Machine Learning in Oscillation Experiments

Fernanda Psihas

Fermilab

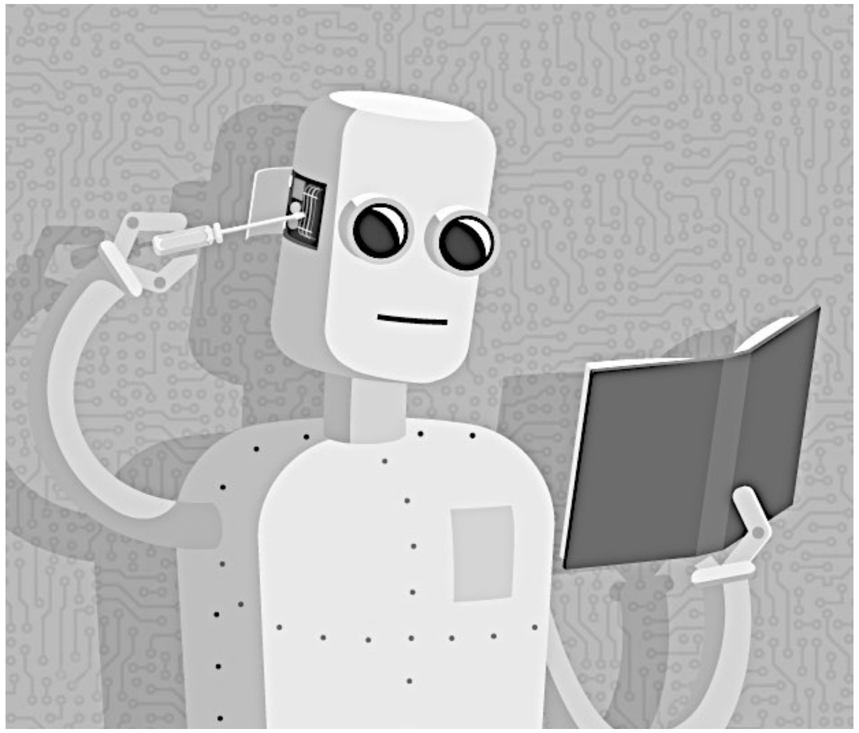
Takeaways

Machine learning techniques have improved the sensitivity of oscillation experiments.

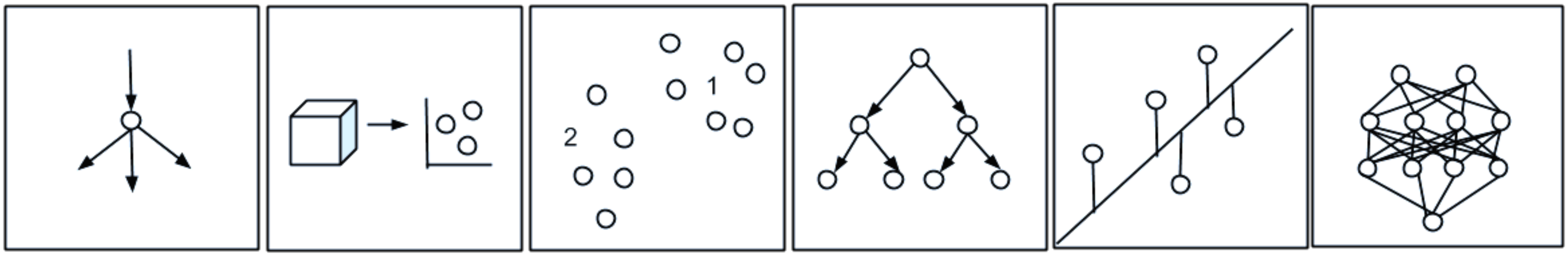
Increasing algorithm complexity **introduces new challenges** in bias and uncertainty quantification.

Oscillations experiments must **solve the bias and uncertainty problem in ML** to enable precision measurements for next-generation experiments.

What Is Machine Learning?

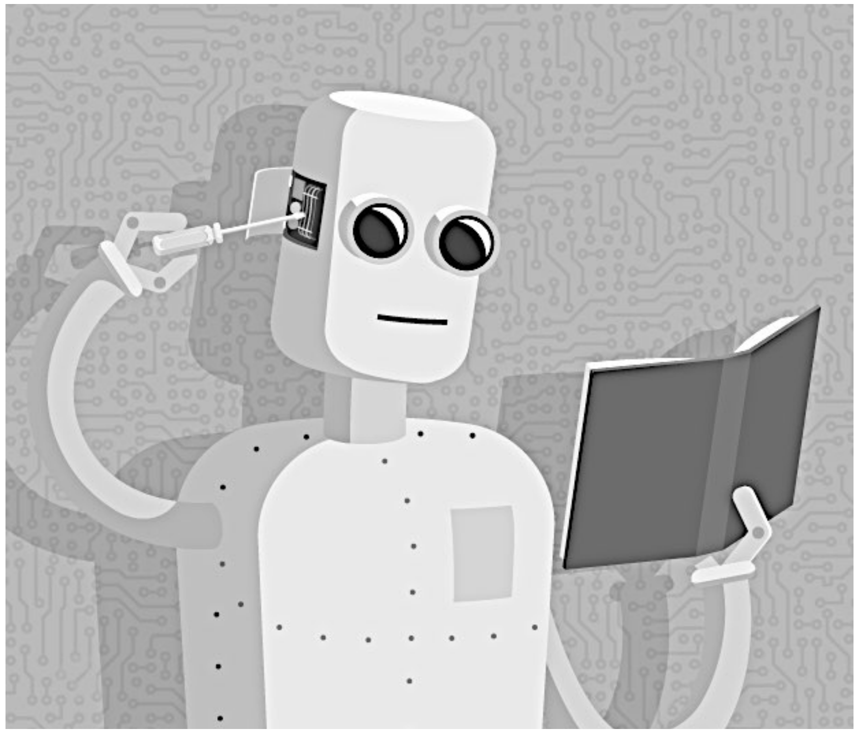


Algorithms
whose **performance**
for a given **task**
improves with **experience**



Artificial Neural Network Algorithms | Dimensional Reduction Algorithms | Clustering Algorithms | Decision Tree Algorithms | Regression Algorithms | Deep Learning Algorithms

What Is Machine Learning?



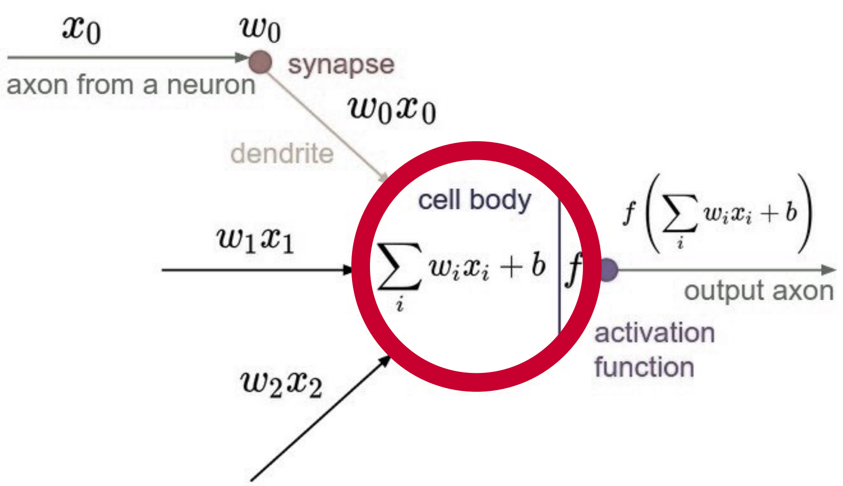
Algorithms
whose **performance**
for a given **task**
improves with **experience**

