Machine Learning in Dark Matter and Neutrino Physics

Methods, case studies, and pitfalls

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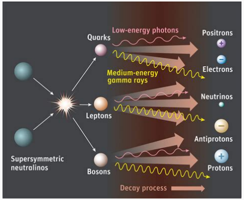
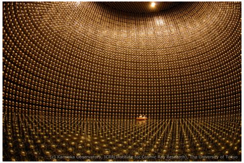
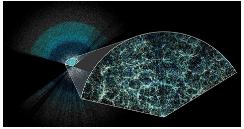
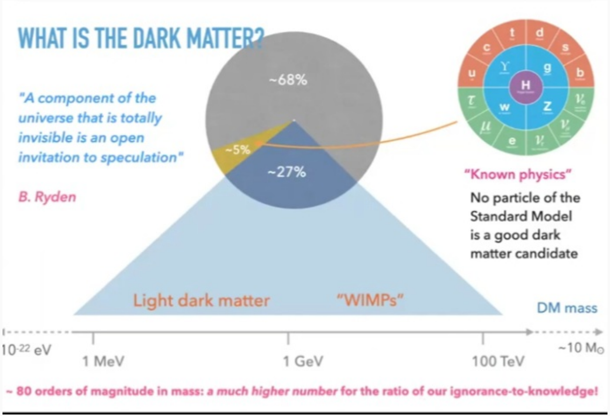
Why Combine Fundamental Physics with Machine Learning?

- **Dark Matter:** Accounts for over 80% of the Universe's matter–energy; its particle nature remains a mystery.
- **Neutrinos:** The "ghost particles" with tiny masses, carrying messages from the Sun, supernovae, and the cosmos.
- **The Grand Challenge:**
    - Signals are extremely rare and faint
    - Backgrounds are enormous and complex
    - Detectors produce massive, noisy datasets
- **This is where ML shines:** uncovering hidden patterns, enhancing event reconstruction, and separating signal from overwhelming noise.








WHAT IS THE DARK MATTER?
"A component of the universe that is totally invisible is an open invitation to speculation"
B. Ryden
~68%
~5%
~27%
"Known physics"
No particle of the Standard Model is a good dark matter candidate
Light dark matter
"WIMPs"
DM mass
10^{-22} eV
1 MeV
1 GeV
100 TeV
~10 $M_{\odot}$
~ 80 orders of magnitude in mass: *a much higher number* for the ratio of our ignorance-to-knowledge!

Astrophysical Evidence for Dark Matter

- **Galaxies:** Flat *rotation curves* show more mass than visible stars and gas.
- **Galaxy clusters:** Dynamics and the *Bullet Cluster* reveal mass not explained by baryons.
- **Gravitational lensing:** Light bending maps invisible matter in cosmic structures.
- **Cosmic Microwave Background (CMB):** Precise anisotropies require $\sim 26\%$ dark matter to fit ΛCDM.

Experimental framing:

- Candidate particles: WIMPs, axions, sterile neutrinos.
- Parameter space often shown as *WIMP mass* vs. *spin-independent cross section* (σ_{SI}).
- Searches: dual-phase liquid xenon TPCs (XENONnT, LZ), cryogenic detectors (SuperCDMS), and others.

Direct Detection of Dark Matter

- **XENONnT (Gran Sasso, Italy):** Dual-phase liquid xenon TPC, multi-ton scale, ultra-low radioactivity. $\Rightarrow$ Set world-leading WIMP limits in 2023.
- **LUX-ZEPLIN (LZ, South Dakota):** Largest LXe detector to date. $\Rightarrow$ 2025 result: 4.2 t·yr exposure, record sensitivity to spin-independent interactions.
- **Other approaches:** Cryogenic detectors (SuperCDMS), bubble chambers (PICO), directional prototypes. $\Rightarrow$ Cover complementary parameter space.

Where Machine Learning makes impact:

- Signal vs. background discrimination (ER vs NR)
- Event classification and quality cuts
- Pulse-shape analysis and denoising
- Anomaly detection $\rightarrow$ search for unexpected physics

Neutrino Physics in One Slide

- **Neutrino mixing:** Flavor states mix via the PMNS matrix. Oscillation probabilities $P_{\alpha\beta}$ depend on Δm^2, mixing angles θ_{ij}, and CP phase δ_{CP}.
- **Key discoveries:** Solar and atmospheric neutrino experiments established oscillations $\Rightarrow$ neutrinos have mass.
- **Major frontiers:**
  - Long-baseline: T2K, NOvA, DUNE (measure δ_{CP}, mass ordering)
  - Atmospheric: Super-Kamiokande, Hyper-K, IceCube (broad energy and baseline coverage)
  - Reactor: Daya Bay, JUNO (precision θ_{13}, mass hierarchy)
- **Where ML helps:**
  - Event classification (signal vs background)
  - Reconstruction of tracks and showers
  - Particle identification (e^- vs μ^-, hadrons, photons)
  - Energy regression and uncertainty estimation

