Deep learning for neutrino interactions with nuclei

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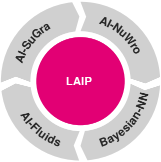
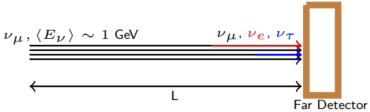


https://kgraczyk.github.io/laip/

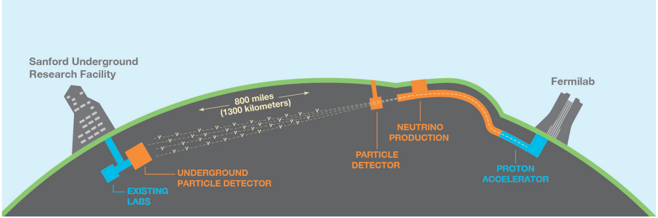
February 19, 2025

Primary Motivation

- neutrinos ν_e, ν_μ, ν_τ,..., fundamental particles
  - weakly interacting, neutral, difficult to detect...
- neutrino oscillations:



  - CP-violation phase $\rightarrow$ the Matter-Antimatter asymmetry
  - Mass hierarchy problem



- **There is a huge experimental and theoretical effort in studying neutrino properties.**
- Deep Underground Neutrino Experiment (DUNE), HyperKamiokande and T2K experiments

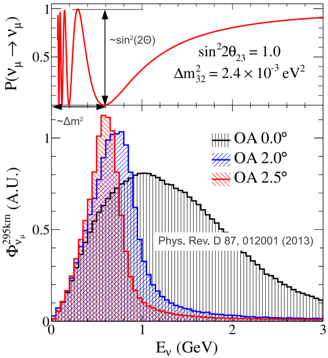
- Accelerator neutrinos:

→ 1 GeV neutrinos interact with Oxygen (HyperKamiokande), Argon (DUNE), ...

- From a precision of about 20-30% in our knowledge of ν-nucleus scattering cross sections to a percent-level precision.
- To study oscillations, we must determine the energy of incoming νs.

$$P(\nu_\mu \to \nu_\tau) = \sin^2\theta_{23}\left(\frac{\Delta m^2_{32} L}{4E_\nu}\right)$$

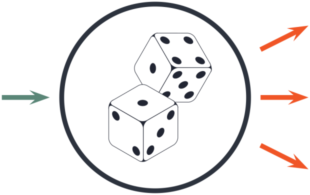
- **neutrino energy**, E_ν, given by some distribution, one must reconstruct energy event-by-event



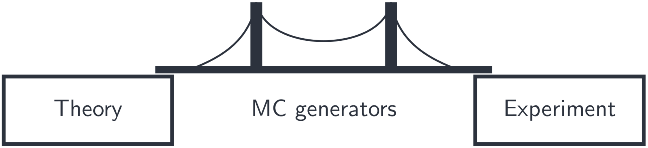
- **Theory meets experiment: a Monte Carlo generator for neutrino-nucleus interaction events!**

- Monte Carlo Generator of neutrino interactions, written in C++
- Developed since 2005 at the University of Wroclaw by Jan Sobczyk *et al.*)
- Optimized for neutrino energy from ~ 100 MeV to ~ 20 GeV
- Handle all kinds of targets, and neutrino fluxes, equipped with detector interface

* open source code, repository: `https://github.com/NuWro/nuwro`

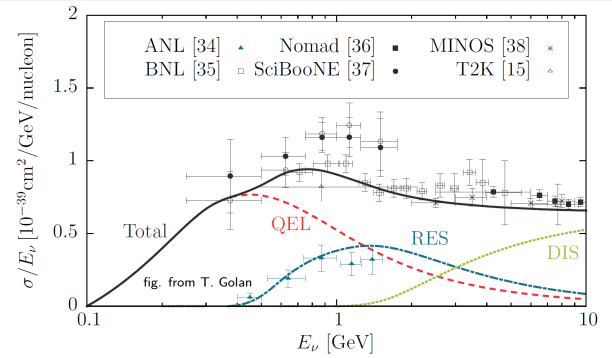


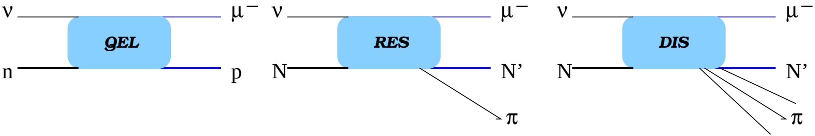
- **For given initial neutrino generates final products of interaction**



figs. from T. Golan

ν-Nucleon scattering





- Neutrino energy reconstructed mainly from the analysis of QuasiElastic (QE) scattering events!