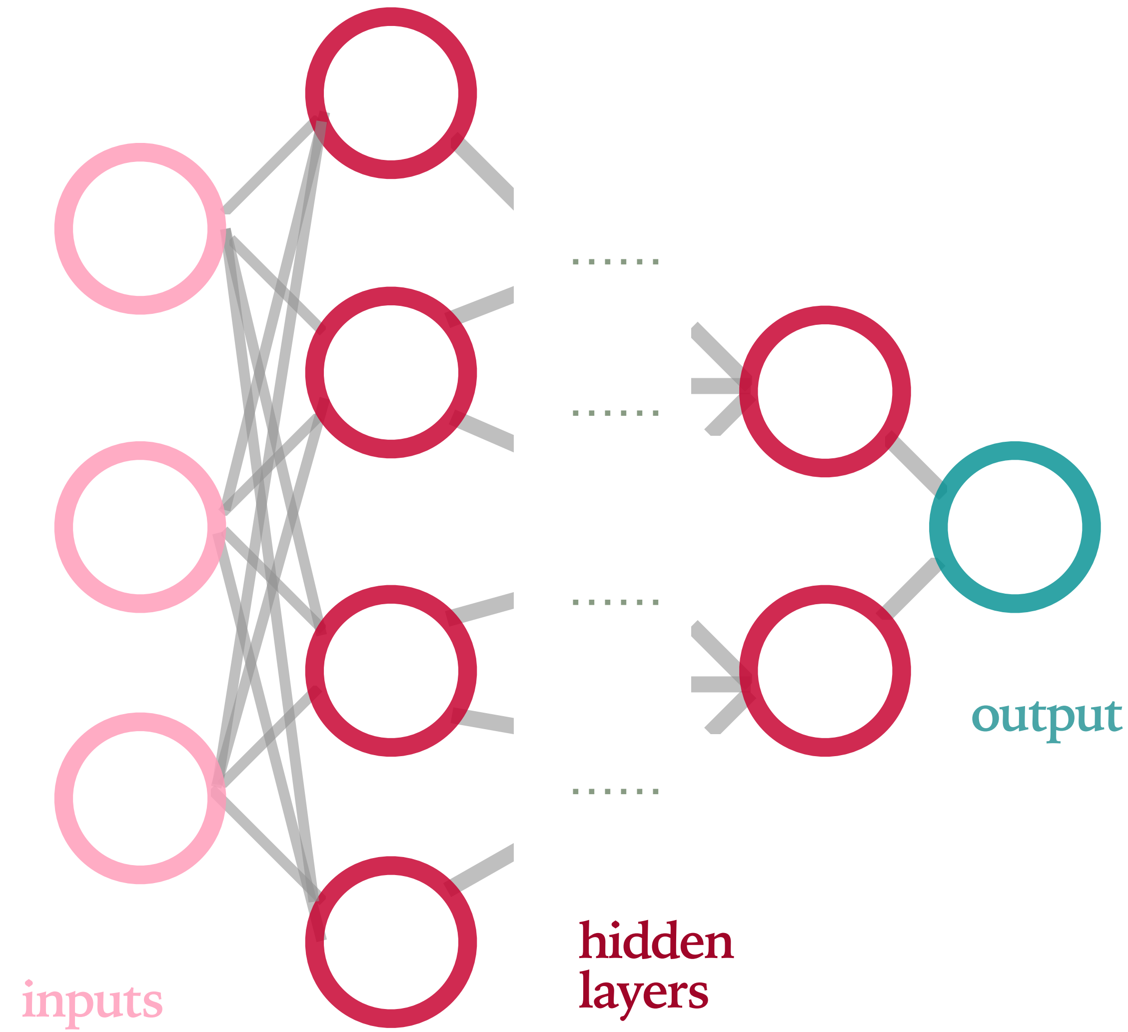
same **operating principle**

increasing **complexity**

Target (function) approximation

A collection of connected units called artificial neurons or **nodes**

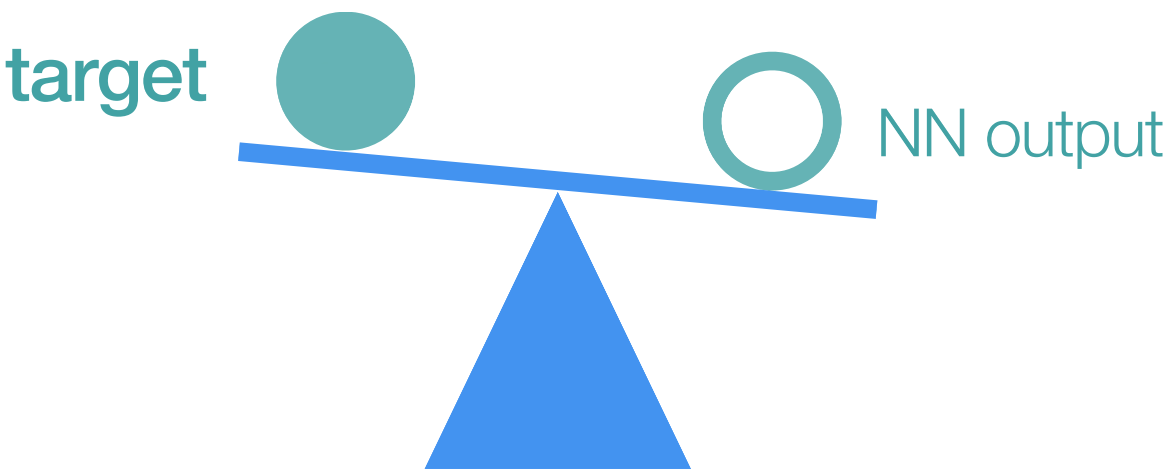


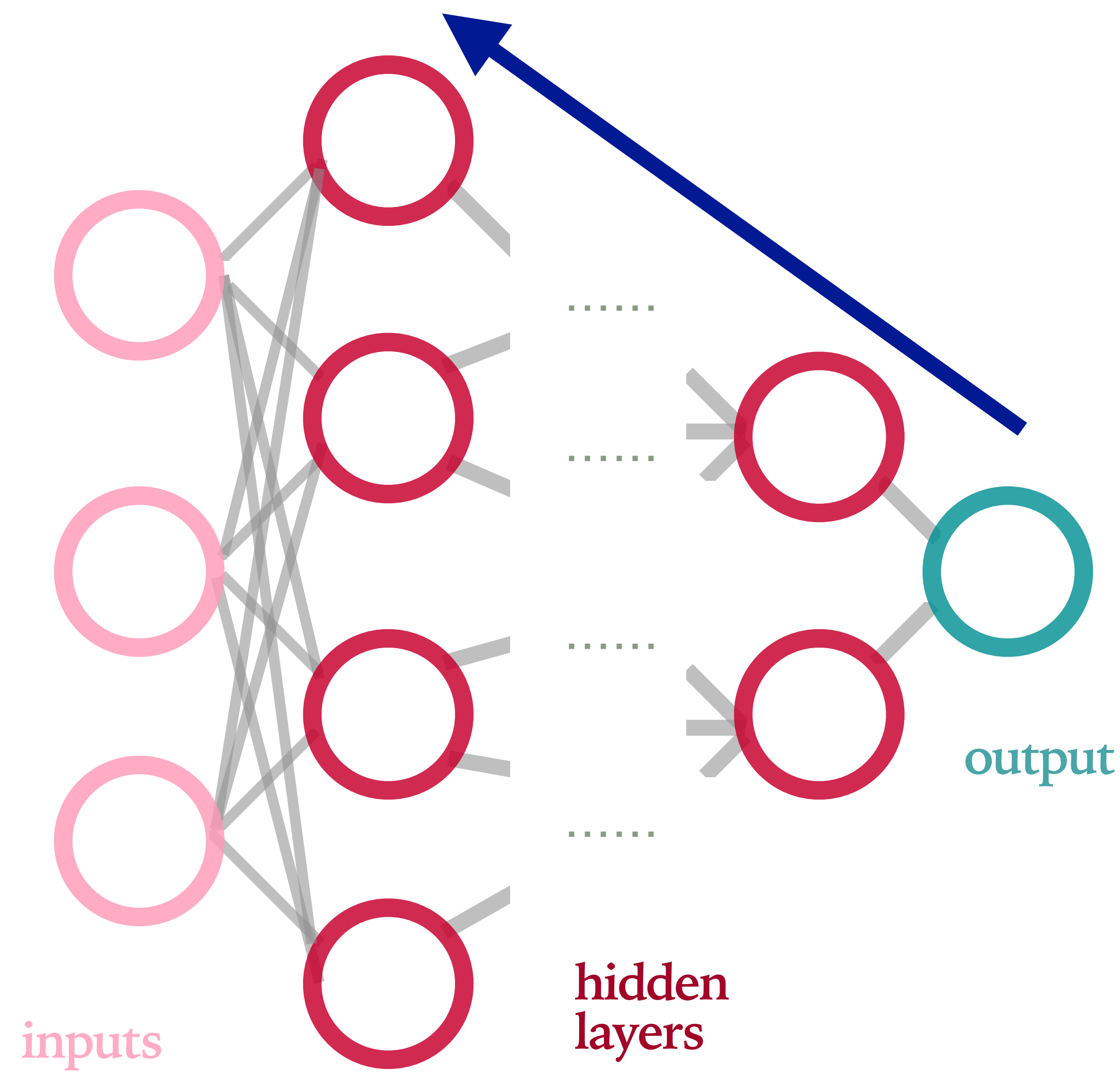


Activation function and weights set values on each node, given some input.

Target (function) approximation

The accuracy of the **output** is quantified with a **loss function**

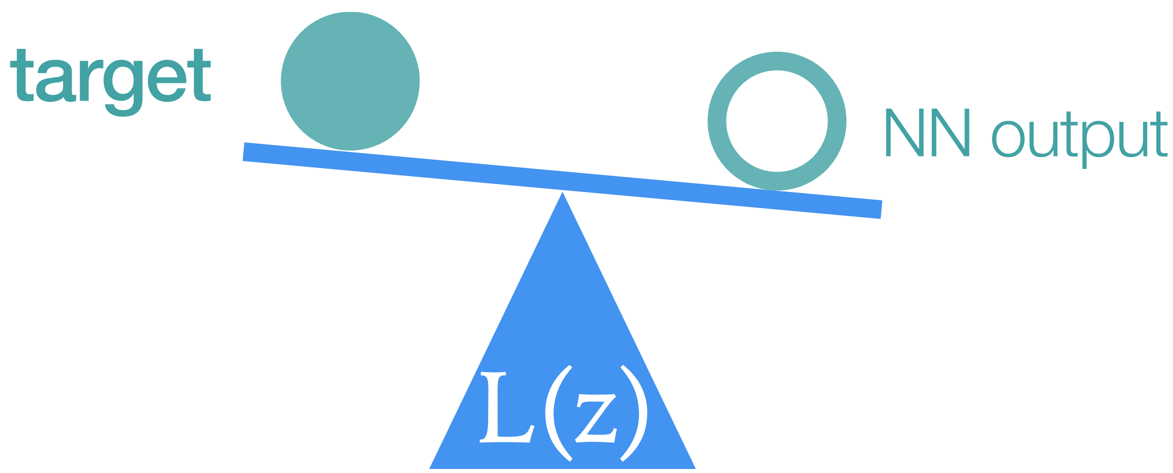




and the **nodes are modified** accordingly. ….. repeat ….

Target (function) approximation

The accuracy of the **output** is quantified with a **loss function**



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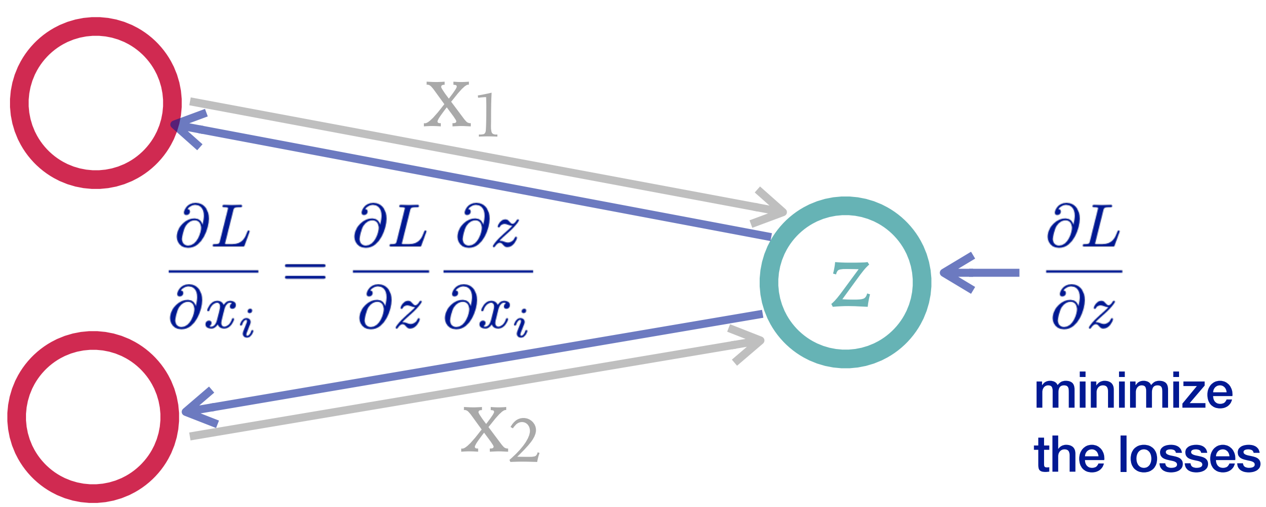
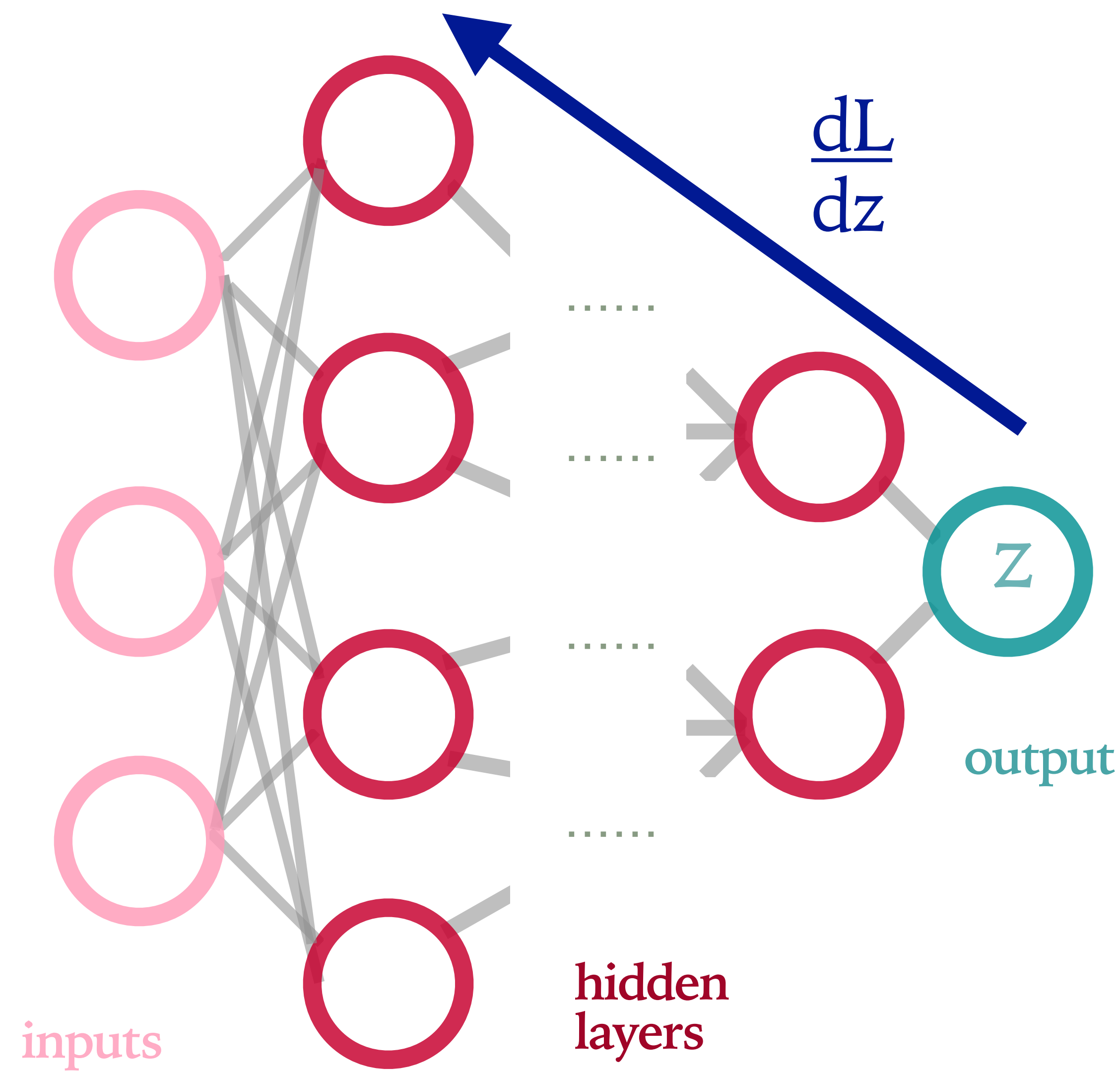
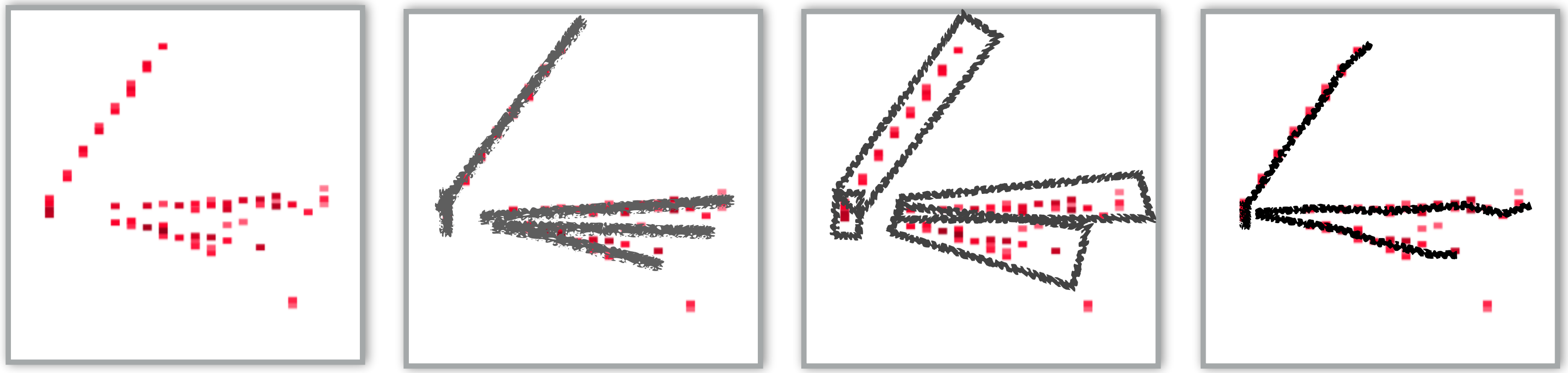




