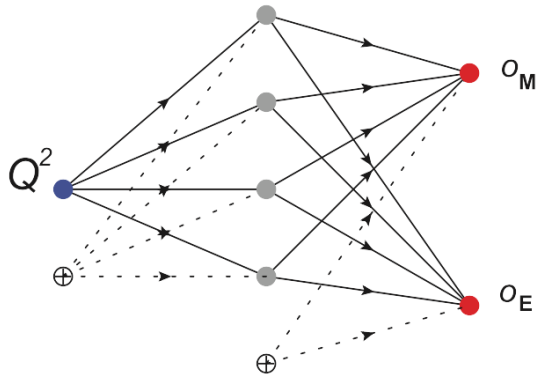
$$\psi_{tag}^L(q) \propto q^L e^{-\frac{\zeta^2 q^2}{2}}$$

- Activation function:** sigmoid, softmax
- Optimization algorithm:** RMSProp method



Proton Radius

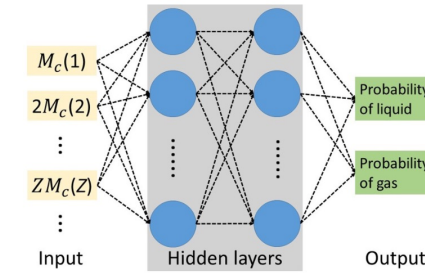
In 2014 *Graczyk & Juszczak, PRC 90 054334 (2014)* used methods of **Bayesian statistics** to **extract** the value of the **proton radius** from the **elastic electron-proton scattering data** in a model-independent way. To achieve that goal they considered a large number of parametrizations (equivalent to neural network schemes) ranked them by their conditional probability $P(\text{parametrization}|\text{data})$ finding as the most probable proton radii found $r_E^p = 0.899 \pm 0.003 \text{ fm}$, $r_M^p = 0.879 \pm 0.007 \text{ fm}$



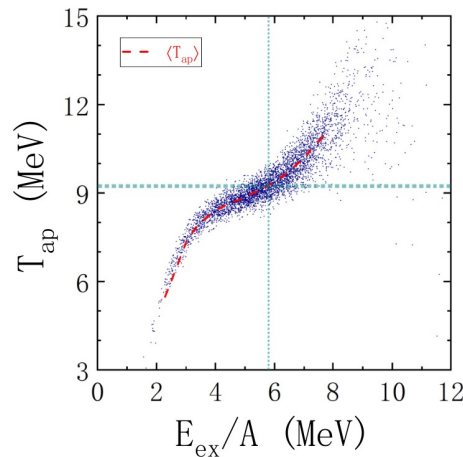
$Q_{\text{cutoff}}^2 \text{ (GeV}^2\text{)}$	$r_M^p \text{ (fm)}$	$r_E^p \text{ (fm)}$	H
1	0.879 ± 0.007	0.899 ± 0.003	1
3	0.883 ± 0.007	0.899 ± 0.003	4
10	0.953 ± 0.065	0.897 ± 0.005	6

Liquid-Gas Phase Transition

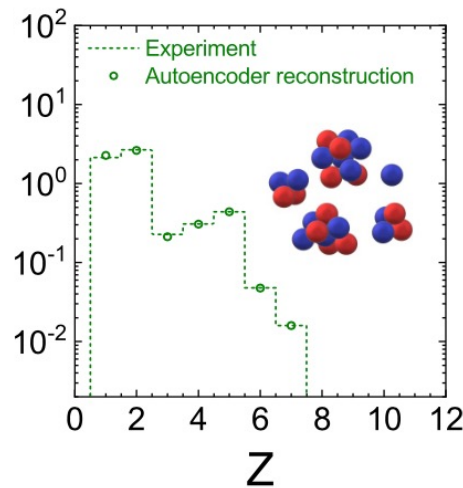
Very recently *Wang et al., PRR 2 043202 (2020)* have shown that **supervised (BNN) & unsupervised (Autoencoders)** machine-learning techniques can be employed **to study the nuclear liquid-gas phase transition**. Based on the experiment event-by-event charge multiplicity distribution, the neural networks are capable of **classifying the liquid and gas phases**, and **determining the limiting temperature** of the nuclear liquid-gas phase transition. They obtain a value 9.24 ± 0.04 MeV, consistent with that obtained by the traditional caloric curve method



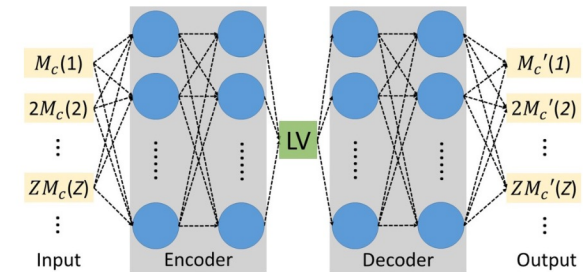
Bayesian Neural Network



Scatter plot of the apparent temperature versus the excitation energy per nucleon



Average charge multiplicity distribution $\langle M_c \rangle(Z)$ of the quasiprojectile fragments



