



in Spin Physics



And the Future of Spin At Fermilab



Dustin Keller with the University of Virginia, October 22

SPIN2021 The 24th International Spin Symposium



18-22 October 2021
Matsue, Shimane Prefecture, Japan

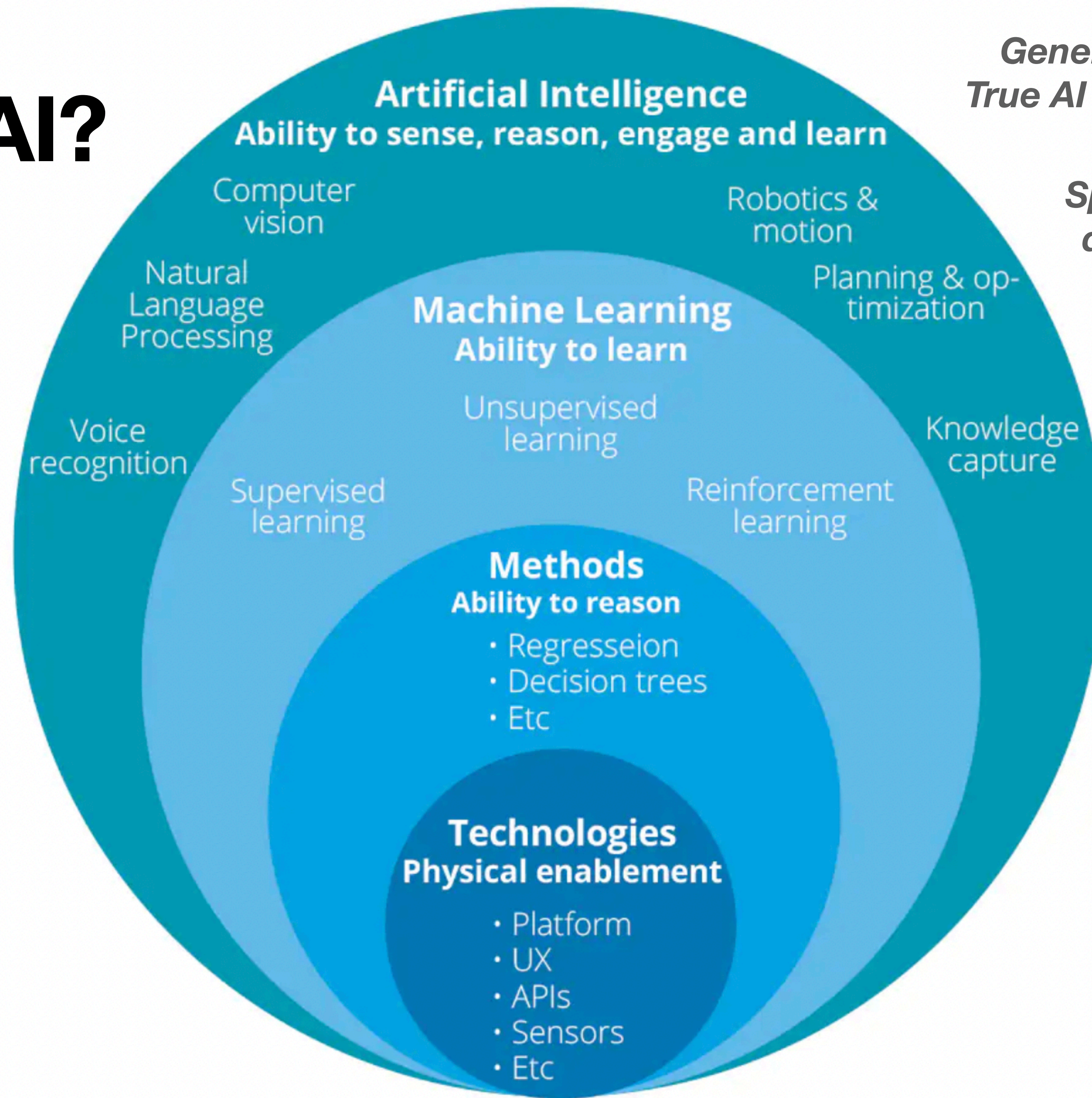


Artificial Intelligence and Spin Physics

and the future of Spin at Fermilab

- What is AI
- Some examples in Spin
- Where are things going
- A bit about gluons
- How does FNAL fit in

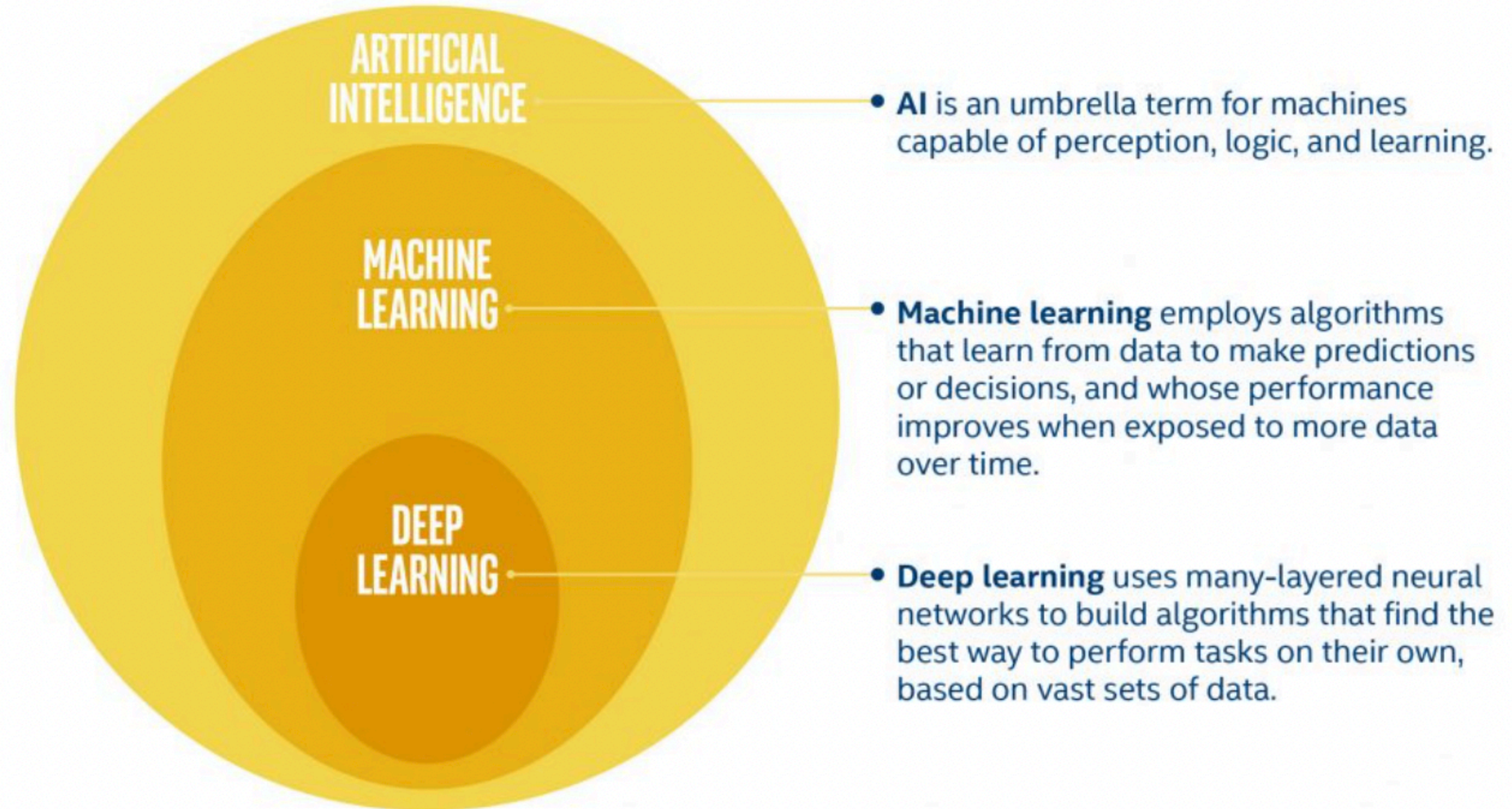
What is AI?