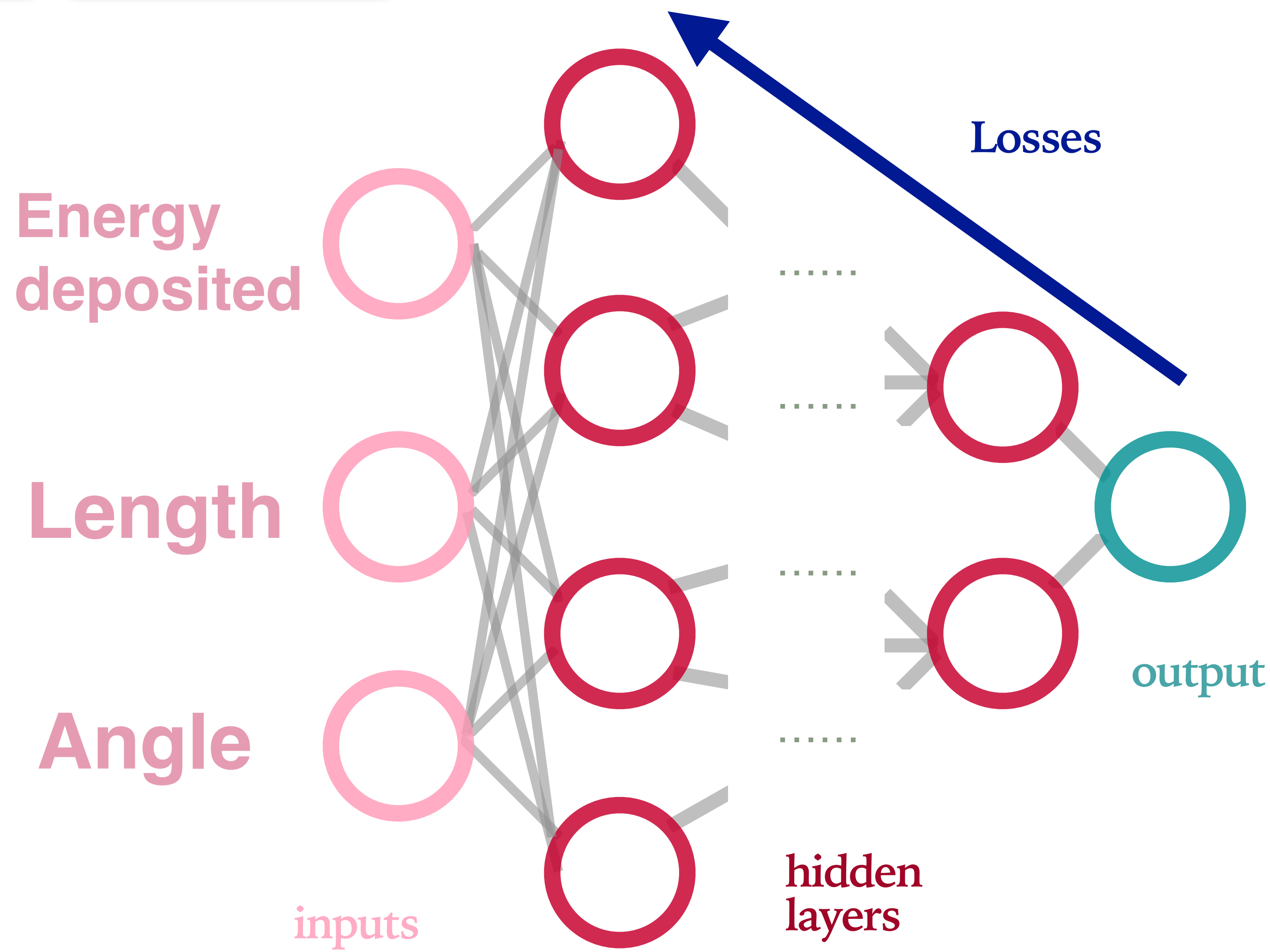
ML in Signal ID & Parameter Estimation



Traditional particle reconstruction.

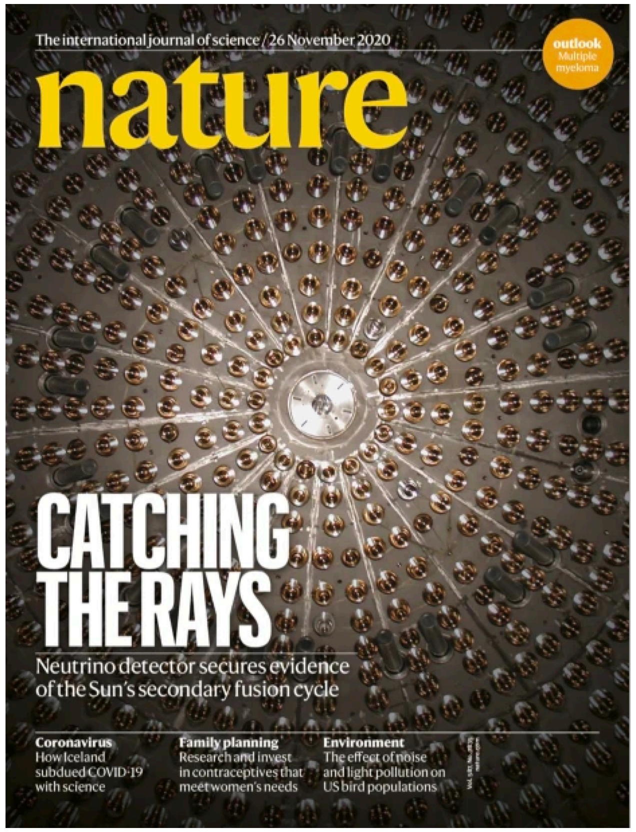
Extract information (features) from the event which can separate signal vs background.

Train NNs with these features from simulation libraries.



Event-by-event tagging of the 210Po decay α **is essential to the CNO detection.**

This is enabled by a Multi-layer perceptron. The **MLP exploits the scintillation time-decay differences from alpha and beta-like events.**

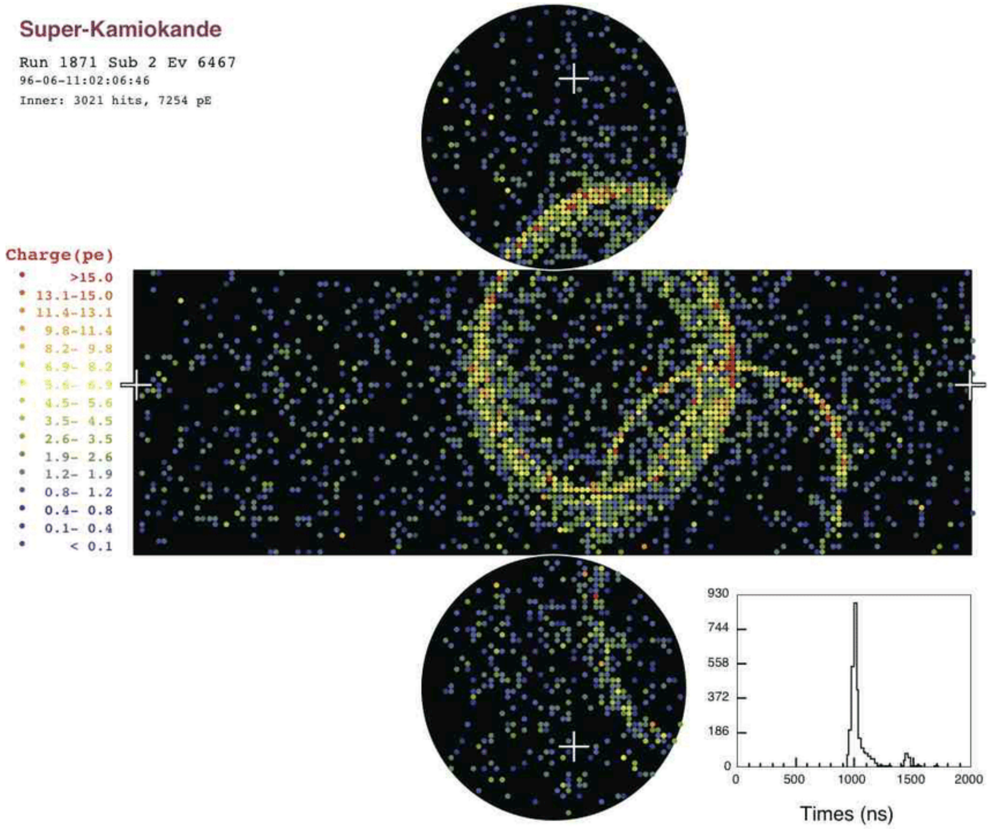


Experimental evidence of neutrinos produced in the CNO fusion cycle in the Sun

The Borexino Collaboration

Nature **587**, 577–582 (2020) | Cite this article

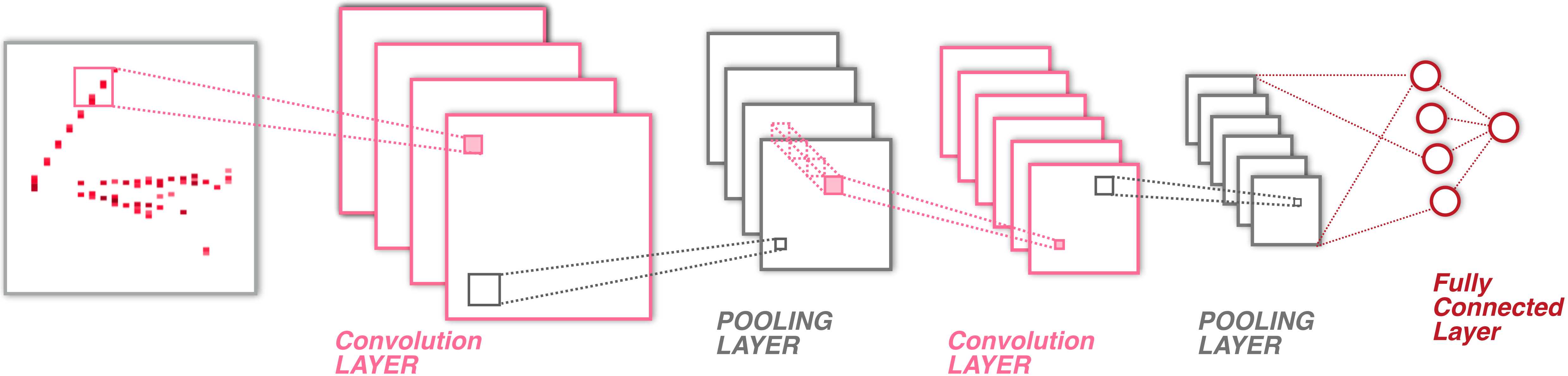
Adoption of BDT improves their multi-site tagging of e CCve-like events, from **34.4% to 46.7% in efficiency.**