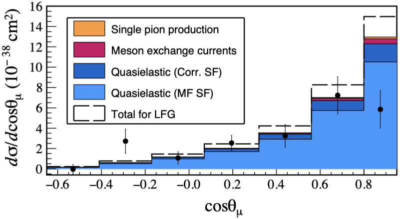
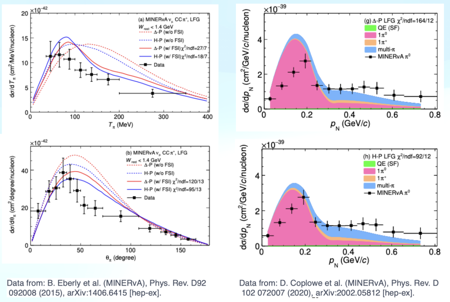
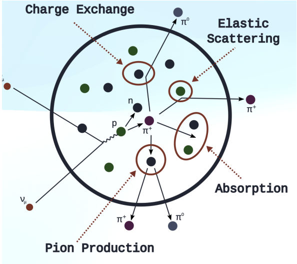
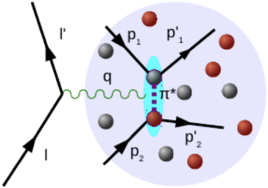


FIG. 2. MicroBooNE CC1p0π differential cross section as



Figs. from Banerjee, Ankowski, Graczyk, Kowal, Prasad, Sobczyk, Phys.Rev.D 109 (2024) 073004





figs. from J. Sobczyk

- We need to simulate ν-Nucleus in realistic conditions
  - $\rightarrow$ Monte Carlo Generator of Neutrino Interactions

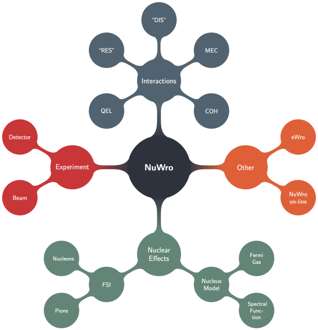
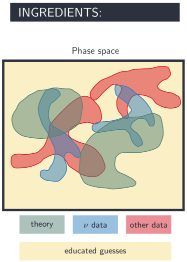


fig. from T. Golan



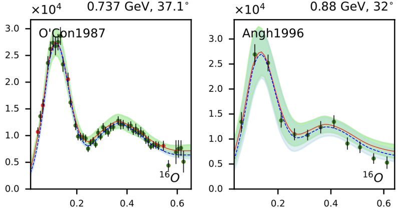
figs. T. Golan

Goals of the Monte Carlo Generator

- Combine various theoretical/phenomenological models with different data types in different kinematic regimes and reaction scenarios.
- Obtain a system that automatically and objectively **updates its knowledge of physics when new data and theoretical constraints are delivered**

ν-Physics vs. e-Physics

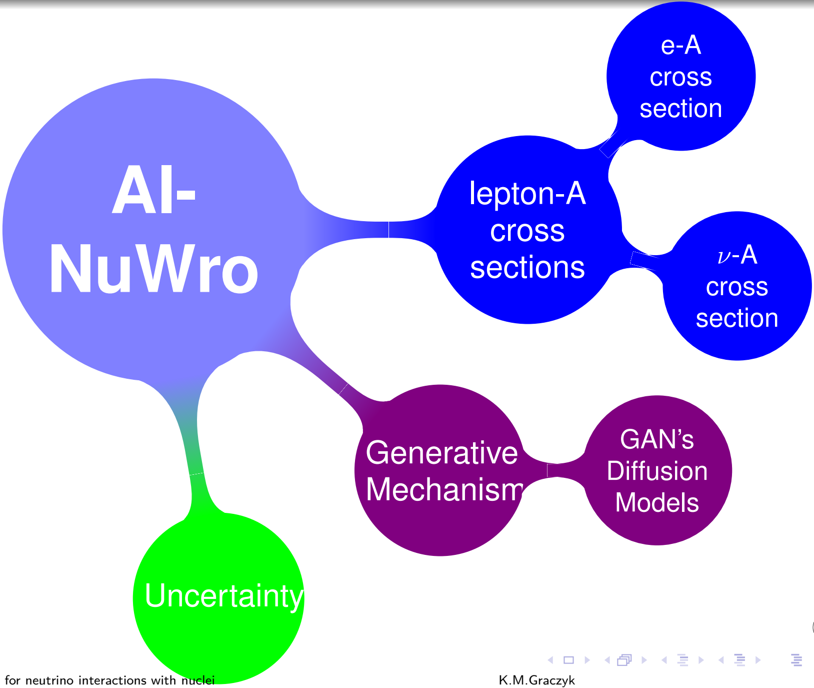
- Scarce ν-scattering data $\leftrightarrow$ informative data for e-nucleus scattering
- Deficiencies in theoretical description of ν-nucleus interactions $\leftrightarrow$ quite well understood e-nucleus scattering physics
- **Similarities between electron and neutrino interactions with nuclear targets**
  - vector-axial contribution, the same nuclear physics



QE, dip, RES peaks are clearly distinguished! Not the case in neutrino interactions!