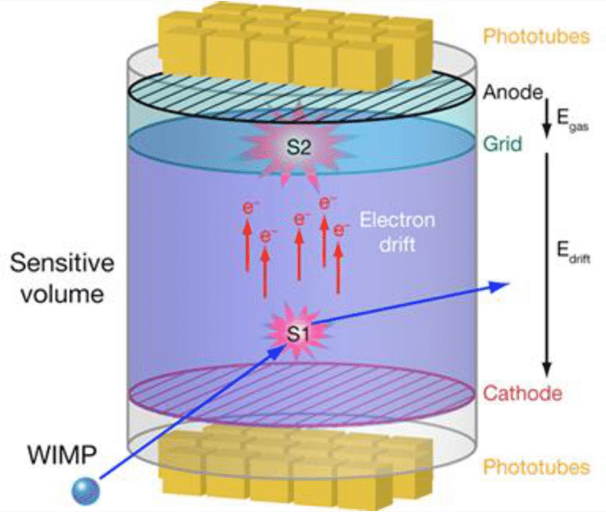
ML Toolkit in HEP (I): Core Methods

- **Supervised learning**
  - **BDTs:** Classic choice for tabular physics features.
  - **CNNs:** Great for calorimeter images or PMT hit maps.
  - **GNNs:** Handle sparse detector hits modeled as graphs.
- **Un-/Self-supervised**
  - **Autoencoders:** Spot anomalies, noise, or unexpected events.
  - **Normalizing flows:** Flexible density modeling and generative tools.

ML Toolkit in HEP (II): Advanced Methods and Tools

- **Simulation-based inference**
  - Likelihood-free approaches using neural ratio/score estimation.
  - Enable direct parameter extraction from Monte Carlo simulations.
- **Practical tooling**
  - ML frameworks: `PyTorch`, `TensorFlow`, `scikit-learn`.
  - HEP-specific I/O: `uproot`, Awkward Arrays, `ROOT`.

From traditional classifiers to end-to-end inference, ML now touches every step of the HEP analysis chain.


Phototubes
Anode
E_{gas}
Grid
S2
e^-
Electron drift
Sensitive volume
E_{drift}
S1
Cathode
WIMP
Phototubes

Case Studies: Machine Learning in Dark Matter Searches

- **Pulse classification & denoising** Separate scintillation (S1) and ionization (S2) signals in liquid xenon TPCs. $\Rightarrow$ ML improves noise rejection and energy resolution.
- **Event selection and background rejection** BDTs, CNNs, and GNNs discriminate *nuclear recoils* (signal-like) from *electron recoils* (backgrounds). $\Rightarrow$ Higher sensitivity to WIMP interactions.
- **Anomaly detection** Autoencoders and normalizing flows identify rare detector pathologies or unexpected event classes. $\Rightarrow$ Keeps analyses robust and open to new physics.
- **Global limit setting** ML-assisted statistical inference propagates systematic uncertainties and combines multiple datasets. $\Rightarrow$ Enables world-leading exclusion limits.

ML enhances every stage of the pipeline — from raw signals to final physics results.

Case Studies: Machine Learning in Neutrino Physics

- **NOvA CVN (Convolutional Neural Network)** Event images from tracking calorimeter are classified directly. $\Rightarrow$ Outperforms traditional reconstruction pipelines for signal/background ID.
- **DUNE CVN** CNNs distinguish interaction channels and event topologies in liquid argon TPC data. $\Rightarrow$ Essential for CP violation and mass-ordering measurements.
- **IceCube with GNNs & Transformers** Graph-based models reconstruct low-energy events using sparse PMT hits. New GNN/Transformer architectures extend to extreme-energy cosmic neutrinos. $\Rightarrow$ Boosts both precision and reach of the detector.

From NOvA to IceCube, ML has become central to neutrino discovery and precision measurement.

Systematics, Robustness, and Interpretability in ML for HEP

- **Domain shift (sim $\rightarrow$ real):** Detector simulations never match reality perfectly. $\Rightarrow$ Mitigation via domain adaptation, event reweighting, and tuned simulations.
- **Calibration & Uncertainty Quantification:** ML scores need probabilistic meaning. $\Rightarrow$ Use Platt scaling, temperature scaling, and coverage checks for reliable UQ.
- **Explainability:** Understanding ML decisions builds trust. $\Rightarrow$ Apply saliency maps, SHAP values, and sanity checks (e.g. input corruption tests).
- **Statistical integrity:** Physics results must remain unbiased. $\Rightarrow$ Blind analyses, nested cross-validation, and correct treatment of trials.

Robust ML in physics means not just accuracy — but reliability, transparency, and statistical rigor.

Practical Guidance: What Tends to Work in HEP ML

- **Start simple, benchmark well** Begin with BDTs or shallow CNNs and strong physics-driven features. $\Rightarrow$ Provides reliable baselines and avoids overfitting hype.
- **Respect detector geometry** Encode spatial/temporal structure (graphs, coordinates, time ordering). $\Rightarrow$ Models learn physics, not spurious correlations.
- **Integrate with reconstruction** ML co-designed with existing reconstruction pipelines generalizes better. $\Rightarrow$ Ensures outputs are physically interpretable.
- **Reproducibility matters** Track seeds, software versions, and hyperparameters. $\Rightarrow$ Guarantees results can be validated and trusted.

Good ML in physics is not just clever models — it is simple, structured, and reproducible.

Outlook: The Future of ML in Dark Matter and Neutrino Physics

- **Next-generation methods** Growing impact of Graph Neural Networks (GNNs) and simulation-based inference $\Rightarrow$ Directly connect raw detector data to physics parameters.
- **Cross-experiment synergy** Joint analyses across detectors with ML-calibrated systematics. $\Rightarrow$ Improved sensitivity and consistency at the global scale.
- **End-to-end pipelines** Moving beyond classifiers toward fully differentiable reconstruction and inference. $\Rightarrow$ Seamless integration of ML with the physics analysis chain.

ML is shifting from a supporting tool to a central driver of discovery in fundamental physics.

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