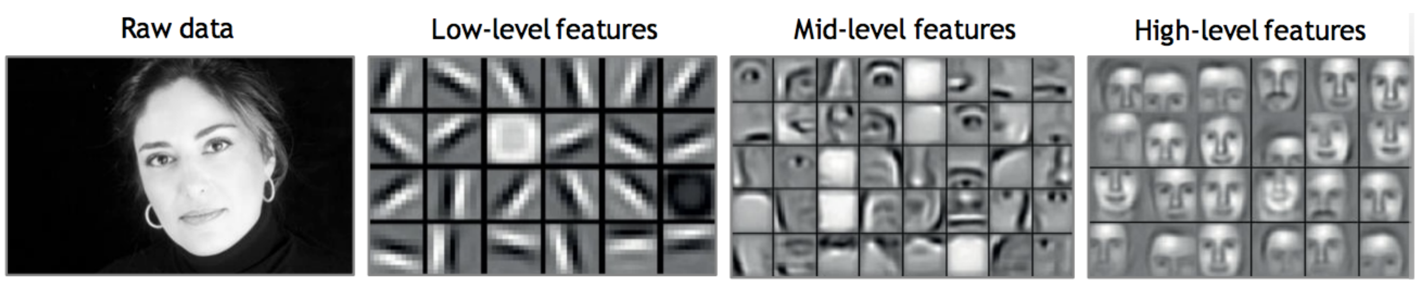


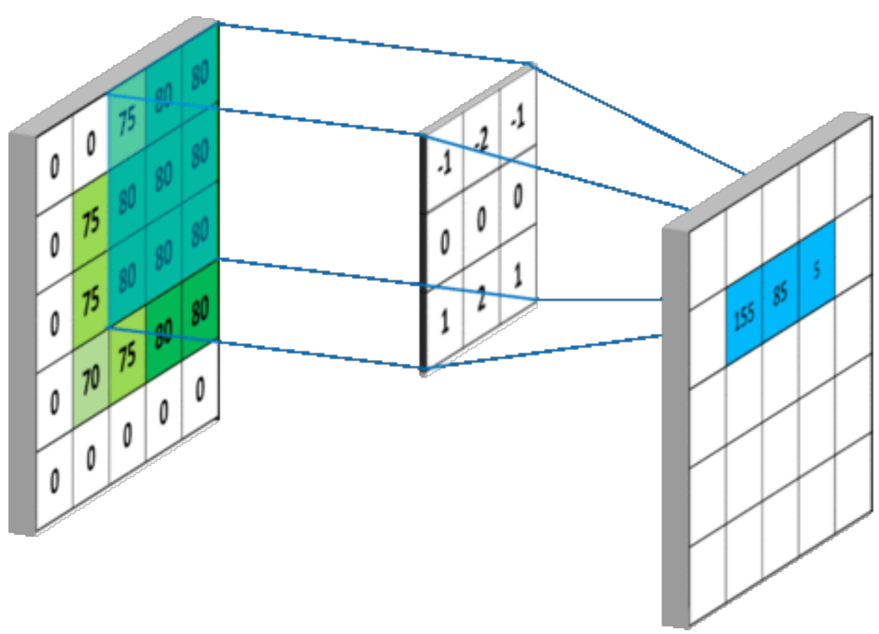
(ICRC2021) Atmospheric oscillations with Super-Kamiokande and prospects for SuperK-Gd - https://pos.sissa.it/395/008

https://arxiv.org/abs/1109.3262

NNs + Feature Extraction



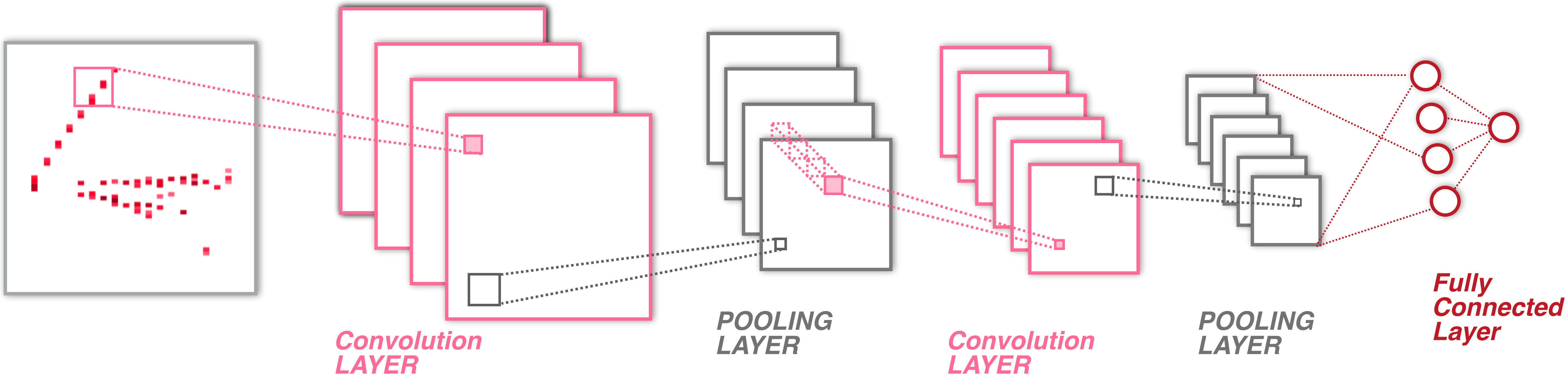


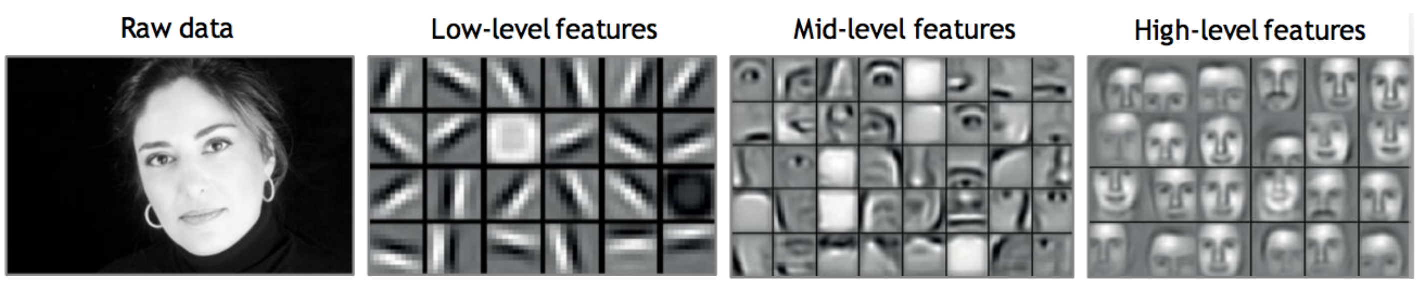


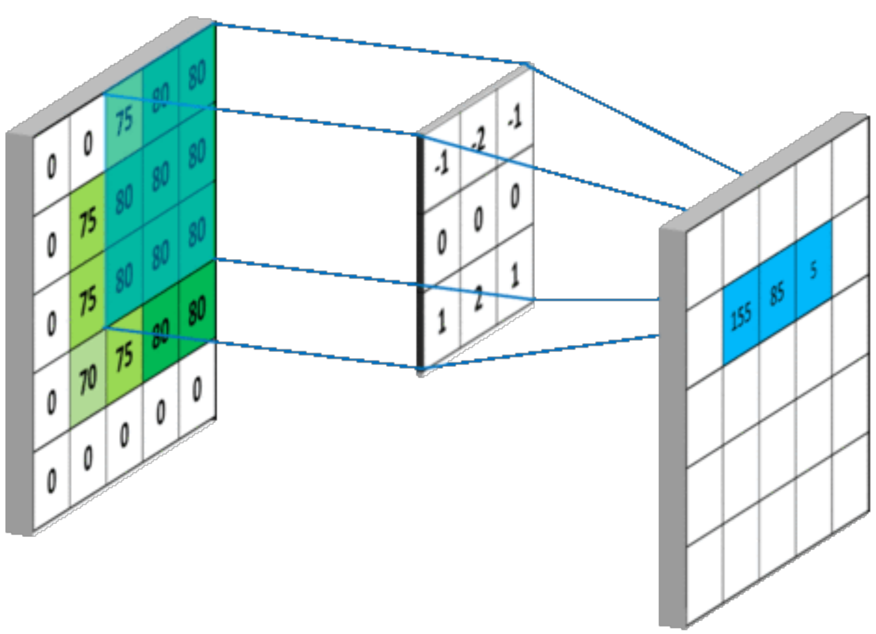
Convolutional neural networks or CNNs eliminate the inefficiencies coming from feature extraction steps upstream by **disentangling from reconstruction**.

Allow the network to **learn and extract features** rather than selecting them a-priori.

NNs + Feature Extraction







Convolutional neural networks or CNNs eliminate the inefficiencies coming from feature extraction steps upstream by **disentangling from reconstruction**.

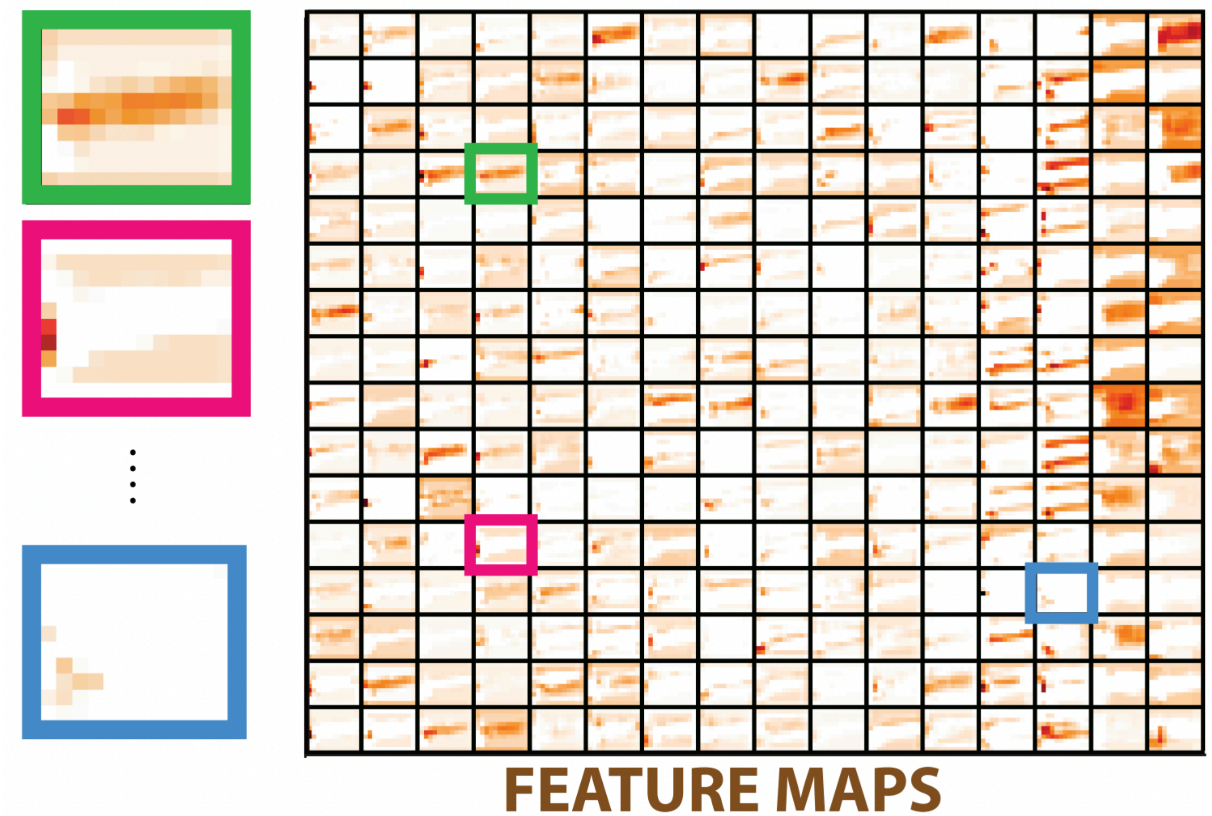
Allow the network to **learn and extract features** rather than selecting them a-priori.

A convolutional neural network neutrino event classifier

A. Aurisano[1], A. Radovic[2], D. Rocco[3], A. Himmel[4], M.D. Messier[5], E. Niner[4], G. Pawloski[3], F. Psihas[5], A. Sousa[1] and P. Vahle[2]

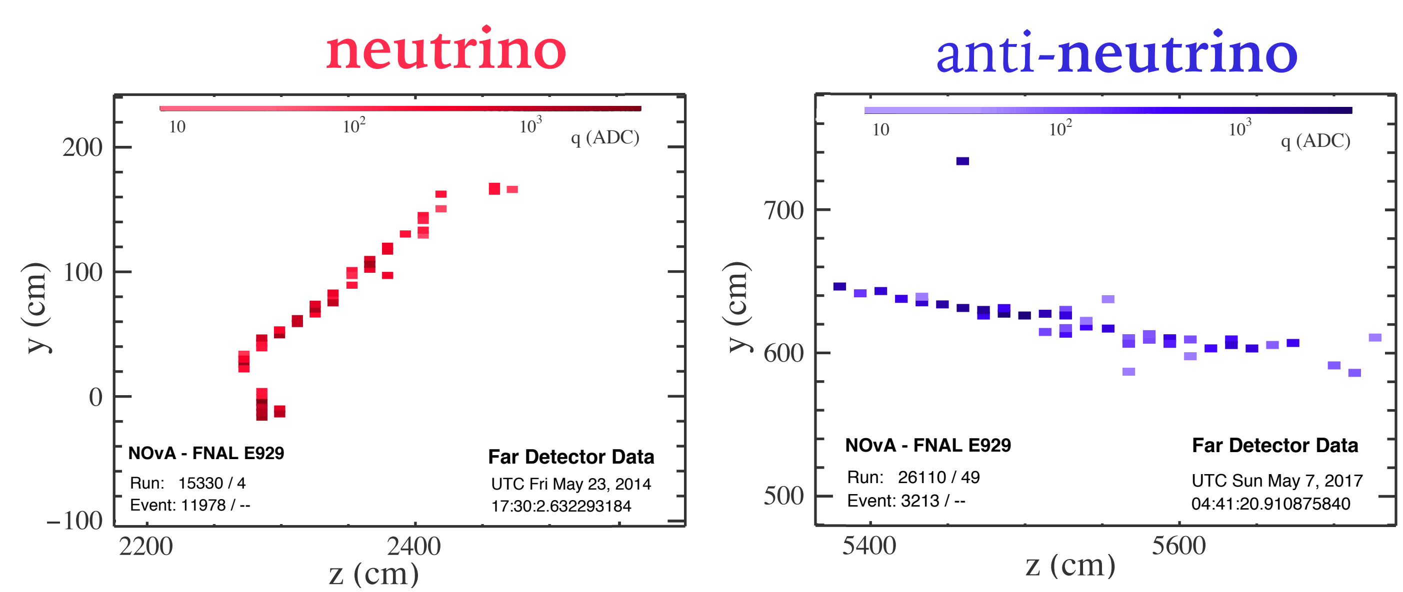
Published 1 September 2016 • © 2016 IOP Publishing Ltd and Sissa Medialab srl
Journal of Instrumentation, Volume 11, September 2016

NOvA uses Convolutional Neural Networks to extract features and classify events.