General AI: Full AI, Strong AI, True AI (designed to do anything)

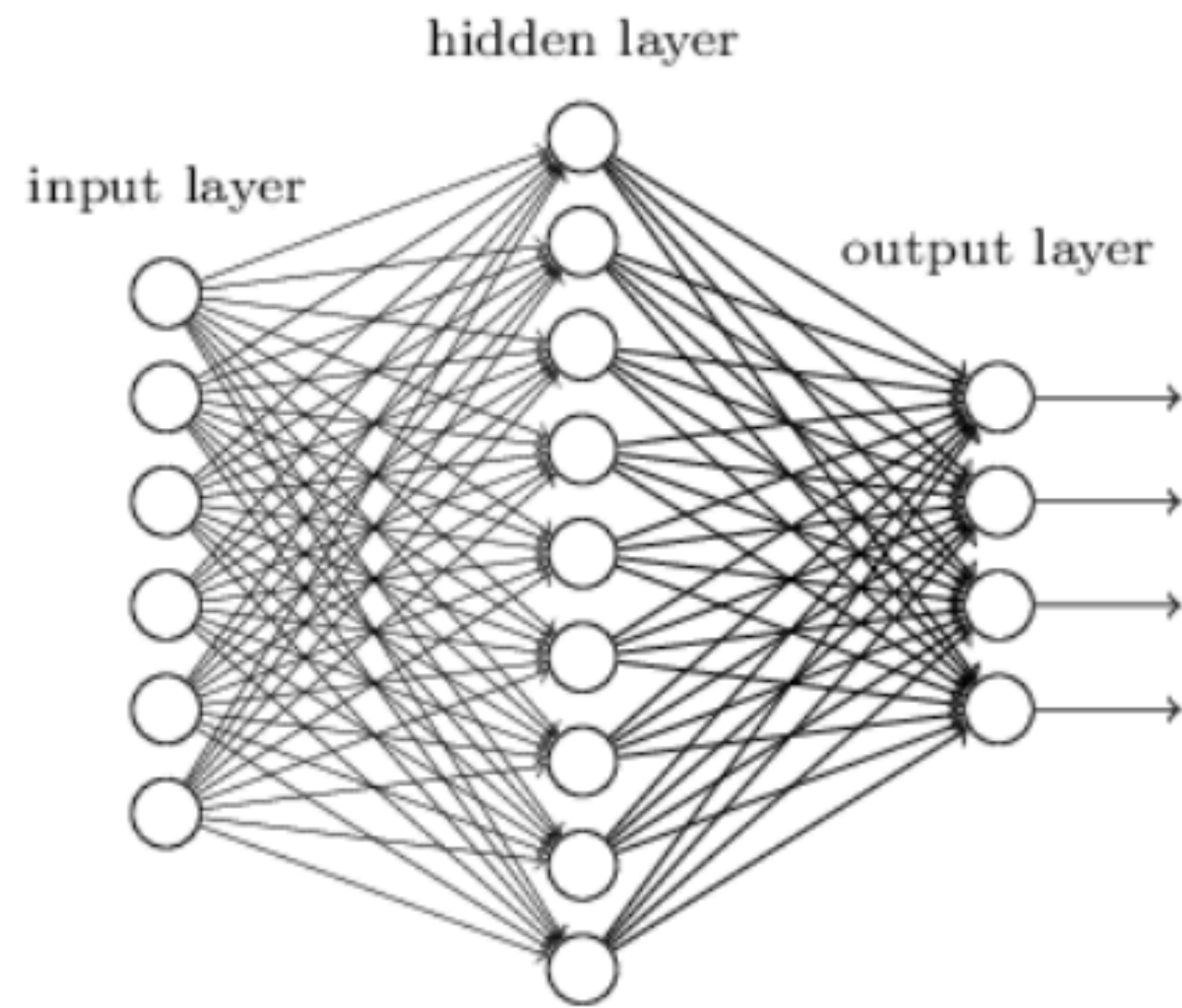
Specialized AI: Designed to do just one task very well