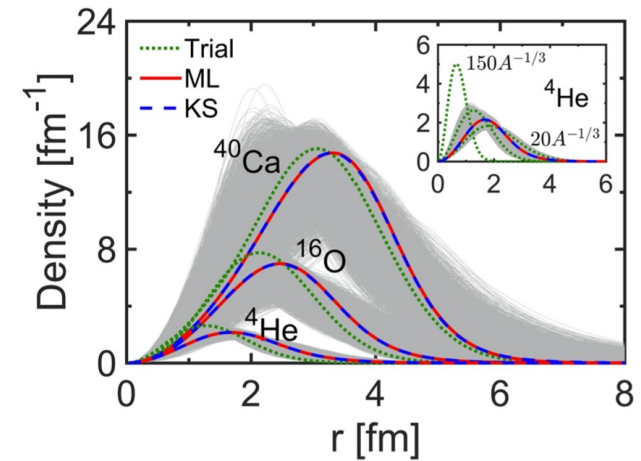
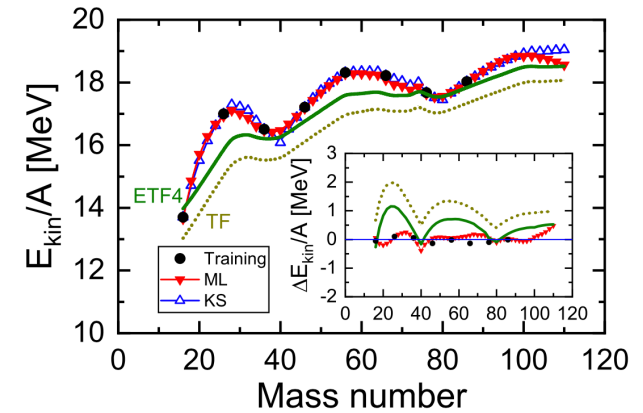
Autoencoder network

Nuclear Energy Density Functionals

Very recently *Wu et al., PRC 105, L031303 (2022)* have **employed the Kernel Ridge Regression (KRR) machine learning model to build an energy density functional for self-bound nuclear systems for the first time**

- By learning the kinetic energy as a functional of the nucleon density alone, they have established a robust and accurate orbital-free density functional for nuclei.
- Self-consistent calculations that bypass the Kohn-Sham equations provide the **ground-state densities, total energies, and root-mean-square radii** with a high accuracy in comparison with the Kohn-Sham solutions

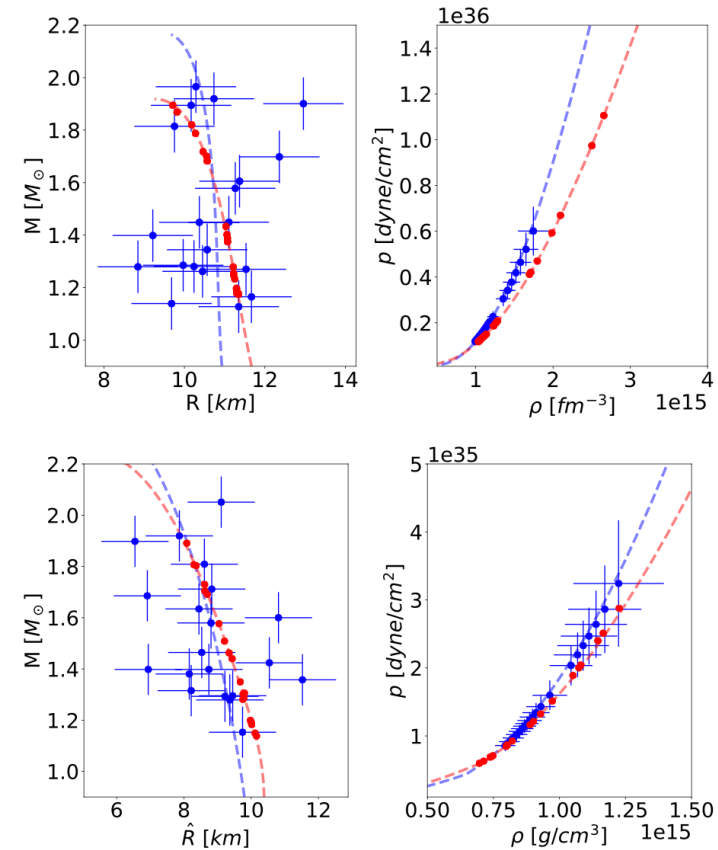
		Kohn-Sham	Machine-Learning	Experiment
${}^4\text{He}$	E_{tot}	-26.3700	-26.3931 (0.0012)	-28.2957
	E_{kin}	35.2138	35.2044 (0.0056)	/
	$\langle r^2 \rangle$	2.1626	2.1628 (0.0002)	1.6755
${}^{16}\text{O}$	E_{tot}	-127.3781	-127.1622 (0.1584)	-127.6193
	E_{kin}	219.2875	218.3458 (0.6882)	/
	$\langle r^2 \rangle$	2.8077	2.8113 (0.0047)	2.6991
${}^{40}\text{Ca}$	E_{tot}	-342.0645	-341.8027 (0.5724)	-342.0521
	E_{kin}	643.1100	642.9145 (1.6875)	/
	$\langle r^2 \rangle$	3.4677	3.4652 (0.0055)	3.4776



Neutron Star EoS

A couple of years ago *Morawski & Bejger, A&A 642, A78 (2020)* applied an **artificial neural network** guided by the **autoencoder architecture** as a method for **precisely reconstructing the neutron star equation of state**, using their observable parameters: **masses, radii, and tidal deformabilities**.