CNNs increased effective exposure by 30% compared to traditional ID methods.

Training on neutrino beam and anti-neutrino beam simulations separately further increased their efficiency for anti-ve signal by 14%

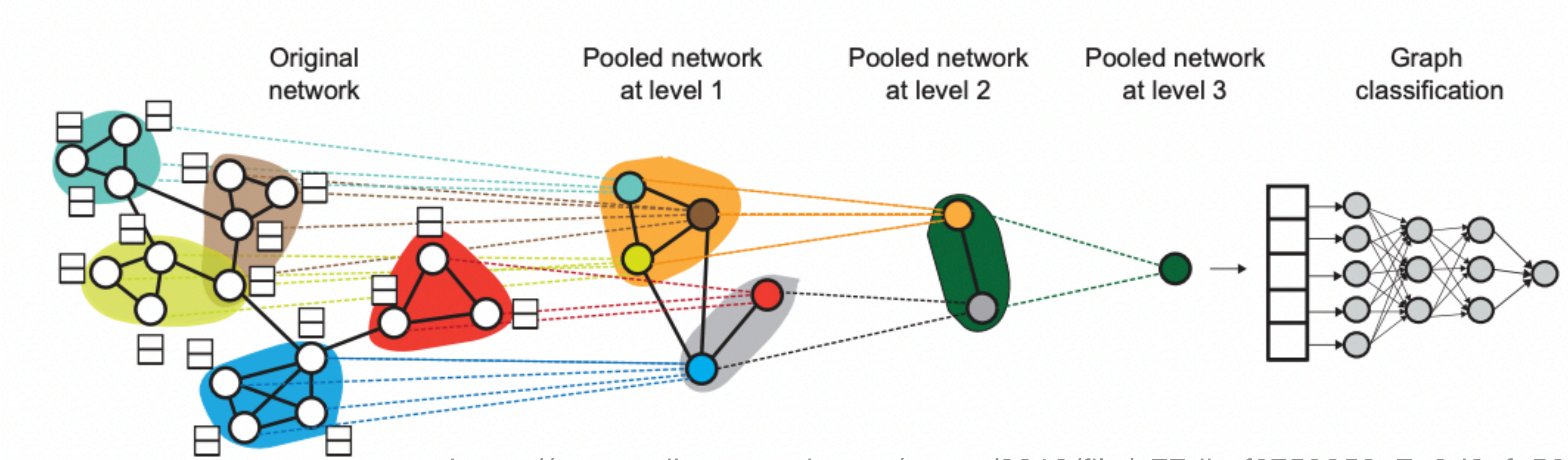


$\bar{\nu}$ **Efficiency Improvement** Training Sample (ID > 0.9)		
$\bar{\nu}_e$ CC Signal	$\bar{\nu}_\mu$ CC Signal	$\bar{\nu}$ NC Signal
14%	6%	10%

Measurement of Neutrino Oscillations and Improvements from Deep Learning. Fernanda Psihas https://inspirehep.net/literature/1672901

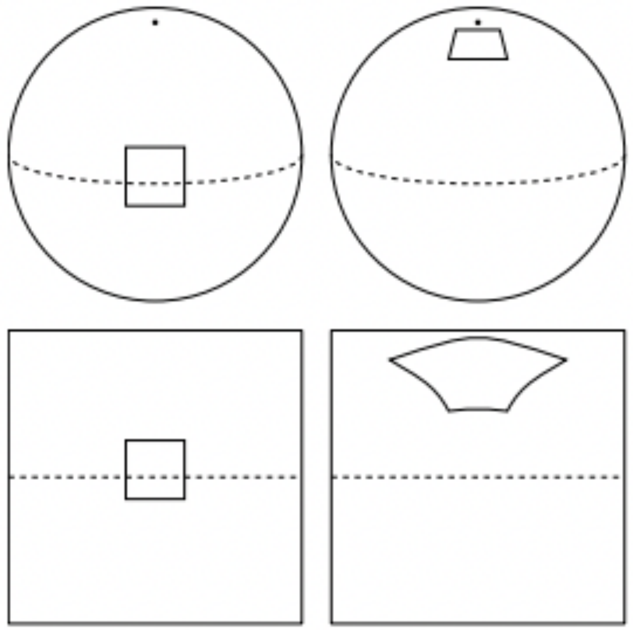
Incorporating Detector Geometry

Graph Neural Networks infer the directional correlations from features and relative positioning of elements in the training data, which is useful for clustering populations.



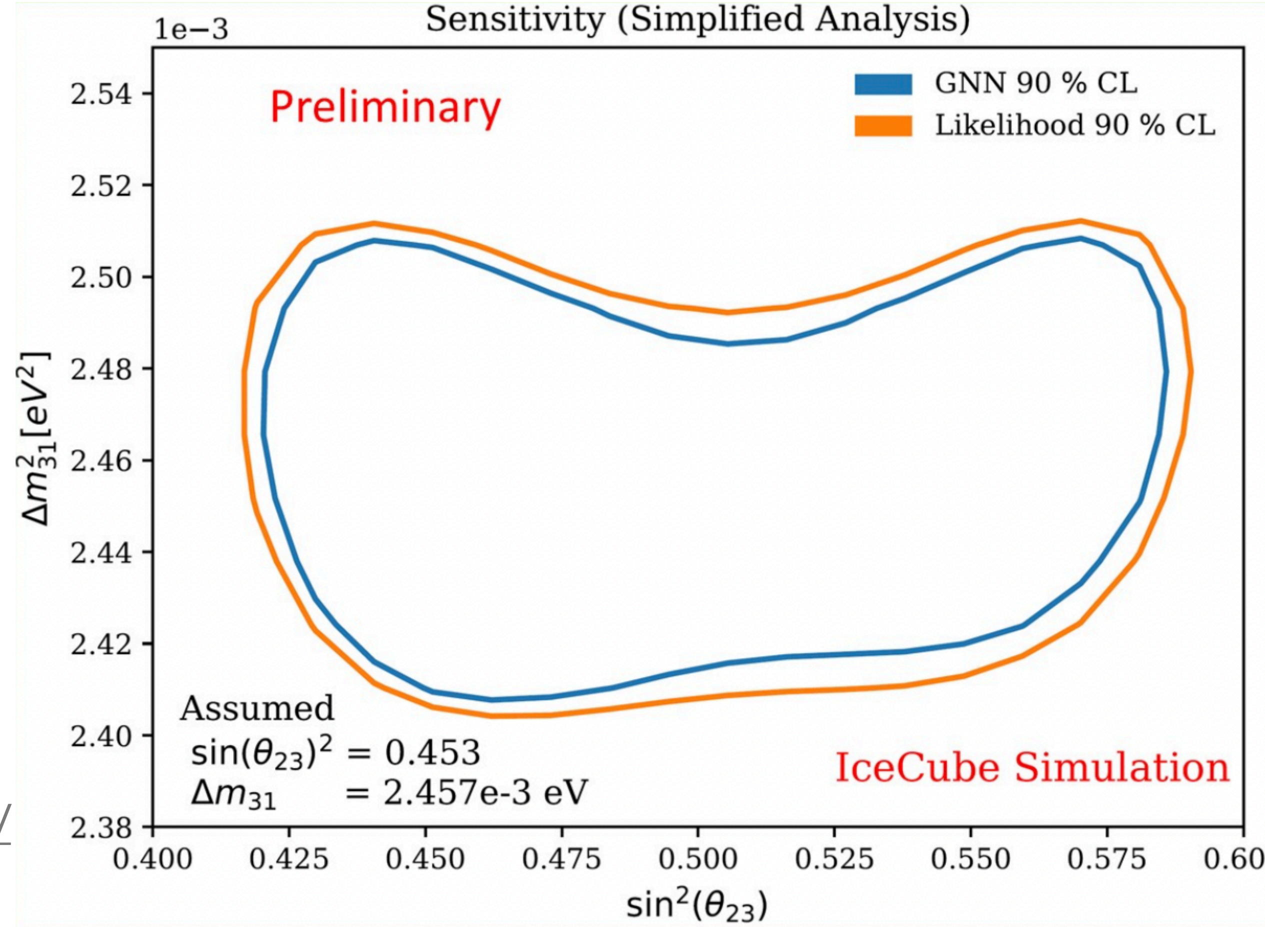
https://proceedings.neurips.cc/paper/2018/file/e77dbaf6759253c7c6d0efc5690369c7-Paper.pdf

Spherical CNNs use projections of 2D arrays onto a spherical plane. Good example of potential for adapting CNNs to detector geometry.



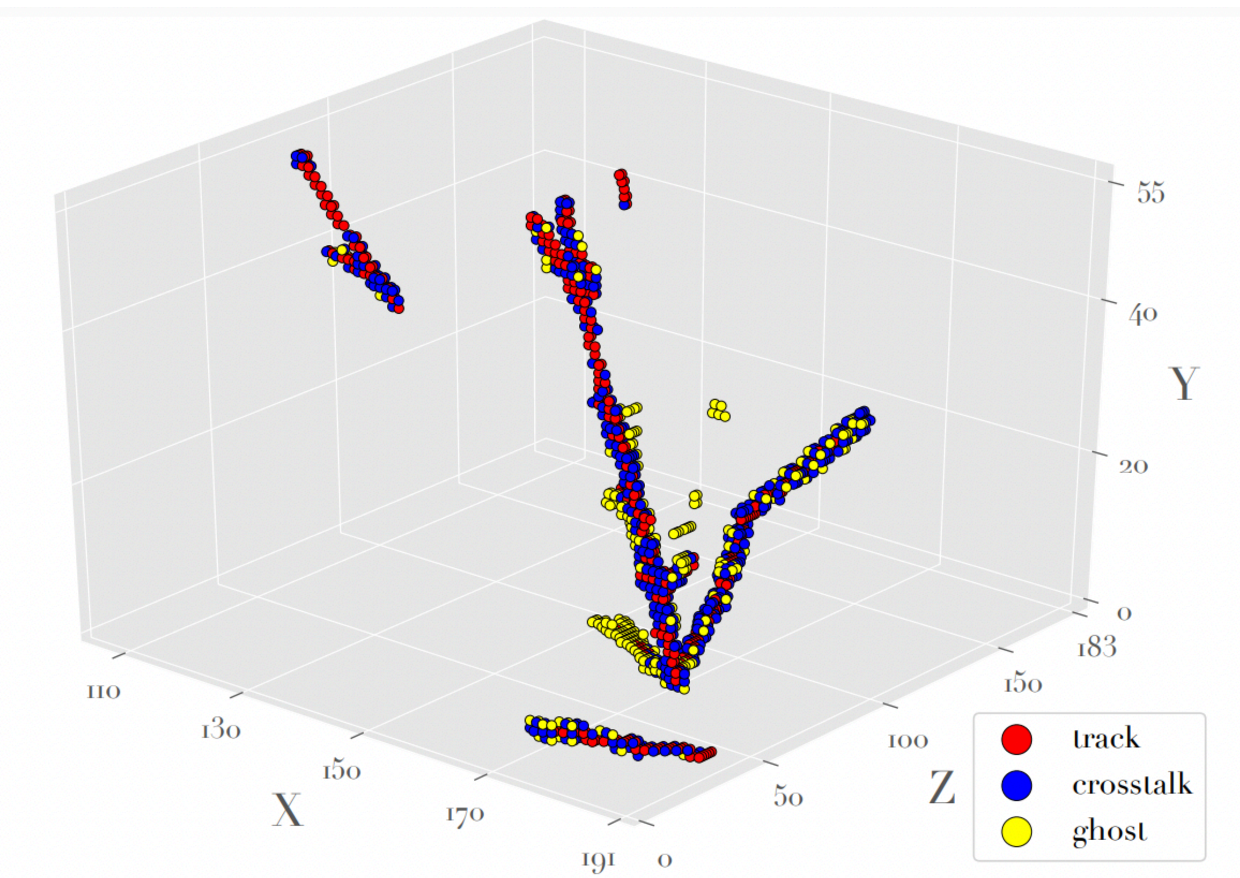
https://arxiv.org/abs/1801.10130

ICECUBE
SOUTH POLE NEUTRINO OBSERVATORY



Graph NNs are natural for clustering PMT signals. GNN based reco. Yields 20% + resolution in energy & zenith. **Expected sensitivity equivalent to 25% more statistics.**

GNNs Neutrino Event Reconstruction. Neutrino 2022 poster. Rasmus Ørsøe. https://indico.kps.or.kr/event/30/contributions/785/



(a) Prediction: voxels are colored based on the GNN predictions.