ARTIFICIAL INTELLIGENCE TERMS



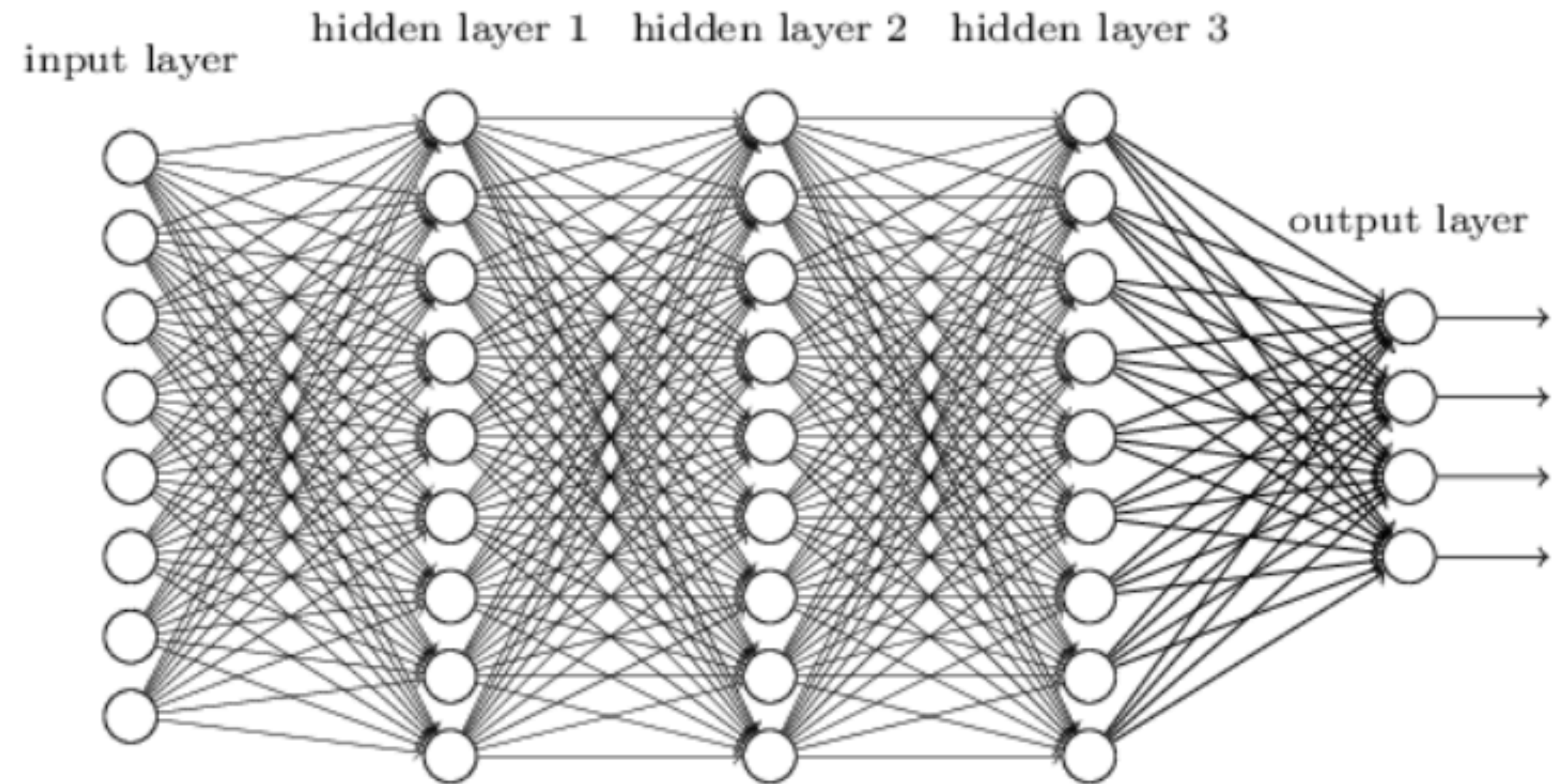
Basic Neural Network

"Non-deep" feedforward neural network



Perceptron Concept

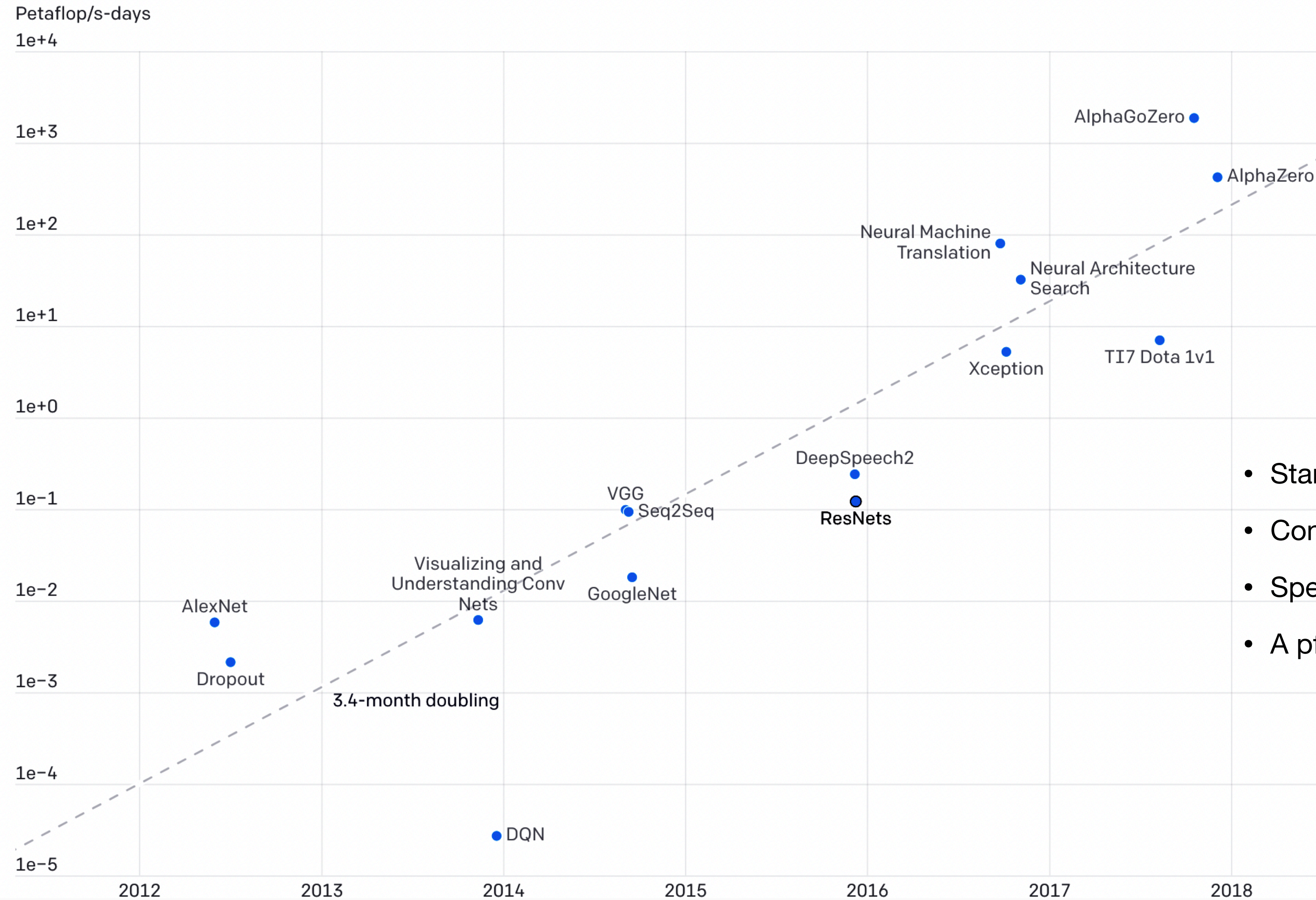
Deep neural network



Evolution Timeline



2045

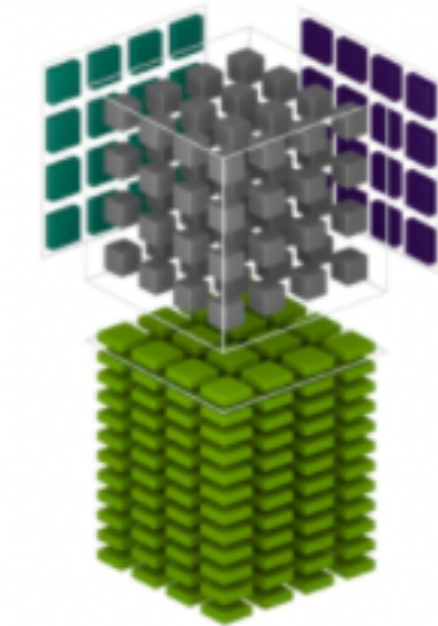
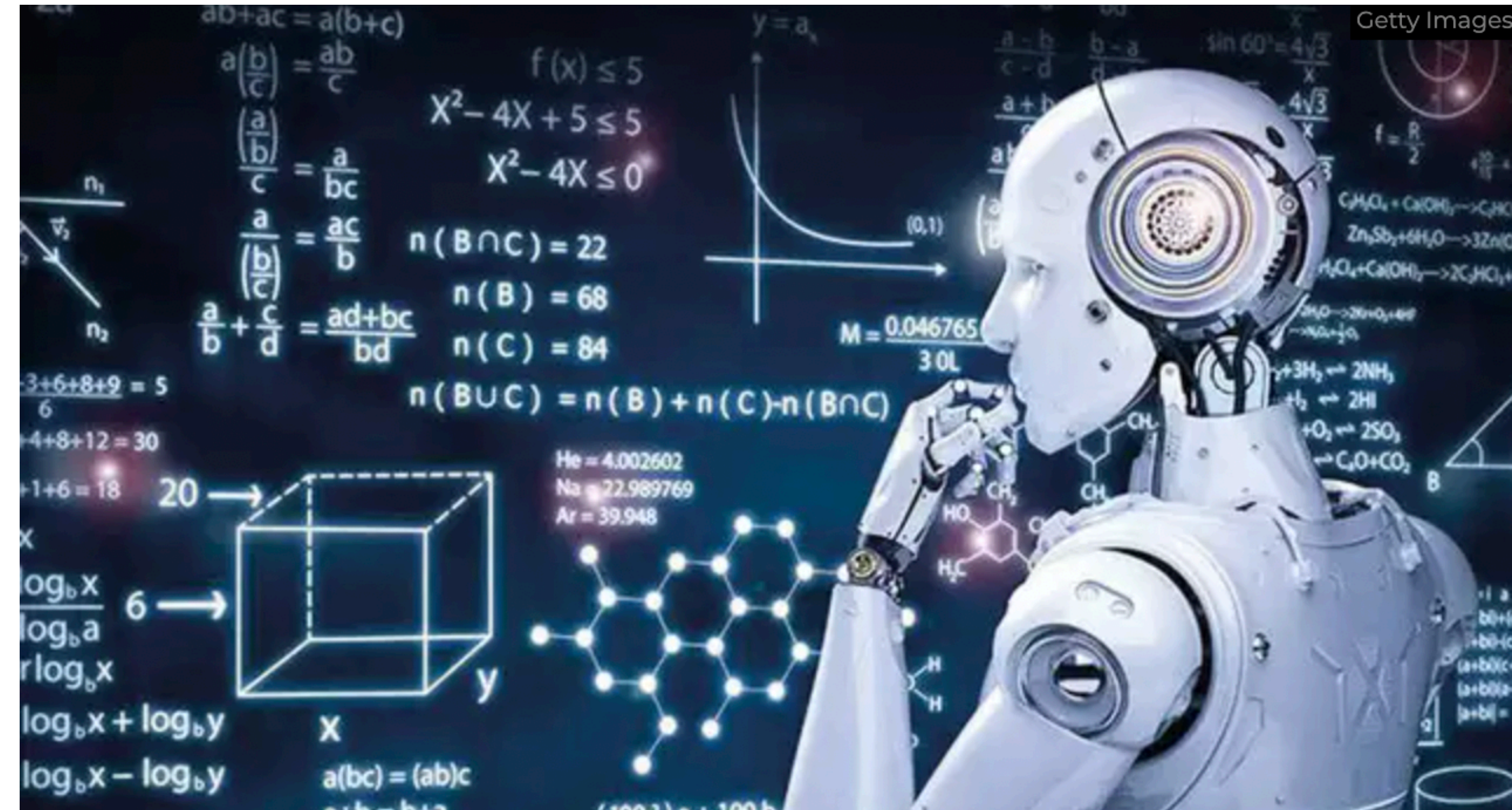


- Starting about 50 years after the perceptron
- Computational power doubling 100 days
- Speed has increased 300K from '12
- A pfs-day: #NN operations/s for 1 day

Some Important ANNs

With applications to our field

- Feedforward Neural Networks
- Radial basis function Neural Networks
- Self Organizing Neural Networks
- Recurrent Neural Networks
- Convolution Neural Networks
- Modular Neural Networks
- Graph Neural Networks



NVIDIA Tensor Cores



GPGPU Computing

[Bogdan Oancea](#), [Tudorel Andrei](#), [Raluca Mariana Dragoescu](#)
[arXiv:1408.6923v1](#)