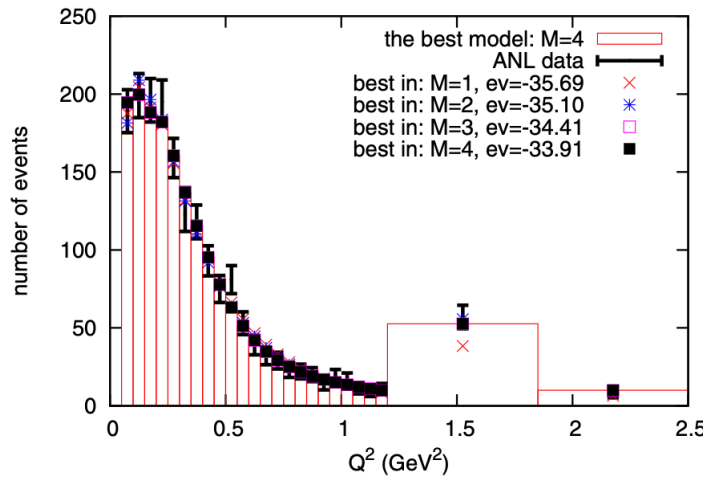
- They constructed **a few hidden-layer deep neural networks** on a generated data set, consisting of a realistic equation of state for the neutron star crust connected with a piecewise relativistic polytropes dense core, with its parameters representative of state-of-the art realistic equations of state.
- They found that neural networks trained with a limited data set are capable of generalising the mapping between global parameters and EoS input tables for realistic models



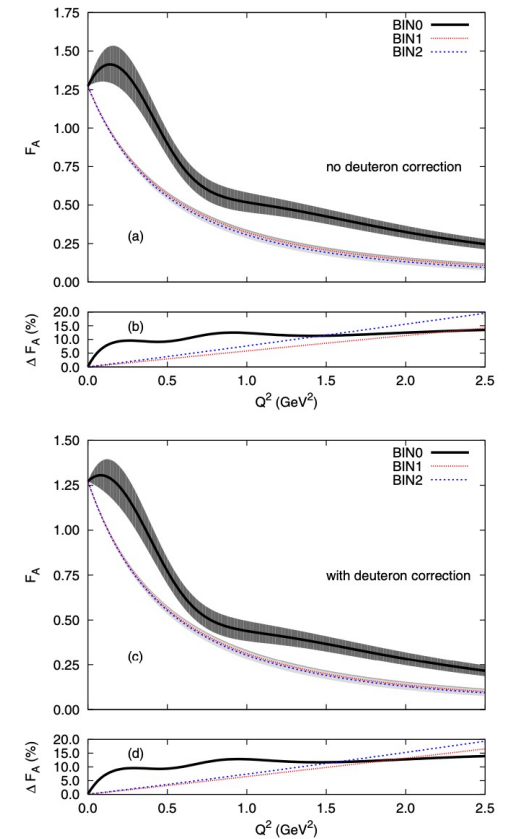
Example of the input data ($M(R)$ measurements and corresponding the ANN reconstructed EoS

Nucleon Axial Form Factor From Neutrino Scattering

In 2019 *Alvarez-Ruso et al.*, *PRC 99, 025204 (2019)* applied the **Bayesian approach for feedforward neural networks with 1 hidden layer and 1-4 hidden neurons** to the extract the nucleon axial form factor from the neutrino-deuteron-scattering data measured by the Argonne National Laboratory bubble-chamber experiment. This framework allows to perform a **model-independent determination of the axial form factor from data**. When the low $0.05 < Q^2 < 0.1 \text{ GeV}^2$ data are included in the analysis, the resulting axial radius disagrees with available determinations. A large sensitivity to the corrections from the deuteron structure was obtained



Distribution of the ANL number of events and the best fits obtained for MLPs with $M = 1-4$ hidden units

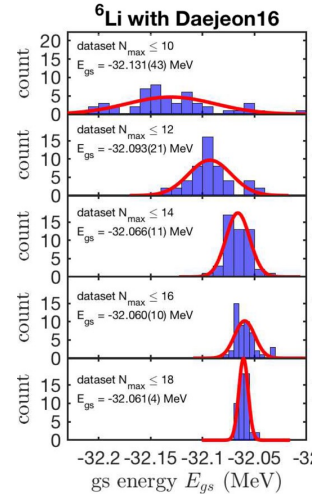
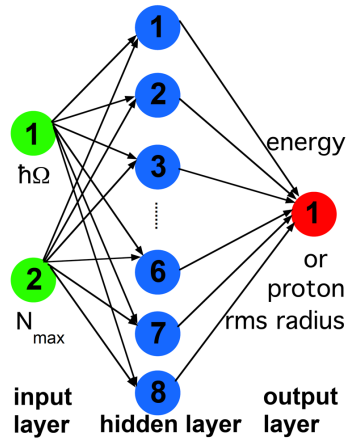