T2K is also using GNNs for removing cross-talk & ghost hits from tracks in preparation for The SuperFGD near detector for **improvements with respect to charge cuts.**

	GNN		Charge Cut		
	Track	Other		Track	Other
Efficiency	94%	96%	Efficiency	93%	80%
Purity	96%	95%	Purity	80%	91%

Graph neural network for 3D classification of ambiguities and optical crosstalk in scintillator-based neutrino detectors Sa´ul Alonso-Monsalve, et.al. https://arxiv.org/pdf/2009.00688.pdf

THIS SLIDE: NOT YET IMPLEMENTED FOR OSCILLATIONS

ML for neutrino oscillations

- Reconstruction
- Background rejection/ classification
- Data quality selections
- Bias reduction
- Hardware triggering
- MonteCarlo generation
- Accelerator operations
- Data-size reduction

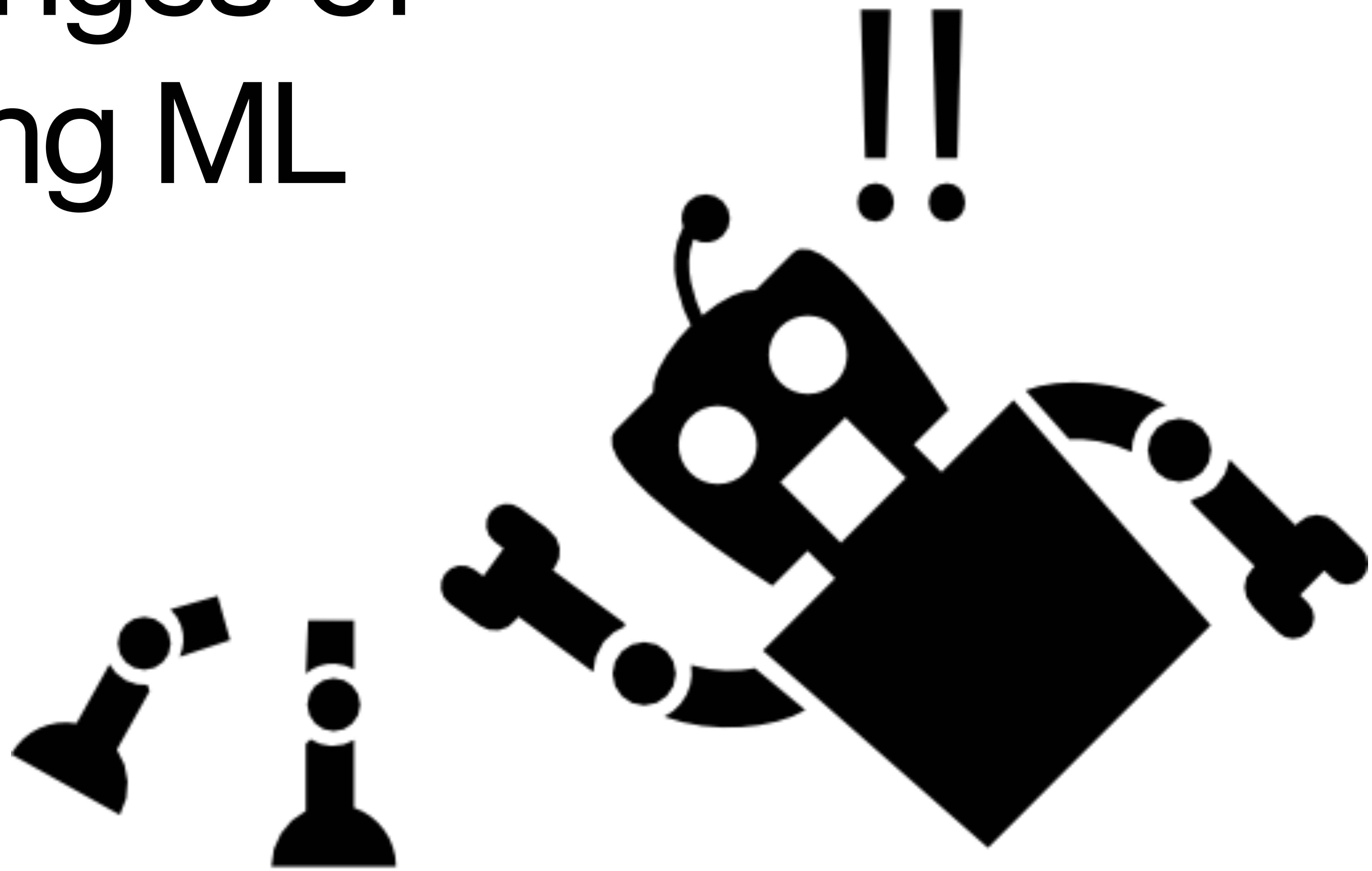
These techniques are improving our current sensitivities and informing experiment design for next-gen experiments, enabling physics analyses that would otherwise be impossible.

A Review on Machine Learning for Neutrino Experiments

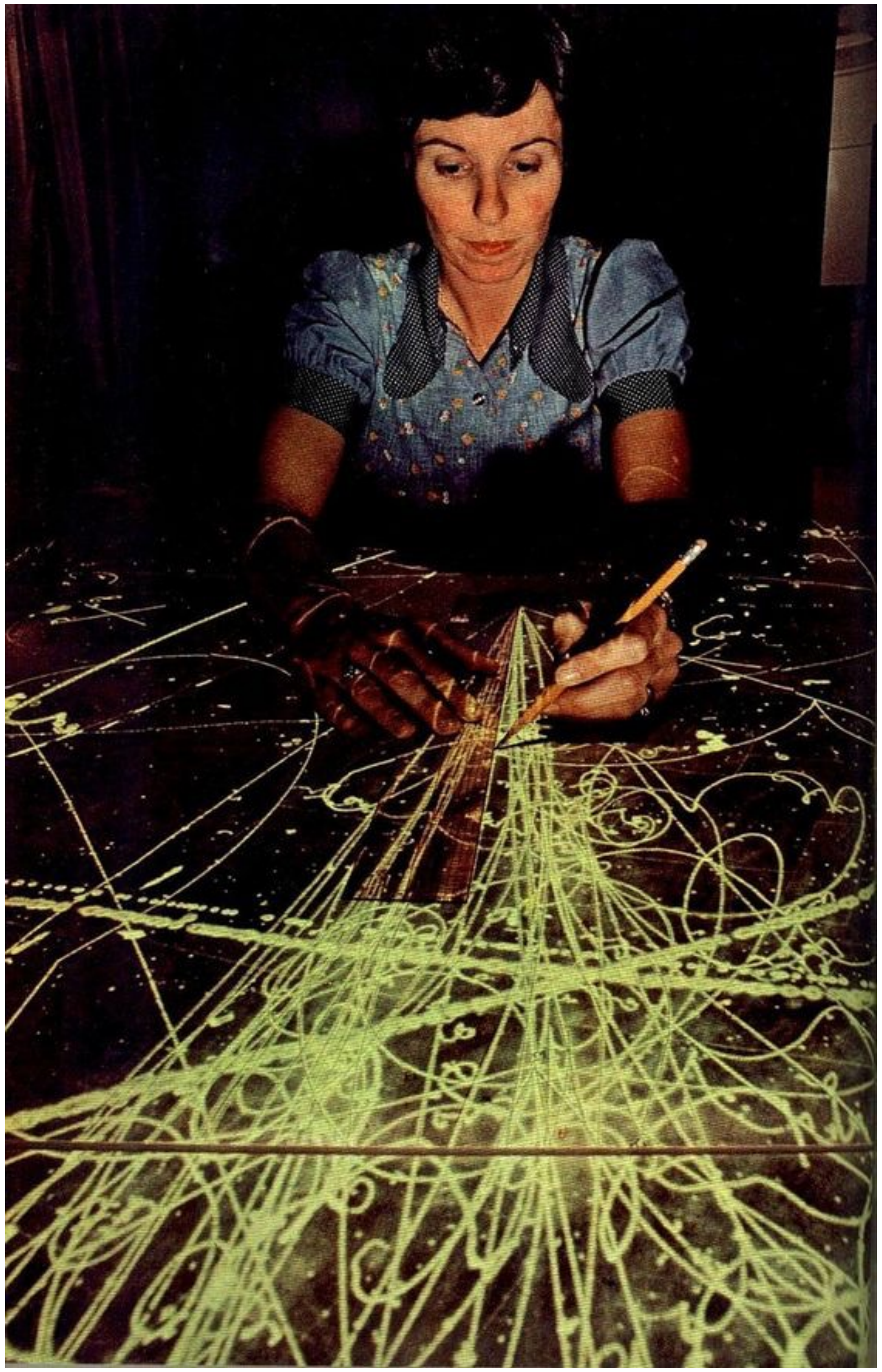
Fernanda Psihas (Fermilab), Micah Groh (Indiana U.), Christopher Tunnell (Rice U.), Karl Warburton (Iowa State U.) (Aug 3, 2020)

Published in: *Int.J.Mod.Phys.A* 35 (2020) 33, 2043005 • e-Print: 2008.01242

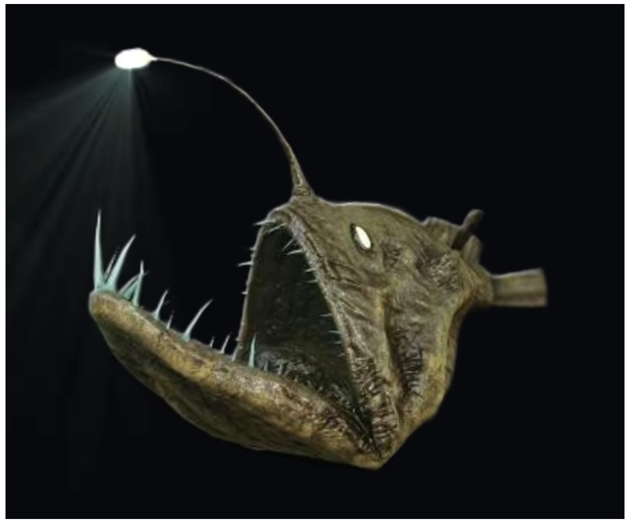
Challenges of applying ML

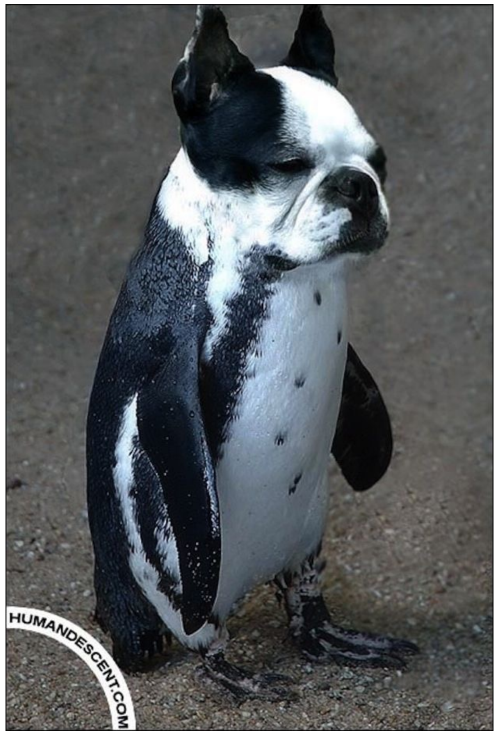


Maintaining sensitivity to new physics



She would know this is **not** what animals look like in nature.