Caffe

Caffe2

Chainer



MATLAB



Microsoft Cognitive Toolkit

mxnet

PaddlePaddle

PyTorch

TensorFlow

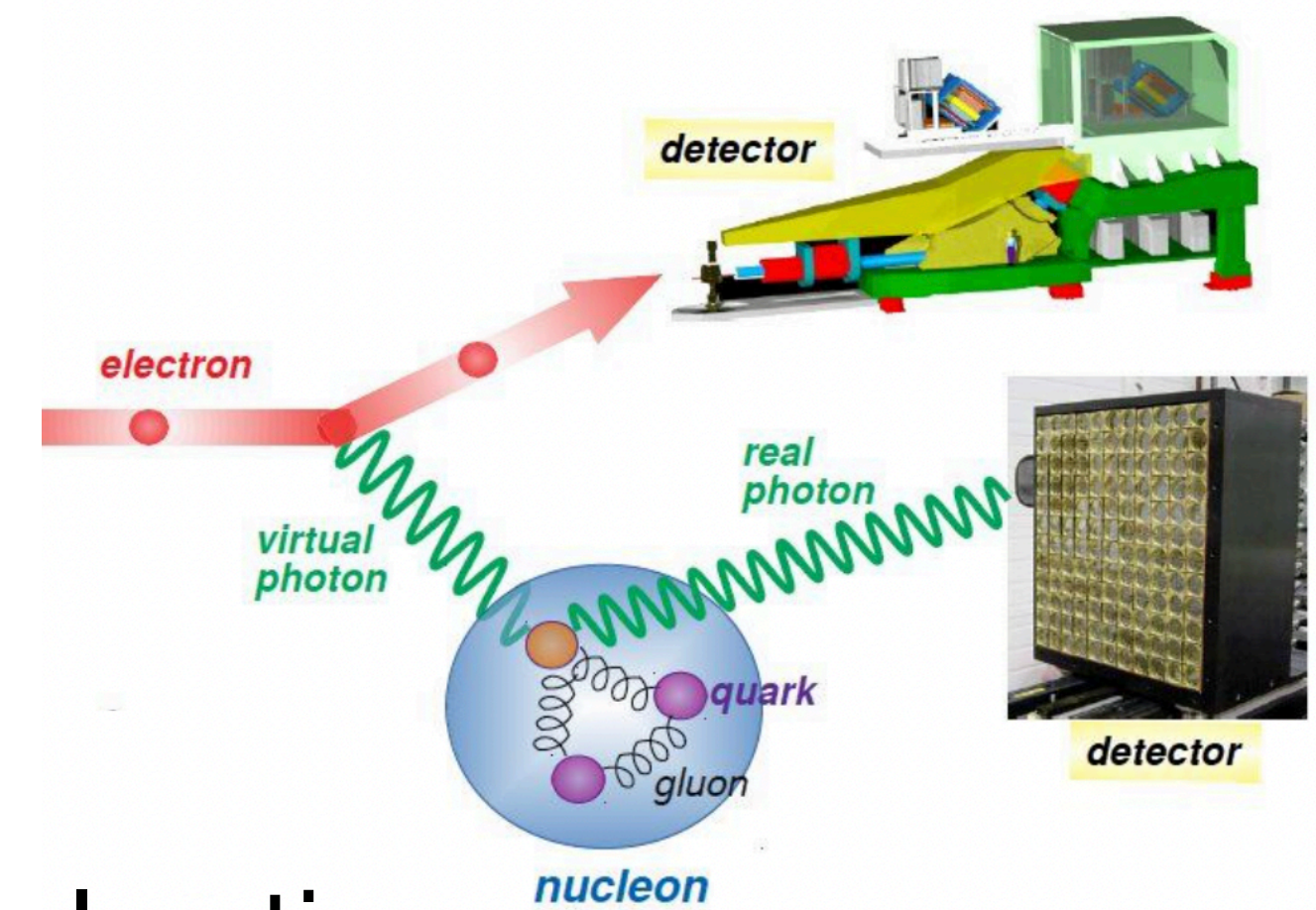
torch

Wolfram Language

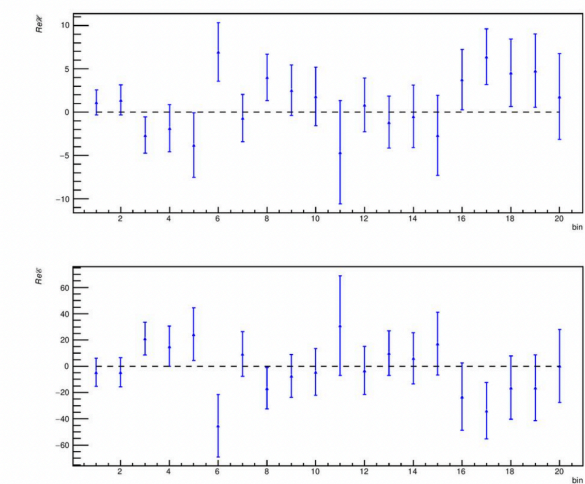
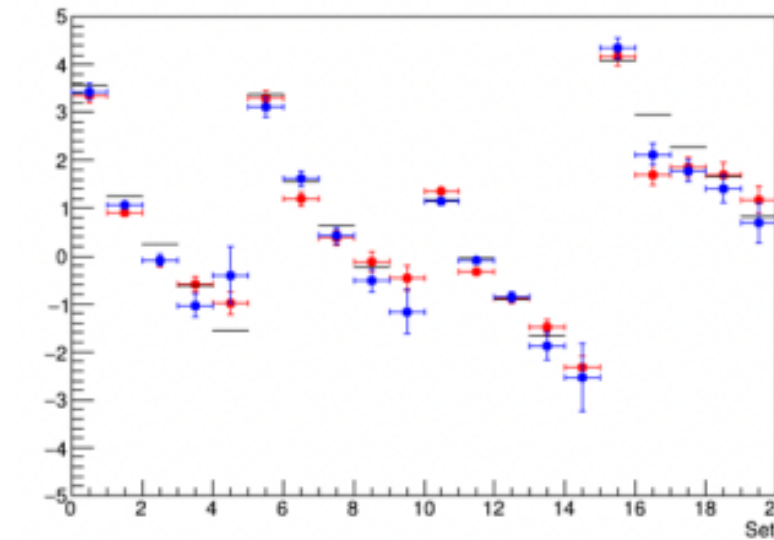
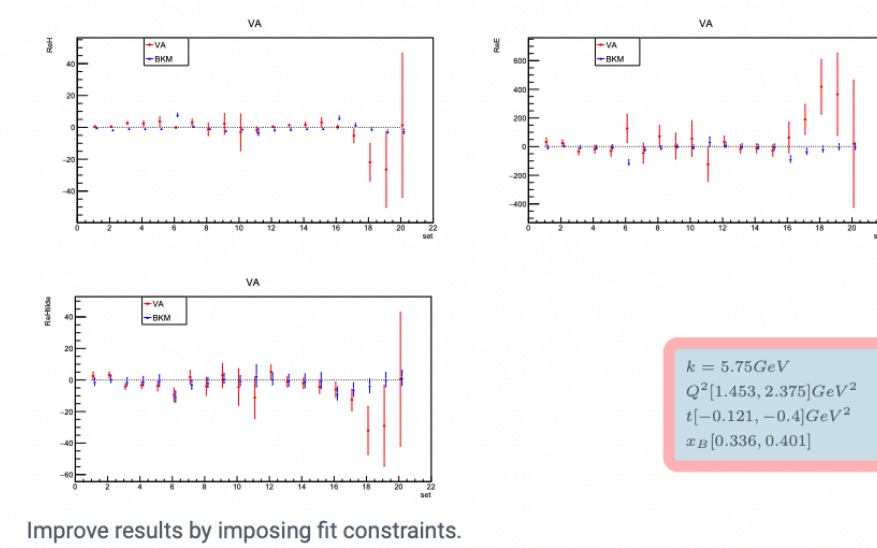
Machine Learning In Nuclear and Particle Physics

- Event-level Classification
- Trigger and Pattern Recognition
- Tracking/Event Reconstruction
- Cluster Reconstruction in Calorimeters
- Jet Representations and Preprocessing
- Jet Tagging
- Regression of detector drifts

- Simulation acceleration
- Systems Automation
- Detector Design
- Accelerator Design
- Optimization of workflow
- Detector Readout Optimization
- Cut Optimization



Machine Learning In Spin Physics



Liliet Diaz: 141. Novel CFFs Extraction in Unpolarized DVCS
JST 21 Oct 2021, 09:10 = EDT 20 Oct 2021, 20:10

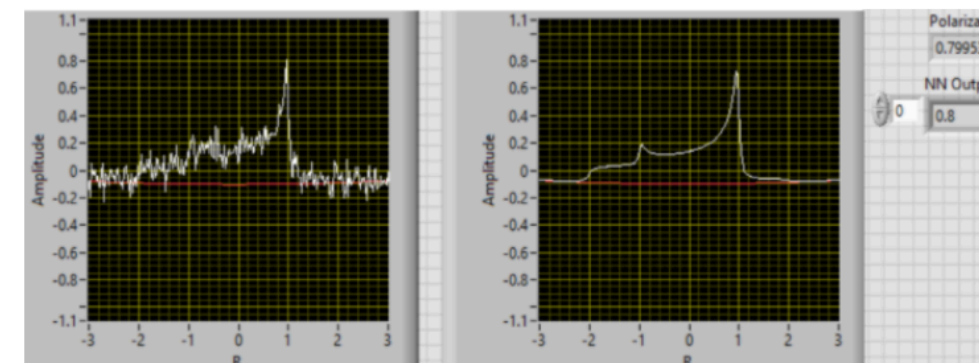
Ishara Fernando: 126. SU(3)-flavor TMD PDFs extraction with global fits & ANN
JST 22 Oct 2021, 09:16 = EDT 21 Oct 2021, 20:16