Best fits of the axial form factor obtained from the analysis of the three data sets: BIN0, BIN1, and BIN2

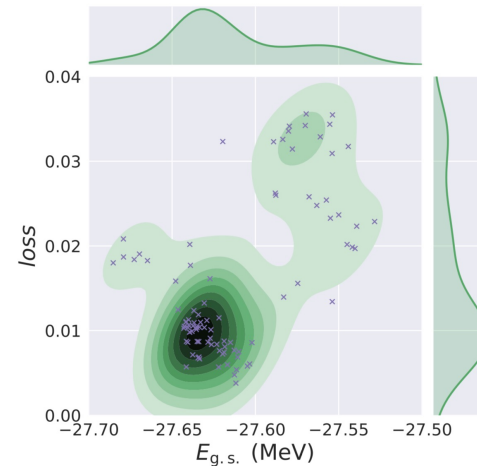
Extrapolation of *ab-initio* nuclear structure calculations

Recently, ANN have been employed to **extrapolate the results of *ab-initio* nuclear structure calculations in finite model spaces**. Particularly:

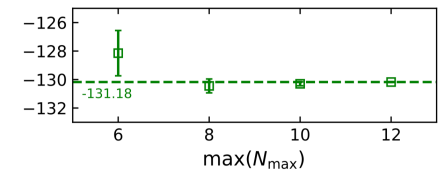
- *Negoita et al., PRC 99, 054308 (2019)* have used a feed-forward ANN method for predicting the **ground state energy and the ground state point proton root-mean-squared radius of ${}^6\text{Li}$** training the network with No-Core Shell Model (NCSM) results, obtained in accessible harmonic oscillator (HO) basis spaces. They showed that an ANN is able to predict correctly extrapolations of the NCSM results to very large model spaces of size $N_{\text{max}} \sim 100$.
- Similarly, *Jiang et al., PRC 100, 054326 (2019)* have also employed an ANN to extrapolate the **ground state energy and radii of ${}^4\text{He}$, ${}^6\text{Li}$ & ${}^{16}\text{O}$** computed with the NCSM and the coupled-cluster (CC) methods.



${}^4\text{He}$ with NCSM+NNLO_{opt}

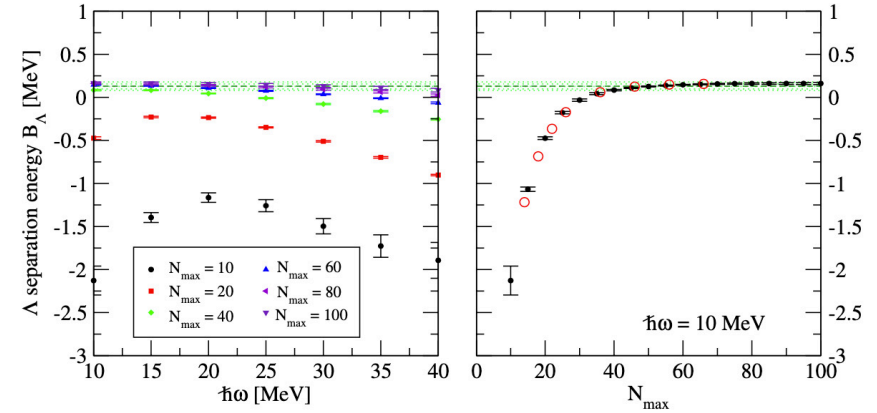
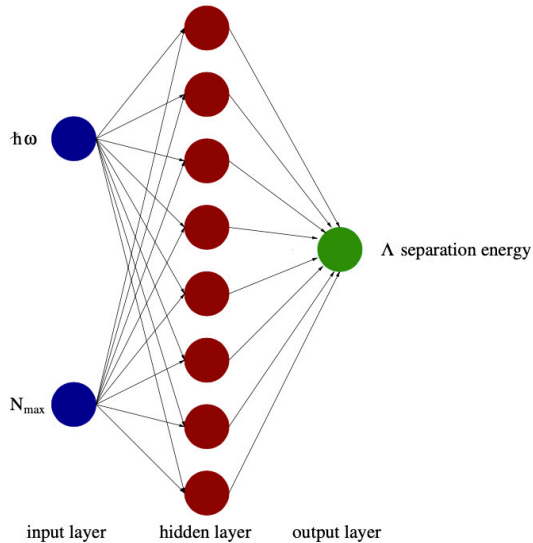


${}^{16}\text{O}$ with CC+NNLO_{opt}



Extrapolation of *ab-initio* nuclear structure calculations

Recently, *I.V.*, [arXiv:2203.11792](#) has employed a feed-forward ANN to **extrapolate at large model spaces** the results of *ab-initio* hypernuclear NCSM calculations for the Λ separation energy B_Λ of the lightest hypernuclei, obtained in accessible HO basis spaces using chiral NN, NNN & YN interactions. A network with **a single hidden layer of eight neurons is enough** to extrapolate correctly the value of B_Λ to model spaces of size $N_{\max}=100$