Goals

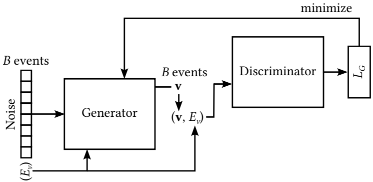
- Transfer a knowledge of nuclear physics from e-scattering to ν-scattering
- Extrapolate the knowledge of physics from one kinematic domain to the other
  Can deep neural networks learn physics?


AI-NuWro
lepton-A cross sections
e-A cross section
ν-A cross section
Generative Mechanism
GAN's Diffusion Models
Uncertainty

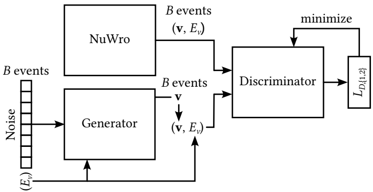
ν_μ-carbon collisions with Generative adversarial network (GAN)

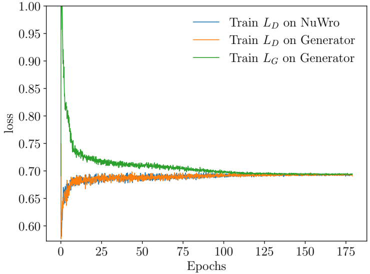
* Bonilla, Graczyk, *et al.*, arxiv:2503.xxxxx
- Optimize two models:

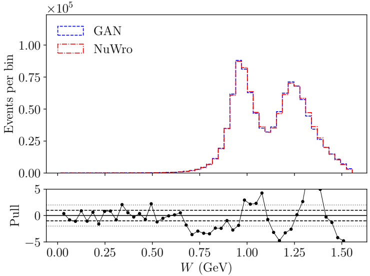
Generator($E_\nu, \ldots$)



Discriminator(Muon kinematics)





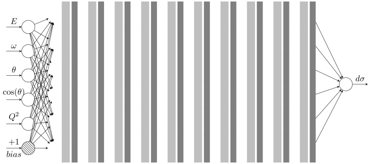


E=1 GeV, inclusive scattering

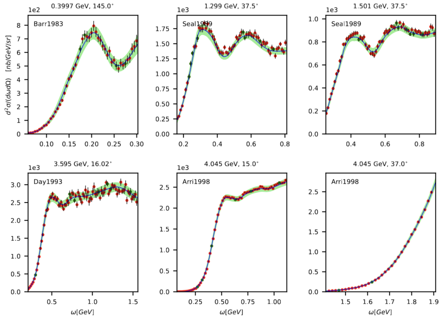
- GANs mimic reality by accumulating physics knowledge.
- Use as a pre-trained model for realistic tuning!
- Utilize the concept of representation learning.

STEP I: Teach deep neural networks nuclear physics:

- Use electron-carbon scattering data: Kowal *et al.*, Phys.Rev.C110 (2024) 2, 025501



Physic-guided Neural Network (PgNN)



training, test data points

STEP II: Did neural networks learn nuclear physics?
If yes, let us take profit from that

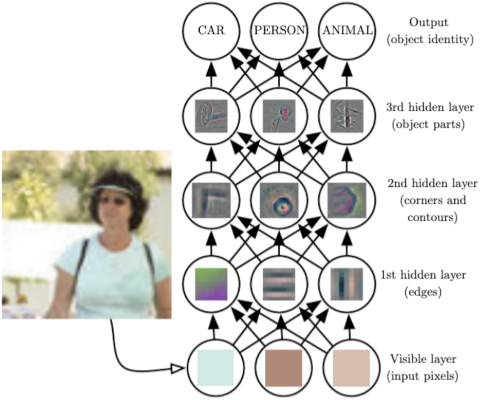


fig from: Deep Learning, Goodfellow, Bengio and Courville

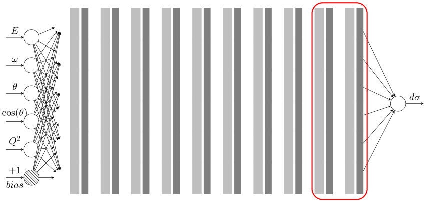
- fundamental concept of deep learning: **representation learning**
- *Transfer learning* known in psychology and education. It refers to the ability of a person who has learned skills in one specific field to easily acquire skills needed in related areas of life.