• Spin Phenomenology (information extraction) →

• Model Polarized Mechanisms in PT → Anchit Arora

• Polarization Enhancement in PT *

• Material Analysis in PT → Librado Anglero

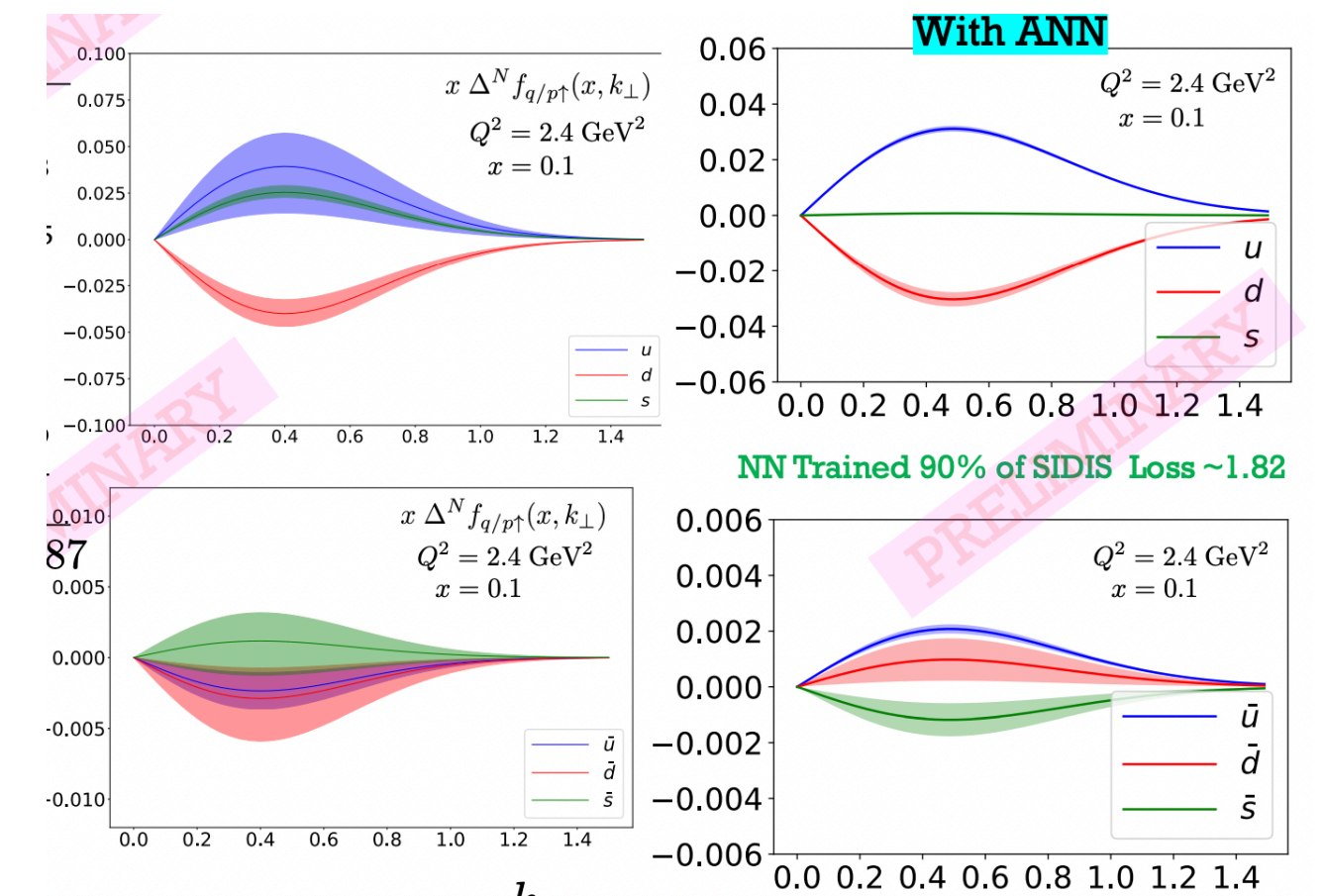


• NMR Measurements → **Devin Seay:** 120. NMR With Machine Learning
JST 22 Oct 2021, 09:40 = EDT 21 Oct 2021, 20:40

• Tracking and Online Monitoring → **Arthur Conover:** 136. Machine Learning Online Monitoring for the SpinQuest
JST 22 Oct 2021, 07:25 = EDT 21 Oct 2021, 18:25

• Construction and Visualization of Models *

• Data Analysis on event level and asymmetry extraction → Multiple folks

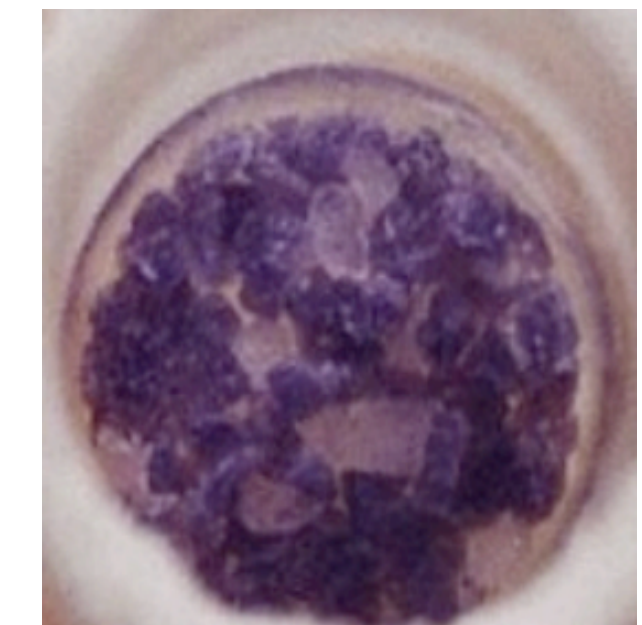


Some Examples In Polarized Targets

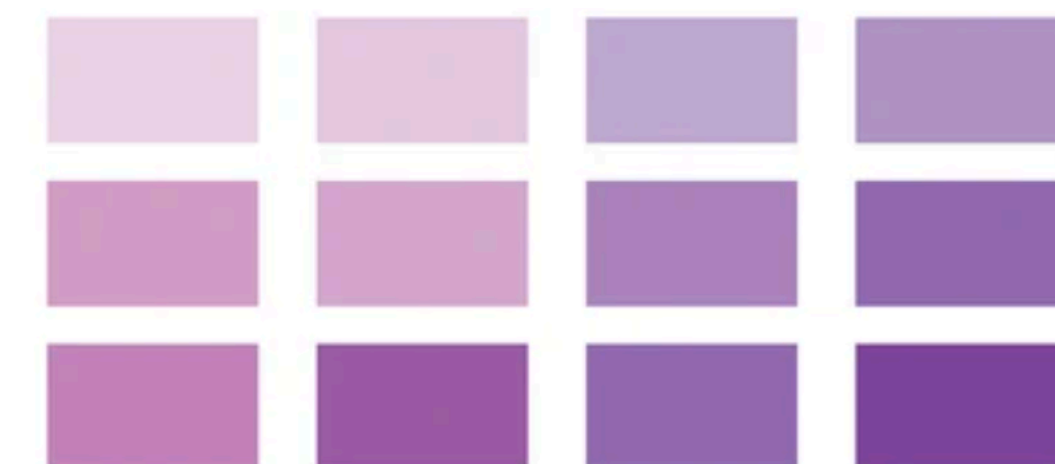
- Traveling-wave electron linac
- Irradiated to $10^{17} e^-/\text{cm}^2$
- 14 GeV $10 \mu\text{A}$ under Liquid Argon ($\sim 87 \text{ K}$)
- Proton knocked out to form free radicals
- Also form color centers
- Material color is correlated to the dose
- Optimized for field and temperature



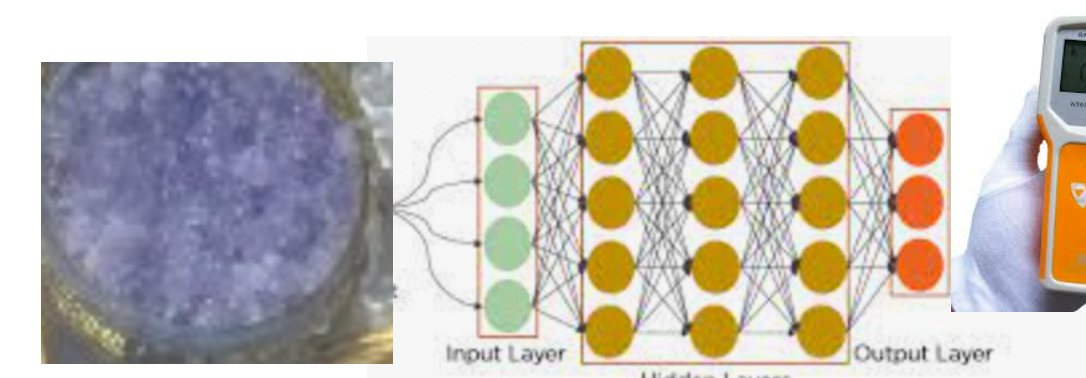
Irradiation Performed at NIST (MIRF Accelerator)