Hypernucleus	ANN Prediction	Experimental Value
${}^3_\Lambda H$	0.16 ± 0.01	0.13 ± 0.05
${}^4_\Lambda H(0^+)$	2.47 ± 0.03	2.157 ± 0.077
${}^4_\Lambda H(1)$	1.37 ± 0.03	1.067 ± 0.08
${}^4_\Lambda He(0^+)$	2.41 ± 0.04	2.39 ± 0.05
${}^4_\Lambda He(1^+)$	1.33 ± 0.03	0.984 ± 0.05

Machine Learning Applications in Nuclear Experiments

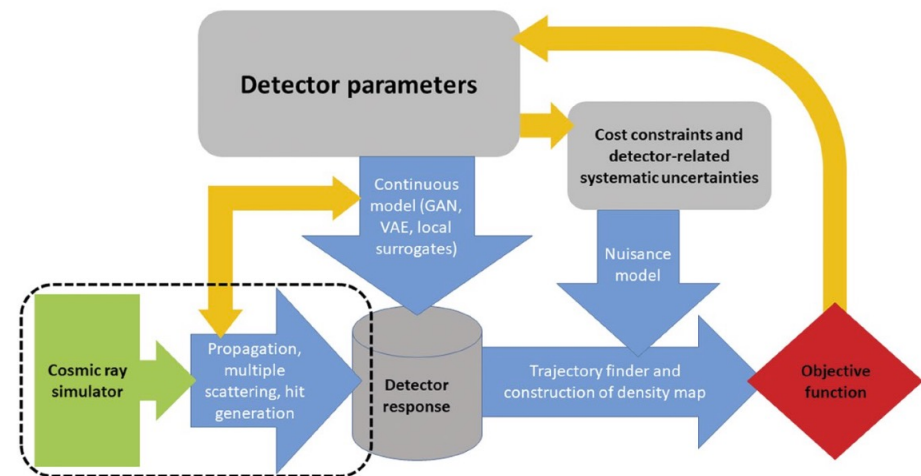
During the last few years, Machine Learning techniques have been applied to the full chain of experimentation including in particular:

- Design of experiments
- Reconstruction & Analysis

In the next I will shortly go over some examples of these two applications

Experimental Design

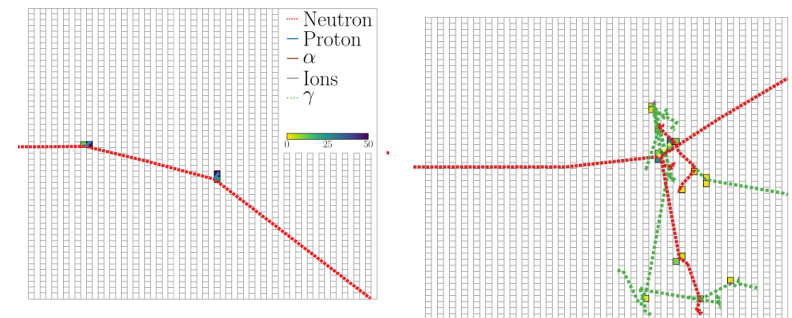
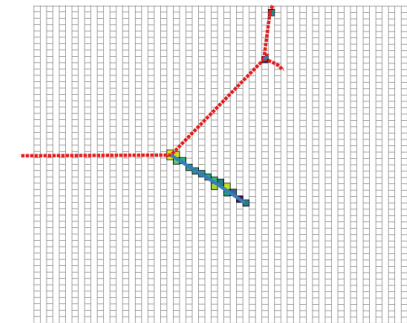
- **Physics and detector simulations** are **critical** for both the **initial design** and the **optimization of detectors** in nuclear physics experiments. Detectors are usually **characterized by multiple parameters** capable of tuning: **mechanics, geometry and optics** of each component
- **Detector design optimization** can be a **large combinatorial problem** characterized by accurate and **computationally expensive simulations**. In this context, ML offers different optimization strategies, spanning from **reinforcement learning** to **evolutionary algorithms**



Conceptual layout of an optimization pipeline for a muon radiography apparatus

Reconstruction & Analysis: Charge Particle Tracking

- At high luminosity, tracking suffers from track candidates that share hits. This results in hits **wrongly identified as “on-track”** and produces **ghost tracks**.
- In high luminosity environments, the **largest fraction of CPU time & memory** in tracking in a traditional analysis is spent on setting up various filters at each measurement site.
- The **improvement** in track seeding resulting from **using ANN and deep learning methods**, yields substantially **faster track reconstruction speed**.
- One of the most common deep learning algorithms employed for **tracking pattern recognition** are **Convolutional Neural Networks (CNN)**
- Machine learning algorithms used for **background rejection** involve topological properties of tracks to isolate signal from background