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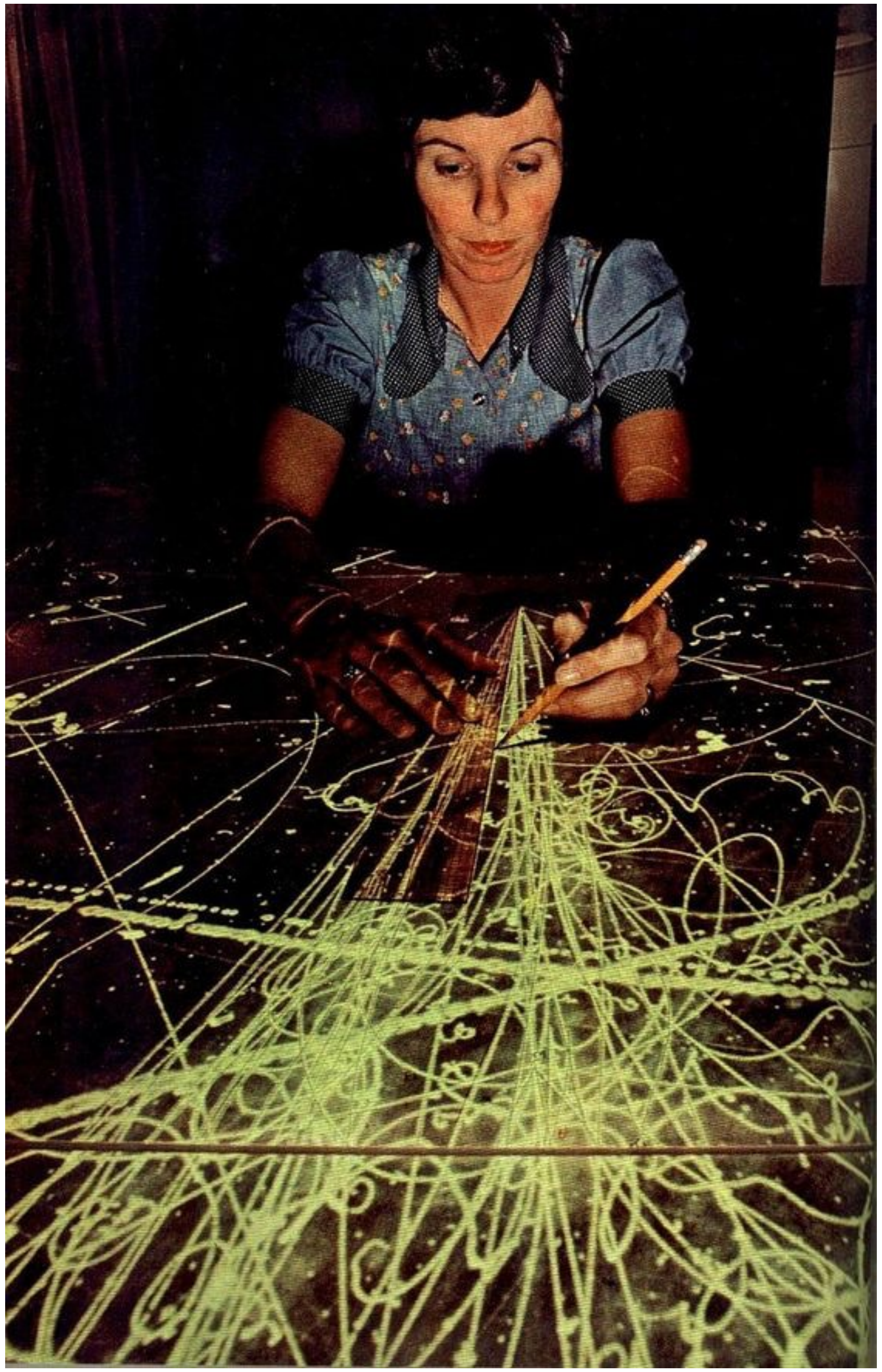

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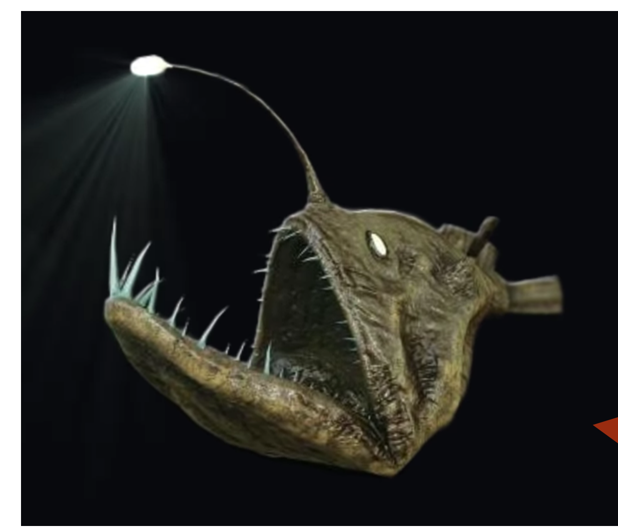
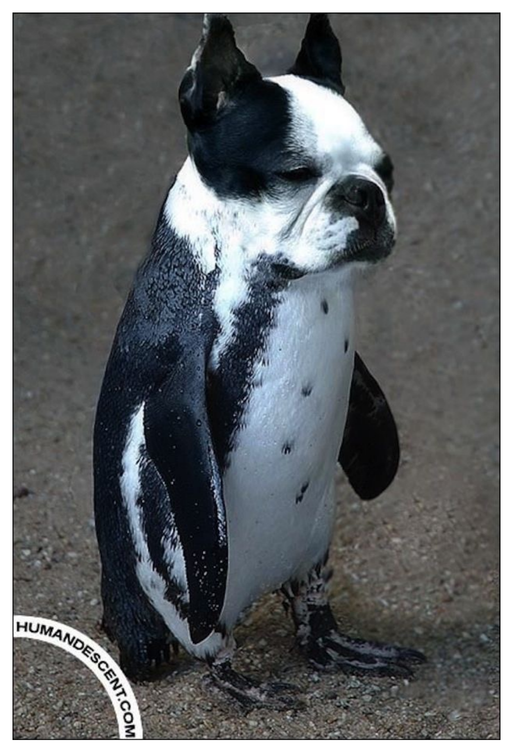




This is a real fish!
Training can enhance or suppress sensitivity to the unexpected!

Model Dependence & Uncertainty

(A) **Cow: 0.99**, Pasture: 0.99, Grass: 0.99, No Person: 0.98, Mammal: 0.98

(B) No Person: 0.99, Water: 0.98, Beach: 0.97, Outdoors: 0.97, Seashore: 0.97

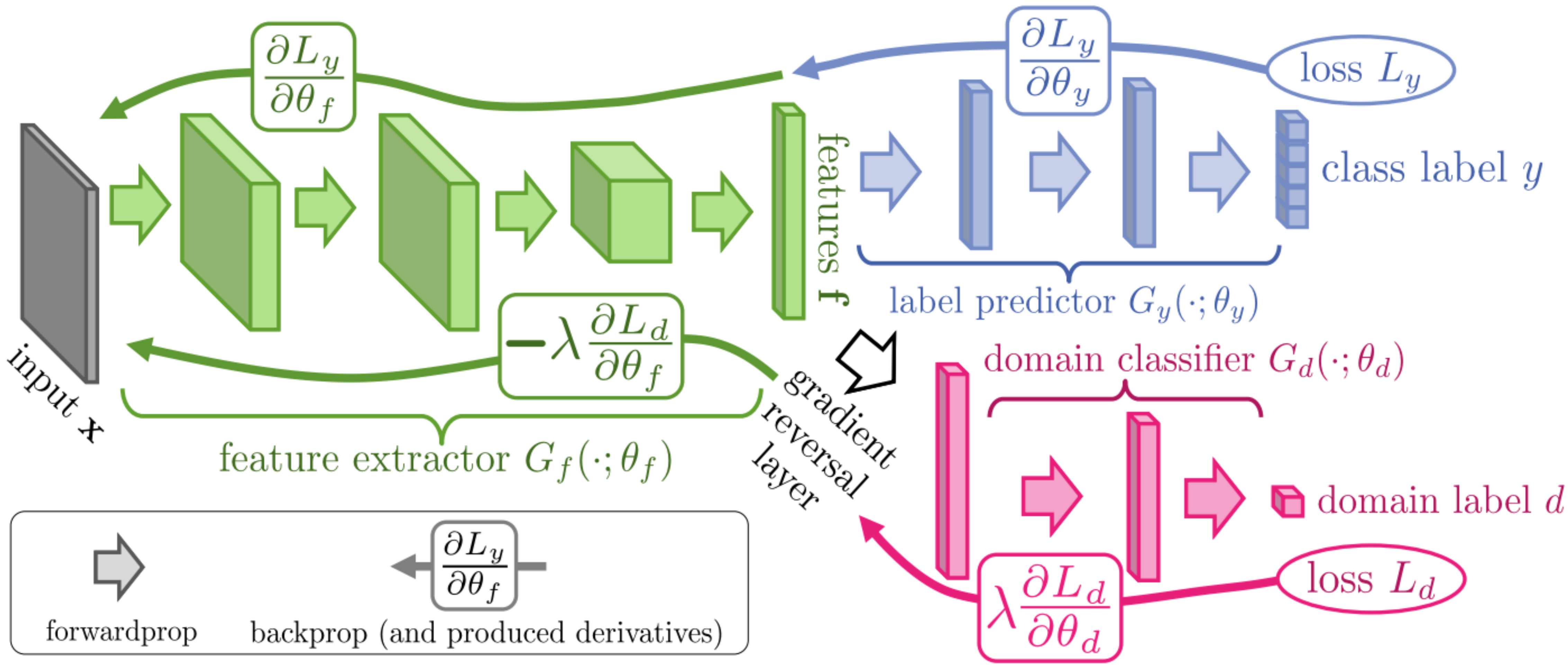
https://arxiv.org/pdf/1807.04975.pdf Recognition in Terra Incognita, October 2018. Conference: 15th European Conference on Computer Vision (ECCV 2018)

The **composition of the training samples** largely impacts network performance.

Are our algorithms **reproducing the model-based distributions** we train with?

Domain Adversarial Networks

A tool for bias reduction



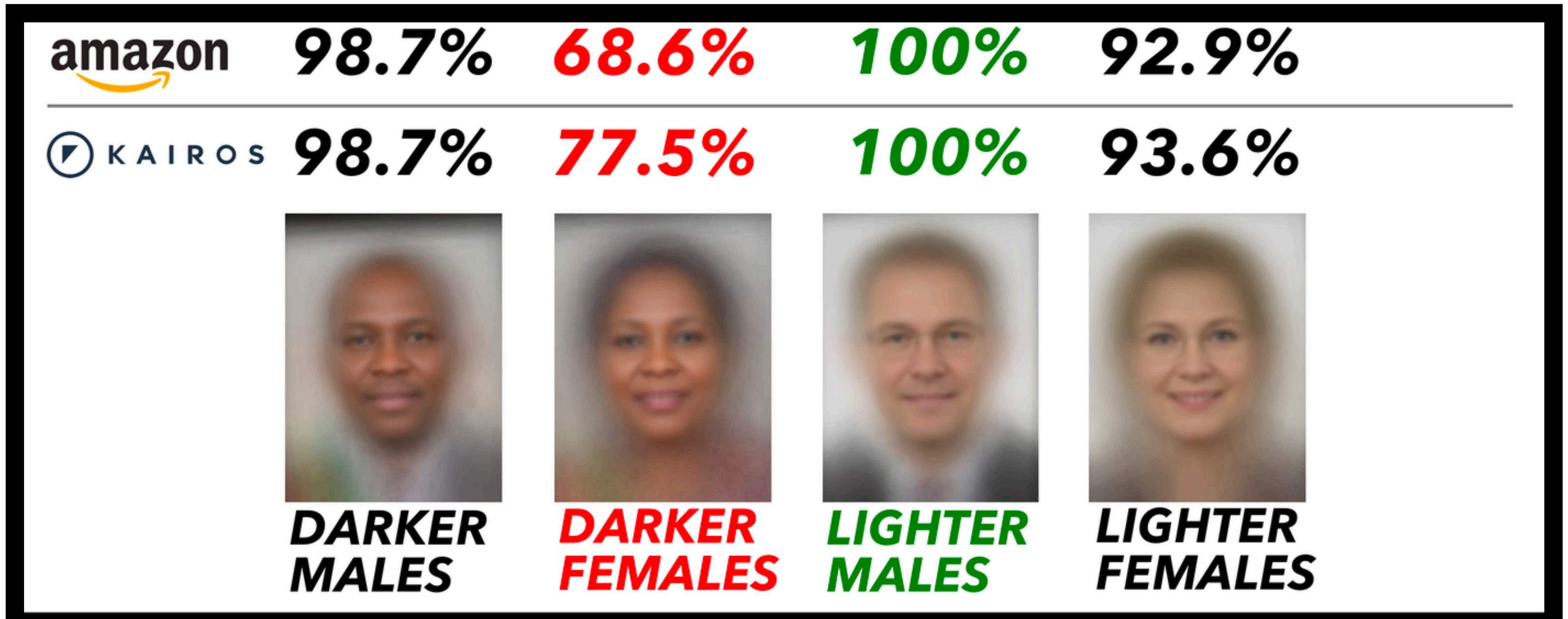
Reducing model bias in a deep learning classifier using domain adversarial neural networks in the MINERvA experiment. G. Perdue, et.al. https://doi.org/10.48550/arXiv.1808.0833

Bias and Unexpected Learning

Robust physical-world attacks on deep learning visual classification.

https://arxiv.org/pdf/1707.08945.pdf. Robust Physical-World Attacks on Deep Learning Visual Classification, June 2018, CVPR DOI:10.1109/CVPR.2018.00175