Work by Jack Beaty, UVA



Material Photo

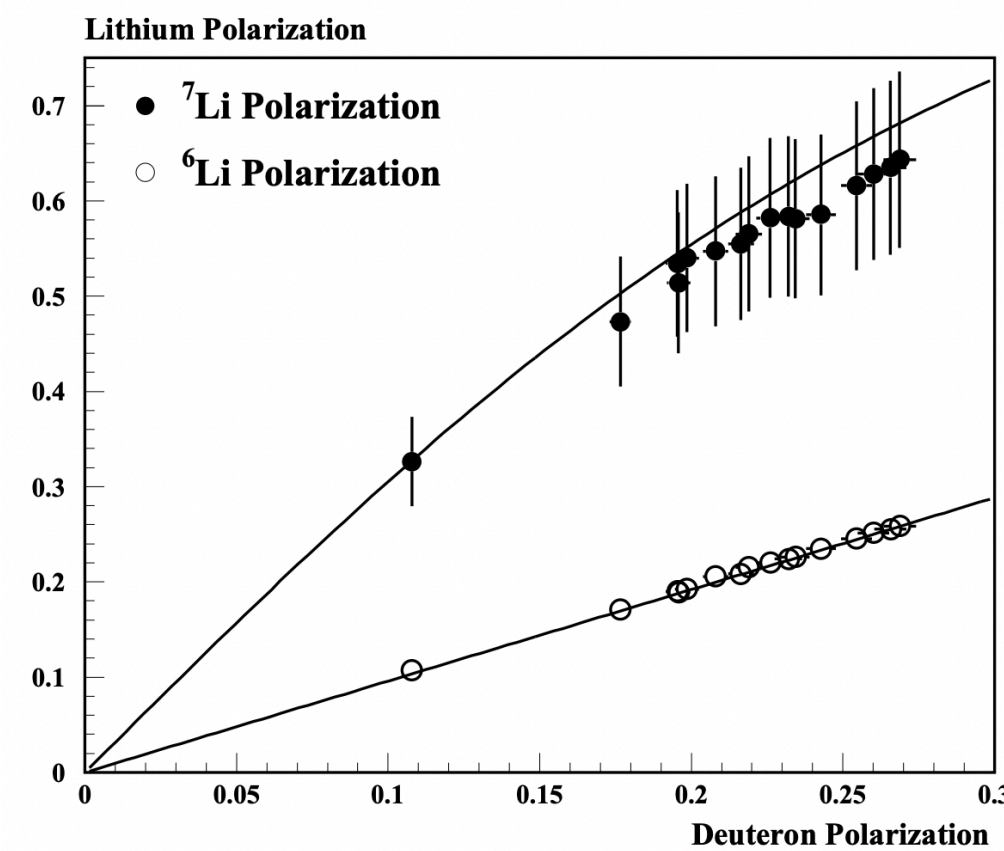


Accumulated dose

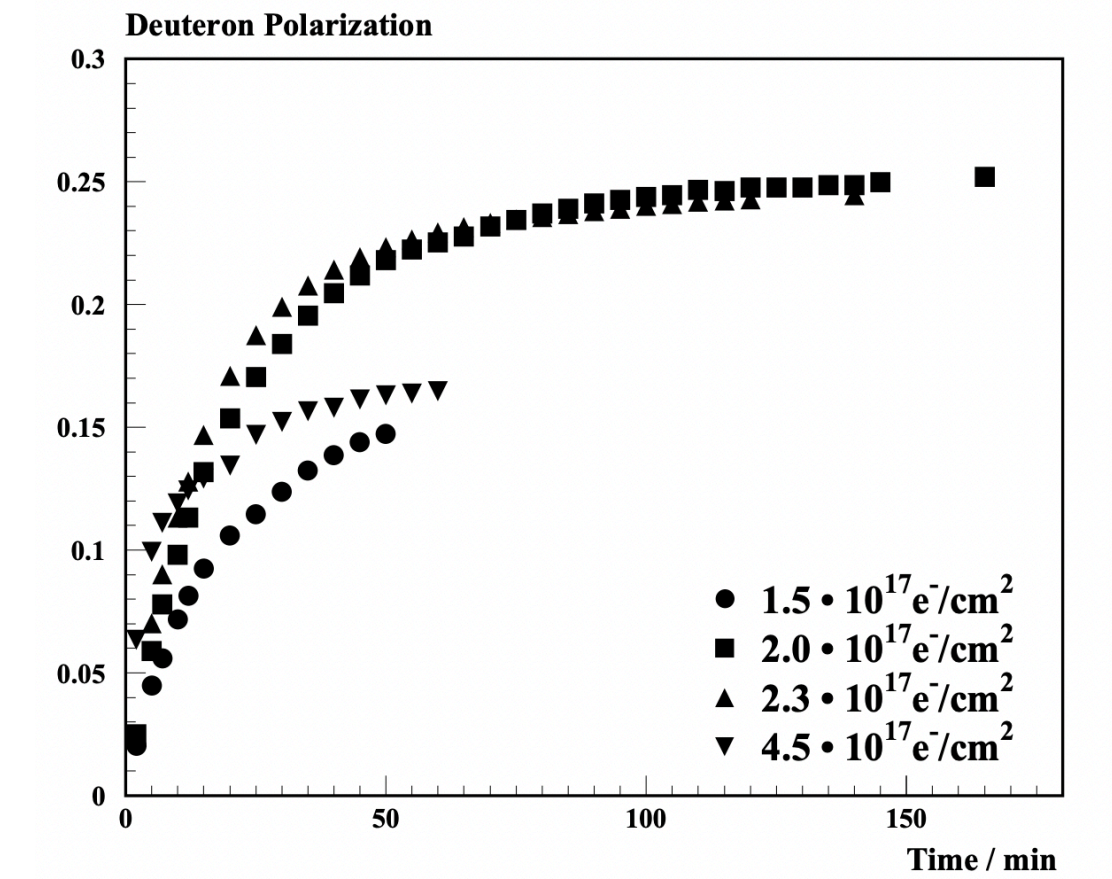
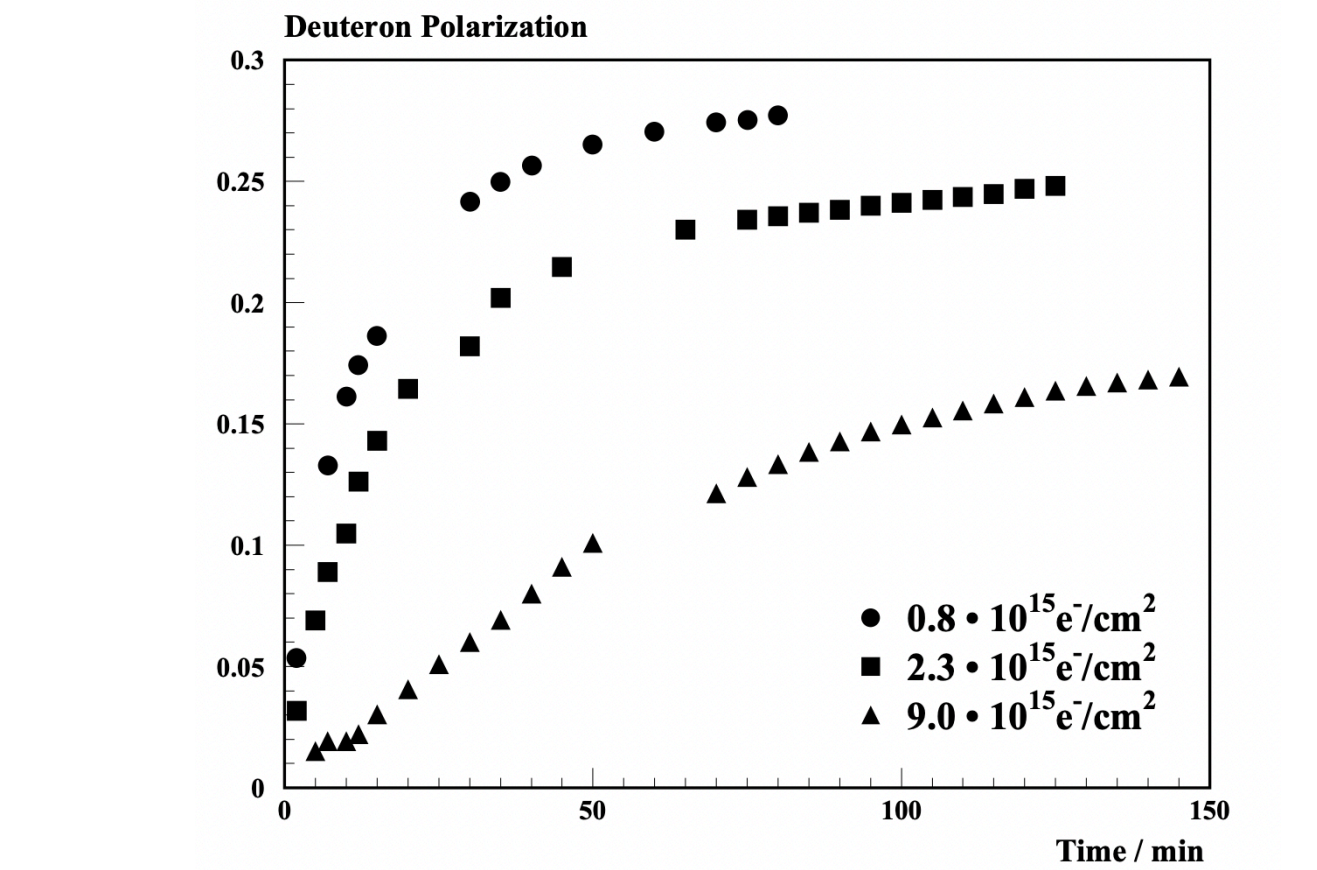
Some Examples In Polarized Targets

Preliminary Predication using ANN Model (3% rel. error)