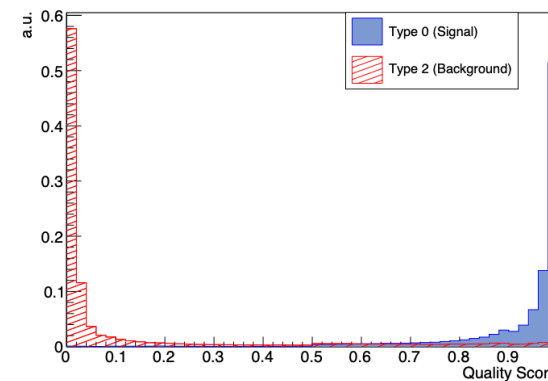
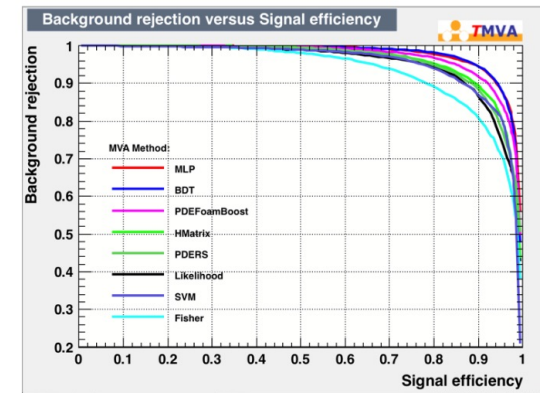


Side view of hit patterns in the NeuLAND detector , created by the interaction of one neutron with a kinetic energy of 600MeV

Reconstruction & Analysis: Calorimetry

The GlueX experiment at Jefferson Lab (Barsotti and Shepherd, arXiv: 2002.09530v1) used **ANN to reduce background in the GlueX forward calorimeter for the detection of photons produced in the decays of hadrons.**

- The **training was done on data using ω -meson decays.**
- Energy deposition characteristics in the calorimeter such as shapes, size, and distribution were employed to discriminate between signal and background, where the background mostly originates from hadronic interactions that can be difficult to distinguish from low energy photon interactions. The **ANN-based algorithm** showed to be a **powerful tool to reconstruct neutral particles with high efficiency** and to **provide substantial background rejection capability**.



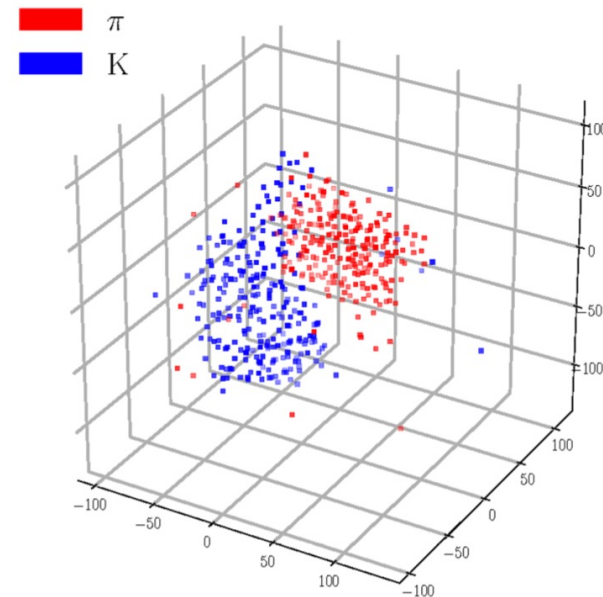
(Top) Performance of the eight different types of multi-variate analysis algorithms that were tested. (Bottom) Classifier output distribution for the MLP when run on the background (red) and signal (blue) training samples

Reconstruction & Analysis: Particle Identification

Particle identification (PID) is done with dedicated detectors capable of identifying certain particle types, such as for example, **Cherenkov detectors** largely used in modern nuclear experiments for identifying charged particles like pions, kaons, and protons corresponding to a wide range in momentum.

Cherenkov detectors are typically endowed with single photon detectors and **the particle type can be recognized by classifying** the corresponding detected hit pattern

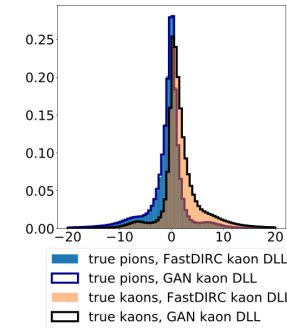
- DeepRICH (Fanelli and Pomponi, Mach. Learn.: Sci. Technol. 1 015010 (2020)) is a recently developed custom architecture that combines **Variational Auto-Encoders (VAE)**, **CNN** and **ANN**. The re-construction performance is fast due to its implementation on GPUs that allow for parallel processing of batches of particles during the inference phase



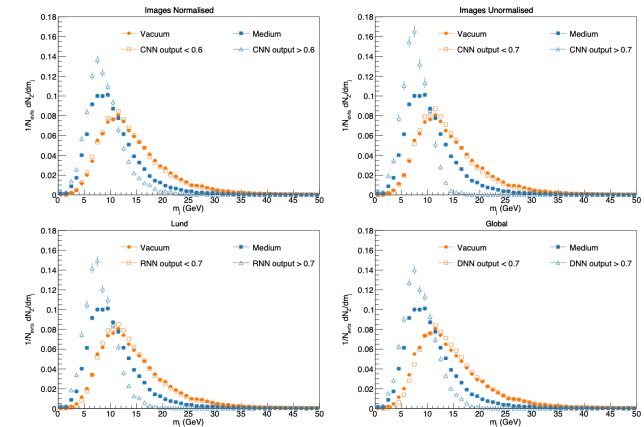
Example of features extracted by the CNN module from π 's and K's at 4 GeV/c (left) and 5 GeV/c (right). These features are then used to classify the particle