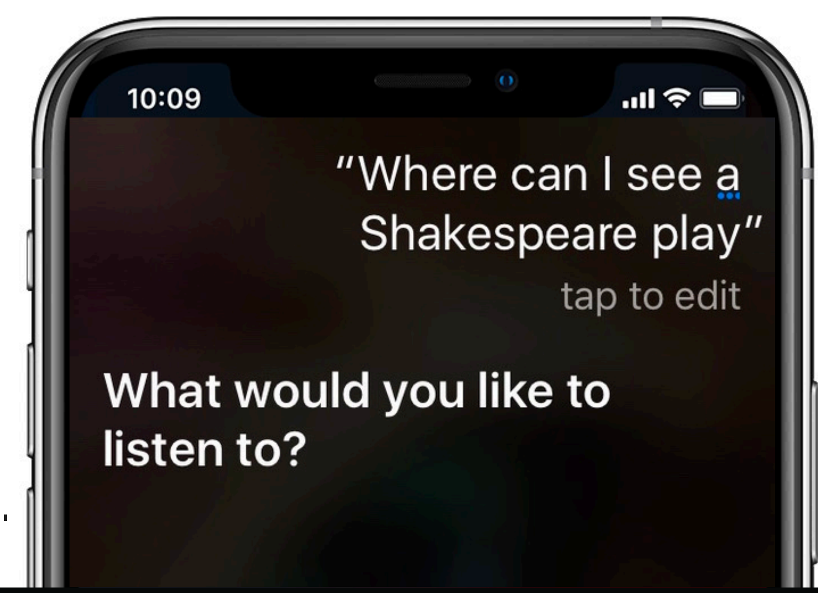
	Camouflage Graffiti	Camouflage Art (LISA-CNN)	Camouflage Art (GTSRB-CNN)
			
Targeted-Attack Success	66.67%	100%	80%



Performance on Facial Analysis Task of Gender Classification

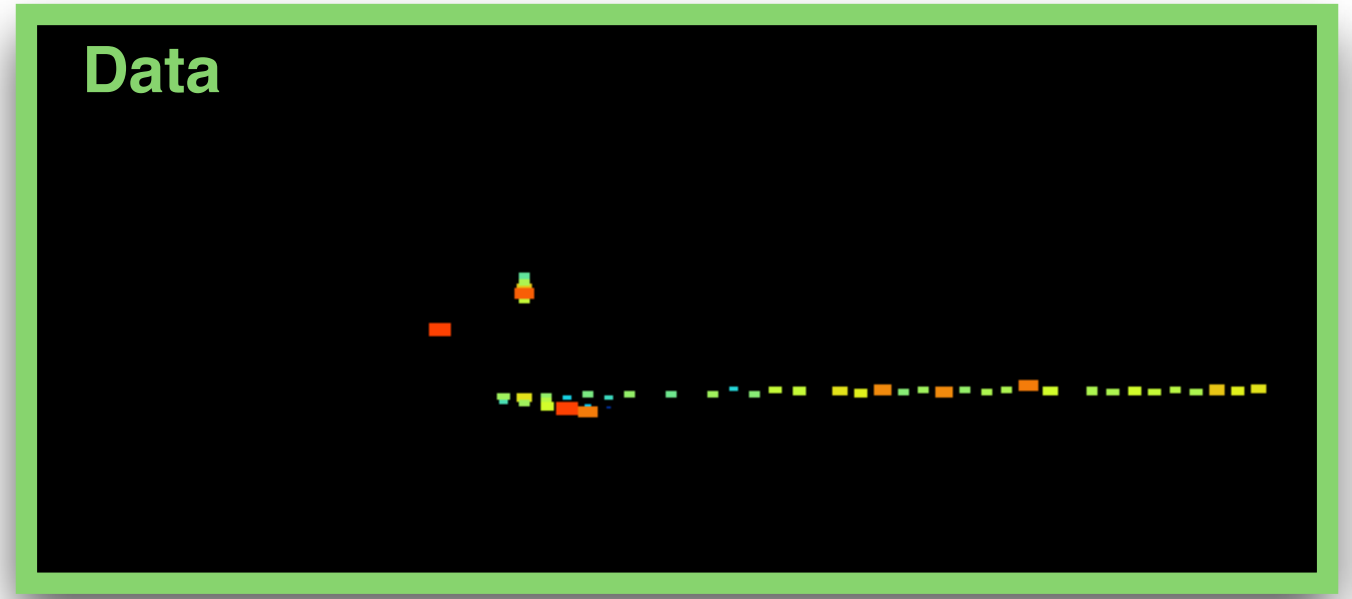
Joy Buolamwini / MIT Media Lab

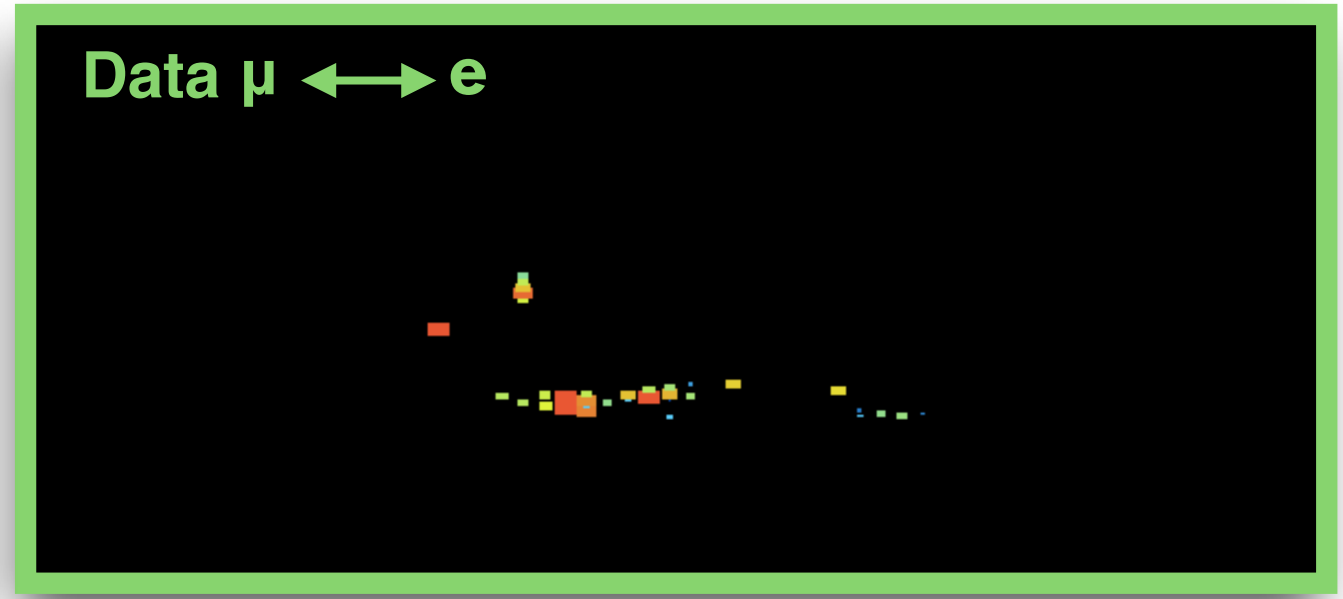
Gender and racial bias in facial recognition algorithms.

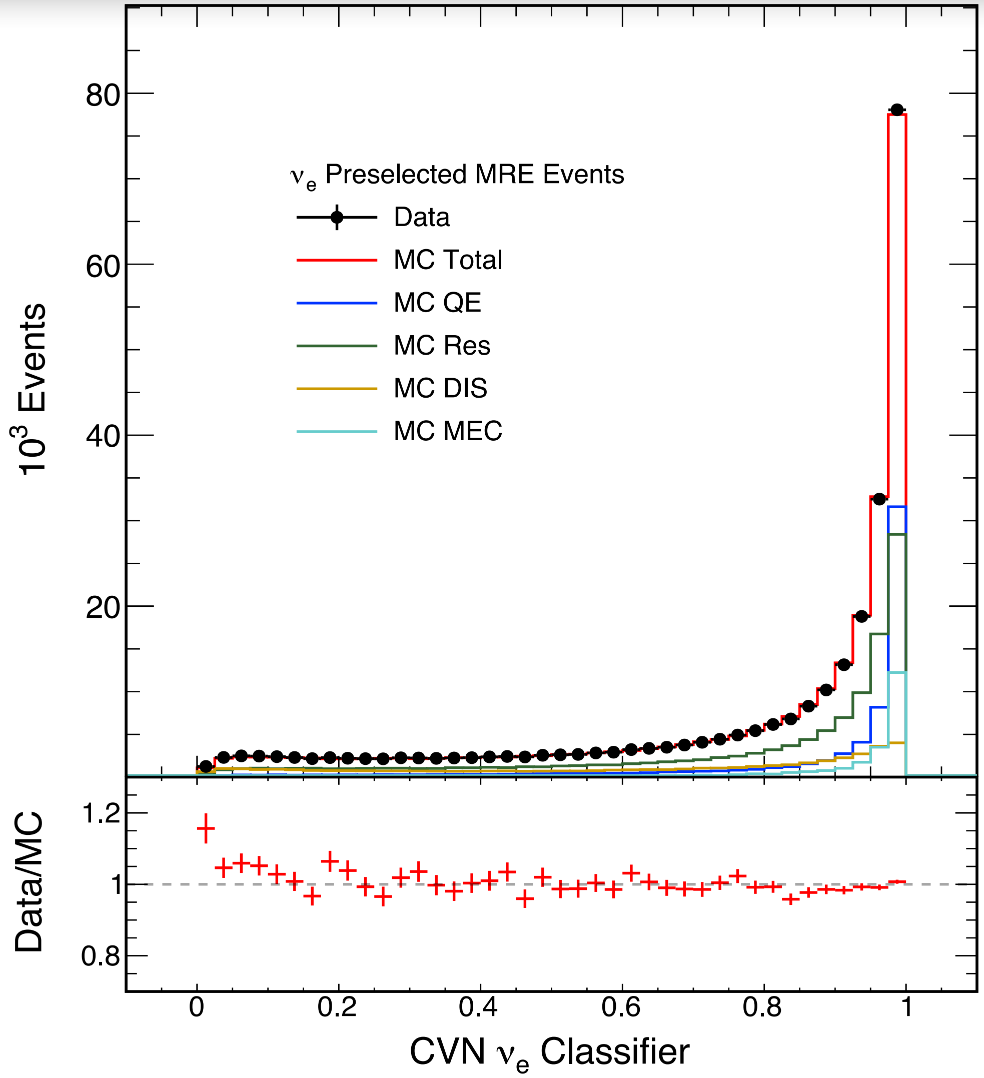


Voice recognition accuracy issues, especially for multi-lingual speakers.

Performance On Real Data







MRE (Muon Removed - Electron):

Select a muon neutrino interaction with traditional ID methods.

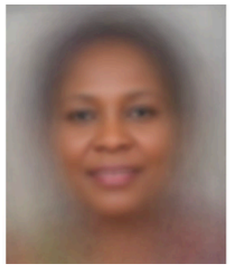
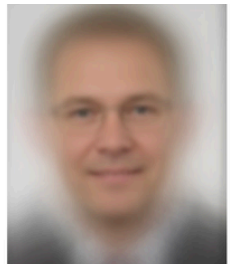
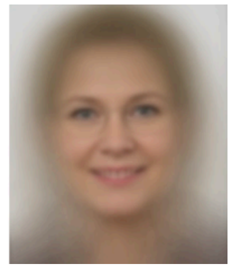
Remove the muon hits and replace them with a single simulated electron of matching momentum.

Data/MC comparisons show less than 1% difference in efficiency.

PID	Sample	Preselection	PID	Efficiency	Efficiency diff %
CVN	Data	262884	188809	0.718222	-0.36%
	MC	277320	199895	0.720809	

Addressing ML challenges to neutrino experiments

… from the research

Bias

Find bias AND reduce bias AND quantify bias

There is NO “unbiased” training sample! (Bias to flat is still bias)


Model Dependence

There is no “model independent” sample! (Non-physical models are still models)

Propagate uncertainties through both model training AND model usage

Design algorithms that minimize across known systematic uncertainties.

Robust training

Compare algorithm performance in real data.

Design labeled-data training sets (test beams, known sources, etc.)

Design further tests of Data-MC robustness.


Sensitivity to new physics

Unsupervised learning to identify missing physics & unexpected learned features

Design tools for interpretability: test extracted features, principal component, etc.

Addressing ML challenges to neutrino experiments

… from the community

ML is part of the particle physics toolkit. With increasing complexity, **increasing scrutiny is required.** Teach the use and interpretation of ML as an essential skill of particle physics research.

Develop techniques for robustness metrics and systematic bias assessment that can become the standard for machine learning applications in particle physics.

Contribute to AI research by developing solutions to the bias and uncertainty questions of the industry broadly.

Particle Physics is Uniquely Applicable to A.I.

DETECTOR DATA

is **information-dense** & **un-labeled**
Many times includes **space correlations**/topology.

SIMULATIONS

Produced at **large-scale** and reproducible from physics principles.
Tunable to better/worse match **real data.**

MEASUREMENTS

Analyses that produce **high precision** measurements
Focus on **uncertainty quantification** and bias assessments.

Conclusions

Machine learning techniques have and will continue to improve our experimental sensitivities in neutrino physics.

Developing expertise as a community will enable us to **face the challenges** introduced by increasing algorithm complexity

Particle physics experiments are uniquely equipped to **solve the bias and uncertainty problem in ML** for next-gen oscillation experiments and the broader community.

Thank you

Thank you for input regarding ML applications across experiments: Yasuo Takeuchi, Nicola Rossi, James Mead, and T2K collaboration.