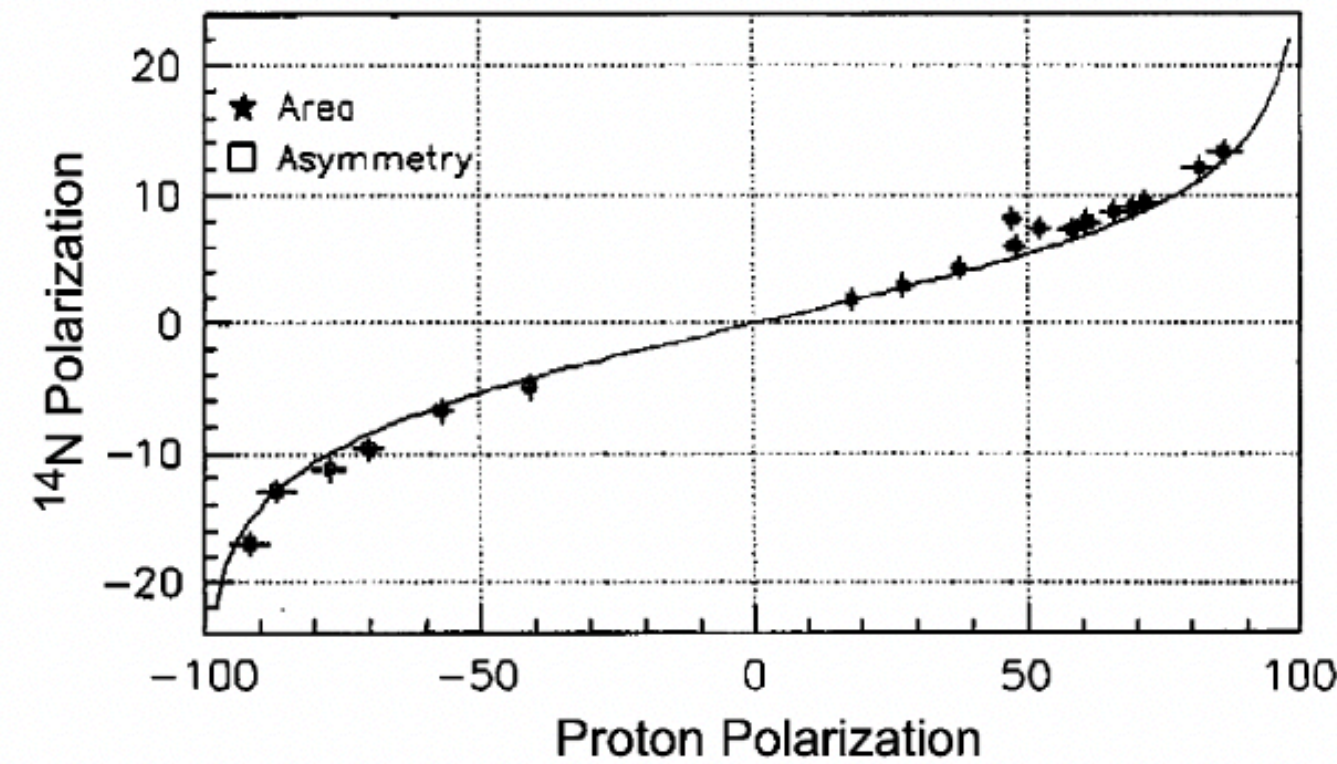
Target	Field (T)	Temp (K)	Dose	P(max)
ND3(D)	6.5	0.7	2.7	68%
LiD(Li7)	7.0	1	3.8	82%
CD2(D)	7.0	1	2.5	73%
LiH(Li7)	7.0	0.5	2.3	93%
LiF(F)	6.0	1	3.3	78%