Reconstruction & Analysis: Particle Identification

- In Derkach et al., NIMRA A 952, 161804 2020, **Generative Adversial Networks (GAN)** have been used to simulate the Cherenkov detector response. This architecture predicts the multidimensional distribution of the likelihood for particle identification produced by-passing low-level details
- Machine learning has been applied to design experimental observables that are sensitive to jet quenching and parton splitting. **CNN** have been **used** for **instance to discriminate quark and gluon jets** (Komiske et al., JHEP 1, 1 2017). Different deep architectures (**CNN**, **Dense ANN**, and **RNN**) have been also used for the classification of quenched jets, and in particular to discriminate between medium-like and vacuum-like jets (Apolin'ario et al., 2021, arXiv:2106.08869v1)
- **BNN** have been used for the **pion, kaon, and proton identification** with tests done on data generated for the BES II experiment (Ye et al., CPC 32, 201 (2008)), combining multiple features from different detectors like drift chamber, time of flight, and shower counter



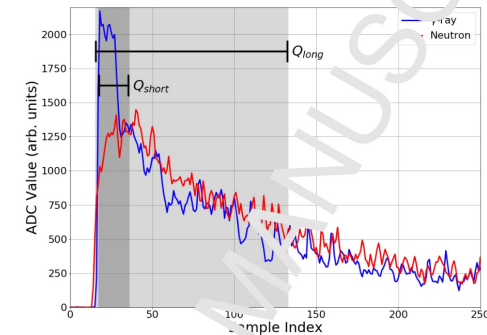
1D projection to kaon delta log-likelihood observables



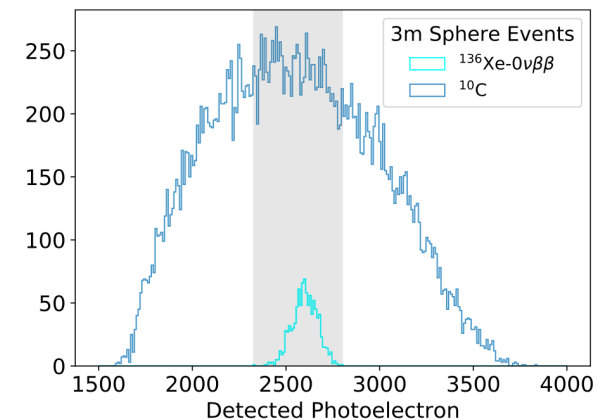
Reconstructed jet mass, for the different Deep Learning architectures

Reconstruction & Analysis: Event & Signal Classification

- Neural network analysis of pulse shapes have been shown to effectively discriminate between neutron and γ signals in scintillator detectors in low-energy experiments (Doucet et al., 2020)
- In post-experiment analyses, deep ANN and CNN (Gavalian et al., 2020; Kuchera et al., 2019; Solli et al., 2021) were used to classify events
- In low-energy neutrino experiments, ML techniques are used to differentiate different physics signal types or signals from backgrounds. (Brice, 1996)
- In $0\nu\beta\beta$ -decay experiments, an ample amount of the target isotope can be loaded in the scintillator, but the detector energy resolution is typically worse than other types of detectors. The KamLAND-ZEN experiment developed CNN and RNN to identify ^{10}C from cosmic-ray spallation in the liquid scintillator loaded with ^{136}Xe (Hayashida, 2019; Li et al., 2019a)



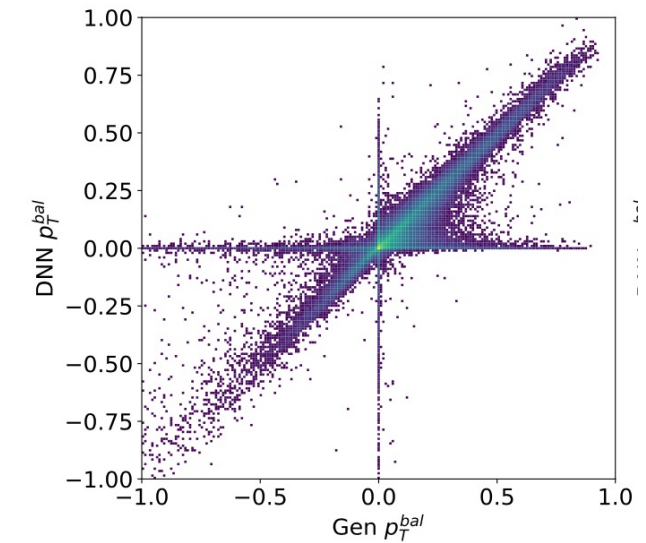
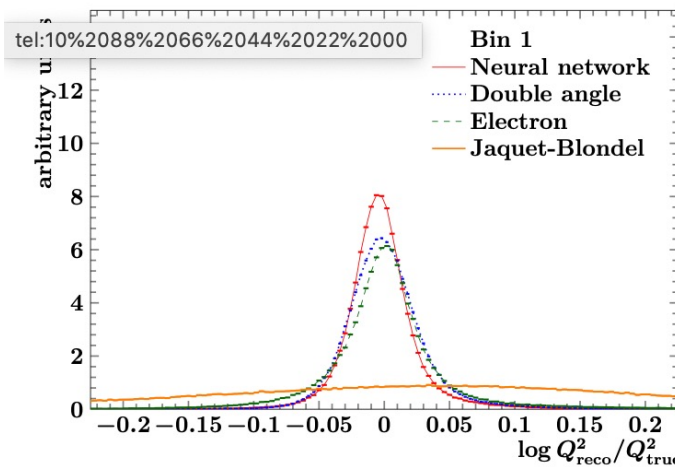
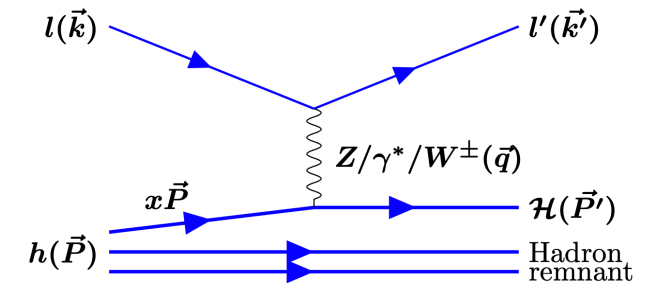
Neutron & γ -ray waveforms