The First Scenario

all layers fine-tuned

The Second Scenario

the last two blocks fine-tuned



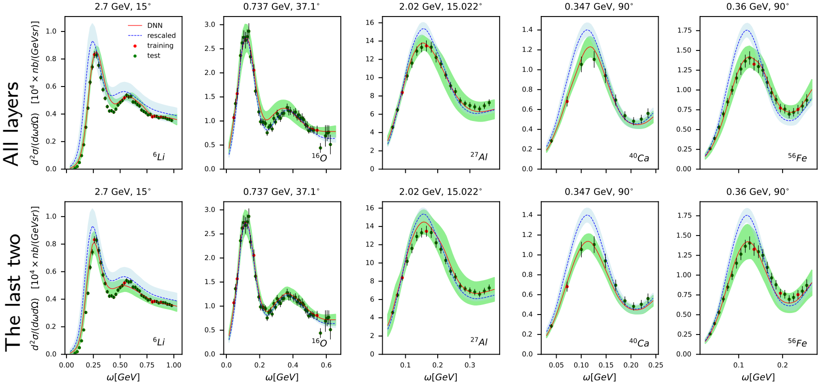
- Consider electron scattering on lithium, oxygen, aluminium, calcium and iron
- For each target consider its own fine-tuning procedure
- To tests transfer learning minimize as much as possible training dataset:

→ **training:test = 1:9**

* Graczyk, Kowal, Ankowski, Banerjee, Bonilla, Prasad, Sobczyk, arXiv:2408.09936

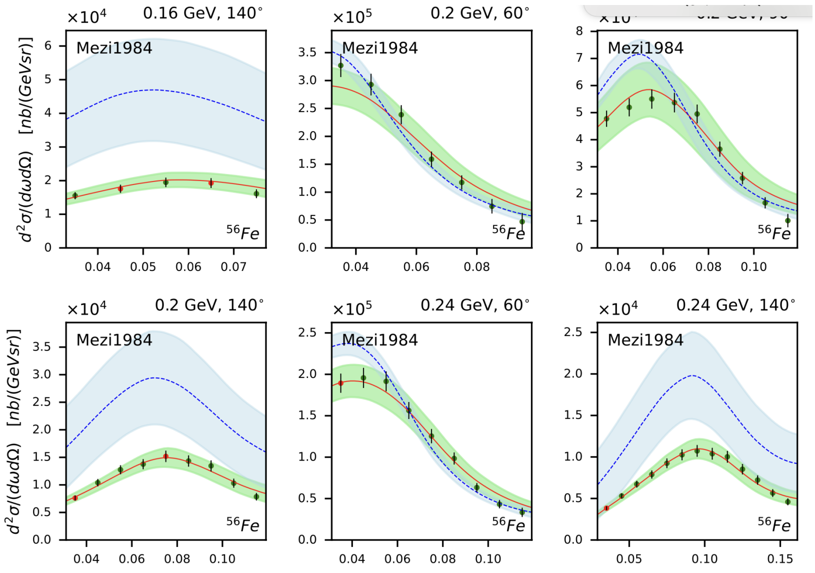
Electron-nucleus cross sections from transfer learning

Fine-Tuning: training (10%), test (90%)



rescaled = (A/12) carbon cross section

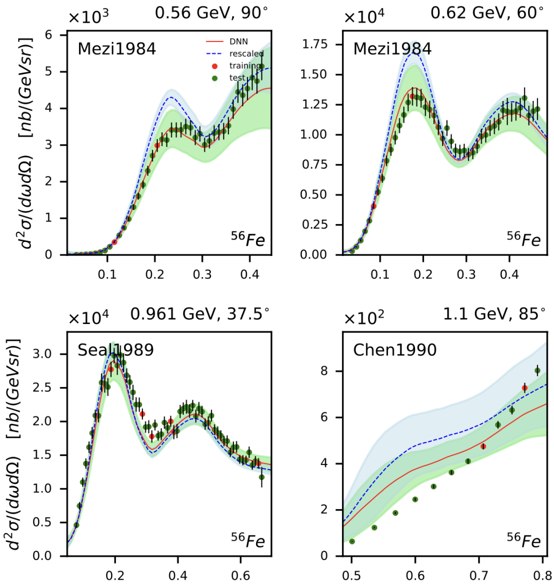
training (10%), test (90%): Iron, all layers fine-tuned



Note that relative normalization parameters (due to nor. sys. uncert.) were taken into account

Summary

- We focus on developing neutrino-nucleus scattering models and implement them in NuWro.
- We have been developing AI-driven models for neutrino-nucleus scattering. This method is promising and broadly applicable.



×10³
0.56 GeV, 90°
Mezi1984
DNN
rescaled
training
test
^{56}Fe
×10⁴
0.62 GeV, 60°
Mezi1984
^{56}Fe
×10⁴
0.961 GeV, 37.5°
Seal1989
^{56}Fe
×10²
1.1 GeV, 85°
Chen1990
^{56}Fe
$d^2\sigma/(d\omega d\Omega)$ [nb/(GeVsr)]