Detected photoelectrons for ^{136}Xe $0\nu\beta\beta$ - decays and ^{10}C β^+ decays generated inside a sphere with 3m radius

Reconstruction & Analysis: Event Reconstruction

- Various reconstruction methods are combined in collider experiments for the precise knowledge of the kinematic variables of the **deep inelastic scattering process**. Each method uses partial information from the scattered lepton and/or the hadronic final state of deep in-elastic scattering and has its own limitations.
- Recently, it has been shown for the **H1** and **ZEUS collider experiments** as well as for simulations of a possible **EIC detector** that **deep learning techniques to reconstruct the kinematic variables** can serve as a rigorous method to combine and outperform existing reconstruction methods (Arratia et al., 2022; Diefenthaler et al., 2021)

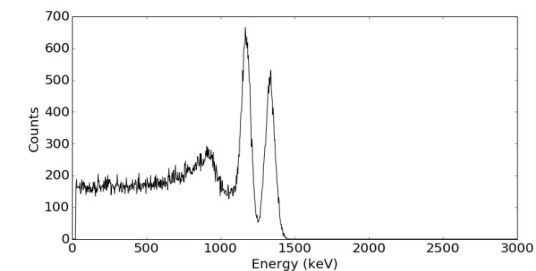


Reconstruction & Analysis: Spectroscopy

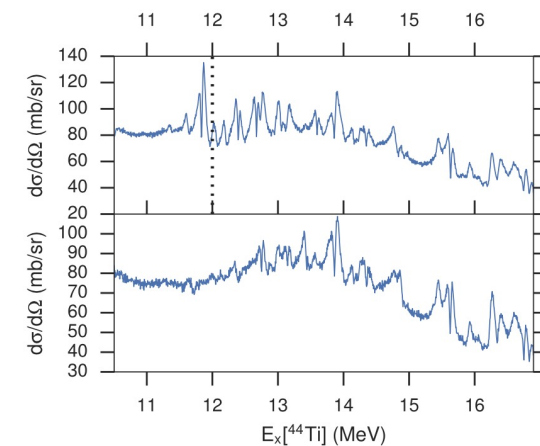
Gamma-ray spectra are used, among other things, for isotope identification and fundamental nuclear structure studies

- **Deep fully-connected neural network** architectures are shown to successfully identify isotopes (Abdel-Aal and Al-Haddad, 1997; Jung et al., 2020; Kamuda et al., 2017; Medhat, 2012) and fit peaks (Abdel-Aal, 2002) in gamma spectra
- Machine learning has also been shown to estimate activity levels in spectra from gamma-emitting samples (Abdel-Aal and Al-Haddad, 1997; Kamuda and Sullivan, 2018; Vigneron et al., 1996)
- **Convolutional neural networks** have demonstrated robustness to spectra with unidentified background channels and calibration drifts in the detectors (Kamuda et al., 2020)
- Charged particle detection is routinely used for spectroscopy. For example, (Bailey et al., 2021) uses ML to analyze signals from double-sided silicon strip detectors to determine α -clustering.

ANN simulated ^{60}Co spectra



Simulated α -clustered (top) and non-clustered (bottom) spectra



A Few Final Words

As I said at the beginning this has been just a **brush-stroke** on the the **basic concepts & ideas** behind **Machine Learning** and its **applications to Nuclear Physics**

- Many exciting results have been achieved but the best is yet to come
- The nuclear physics community is eager to embrace the diverse toolbox of tricks offered by Machine Learning
- To solve many complex problems in the field and facilitate discoveries, multidisciplinary efforts are required involving scientists in nuclear physics, computational science, applied math, and statistics are required

Once more:

- ✧ You for your time & attention
- ✧ The organizers for their invitation