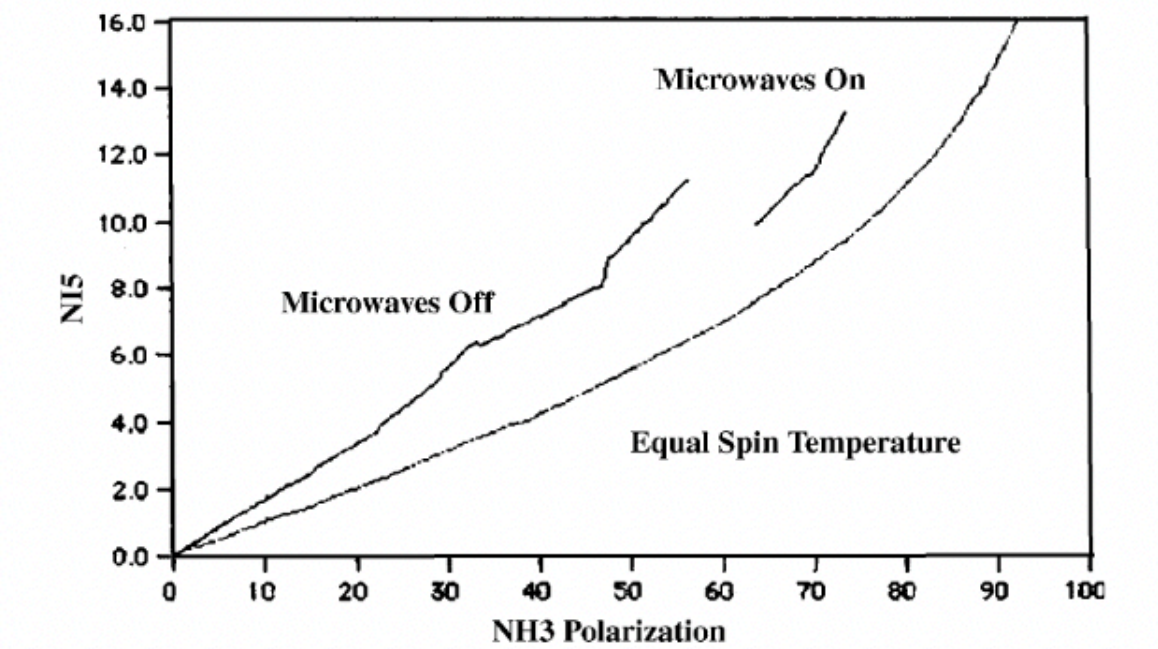
S. Bultmass et al, NIM 425 (1999) 23-36



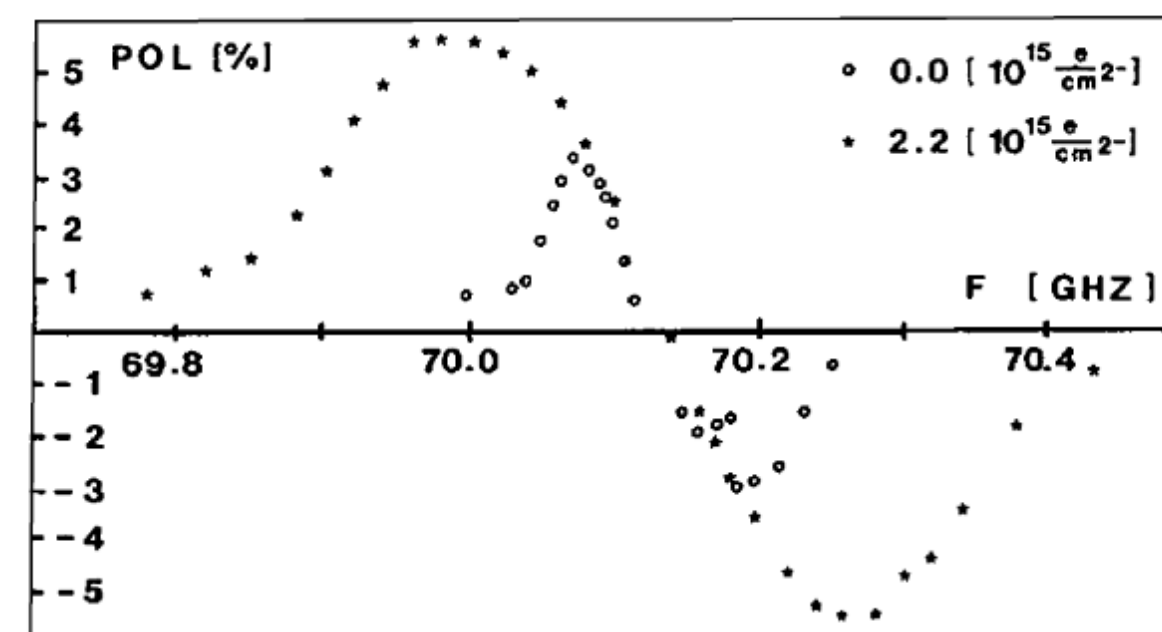
S. Bultmass et al, NIM 425 (1999) 23-36



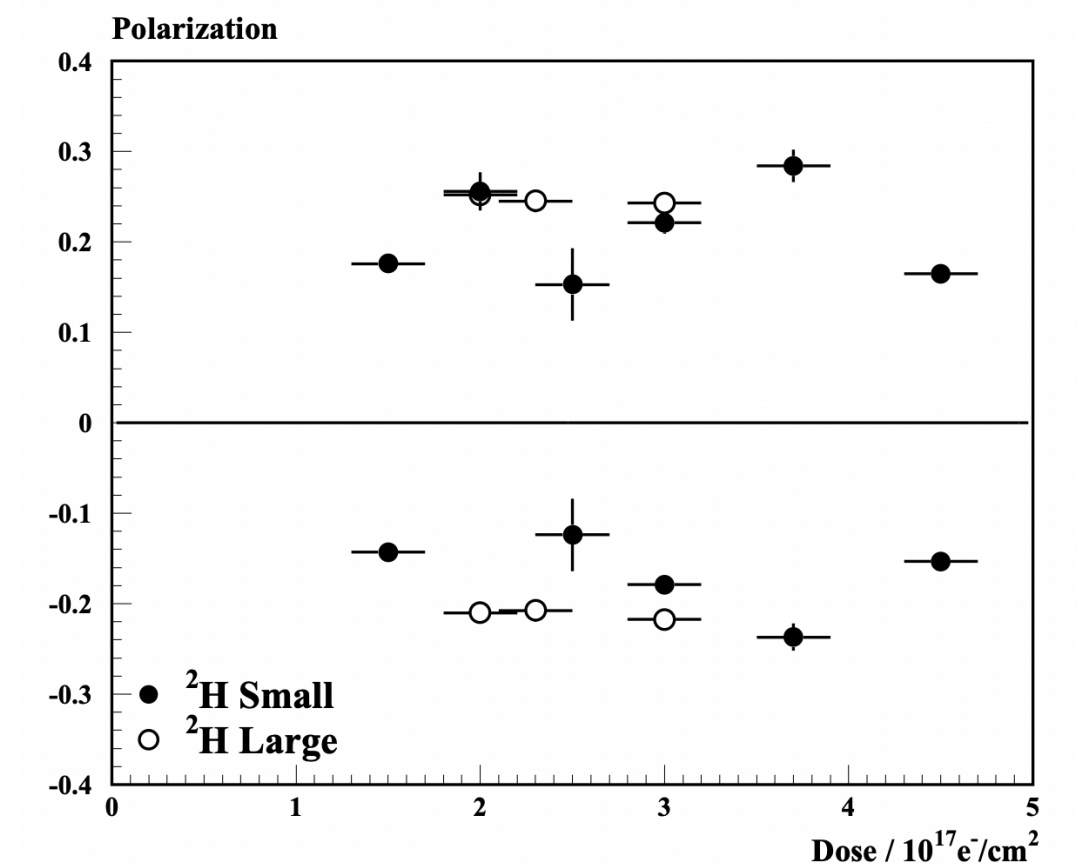
D. Crabb, W. Meyer, Annu. Rev. NPC (1997) 47



W. Meyer, NIM A526 (2004) 12-21



W. Meyer, NIM A526 (2004) 12-21



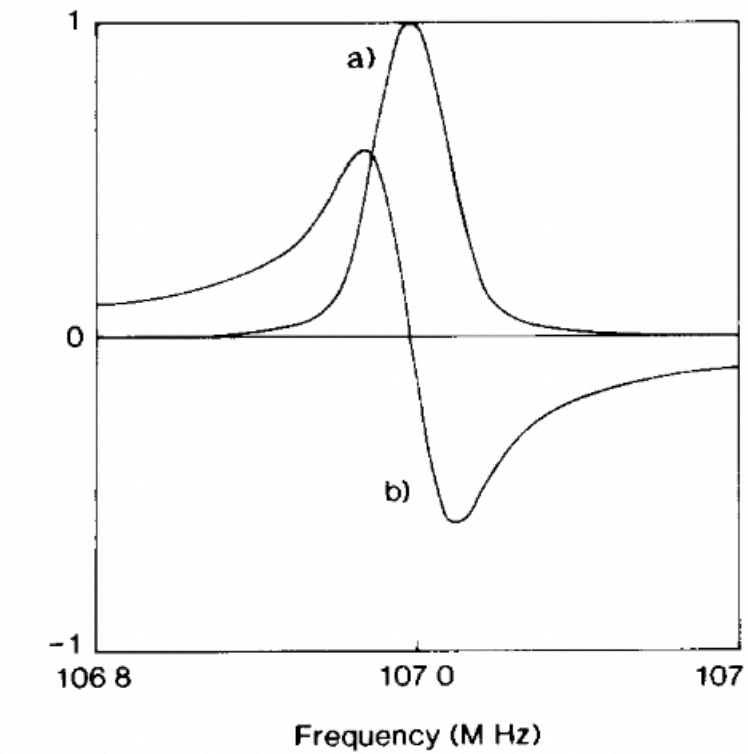
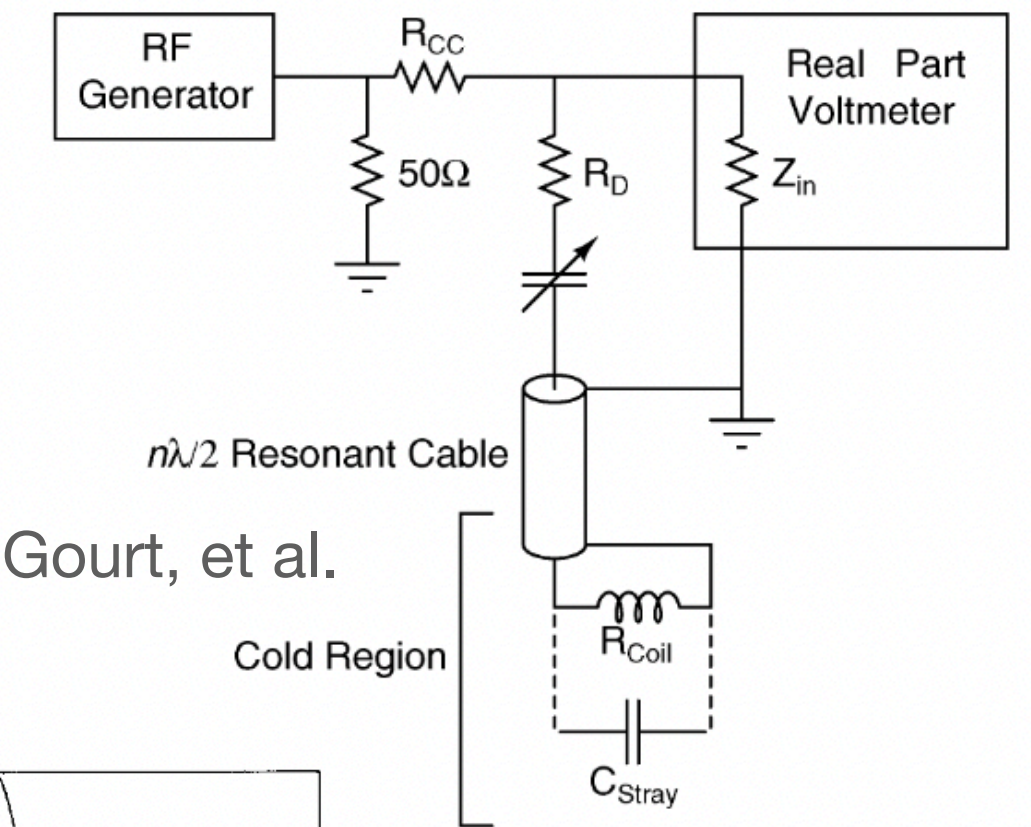
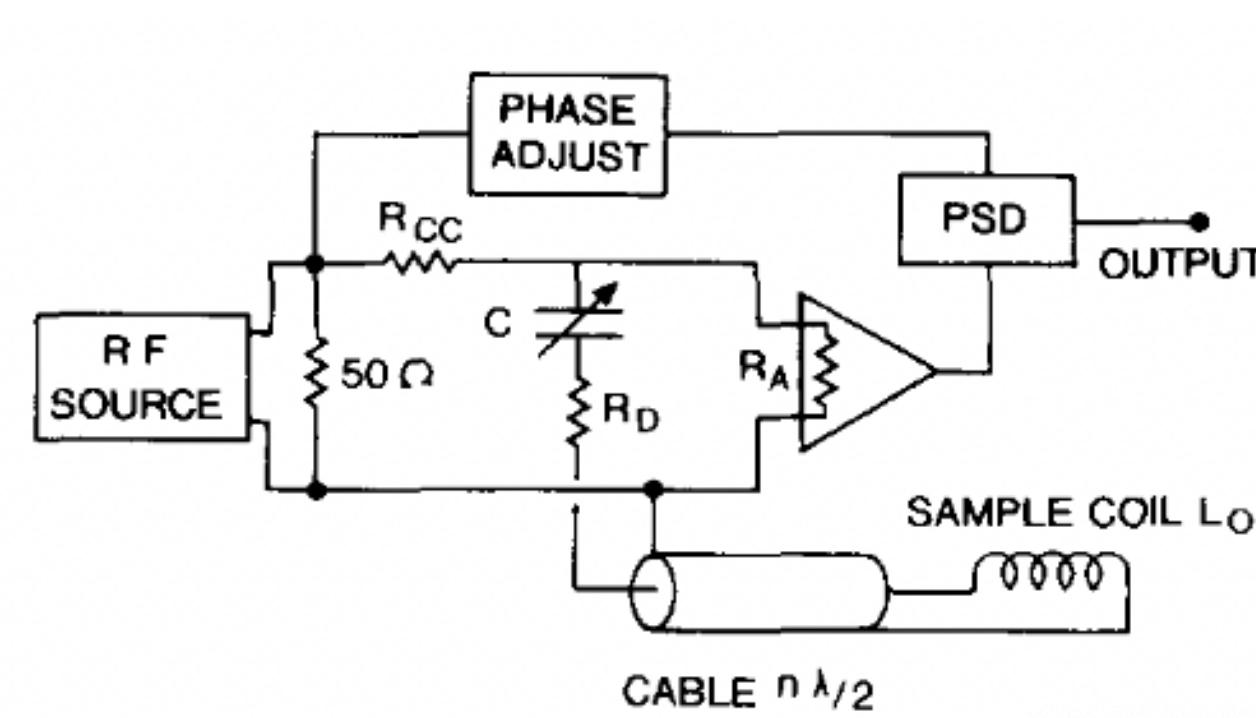
Some Examples In Polarized Targets

Design Needed

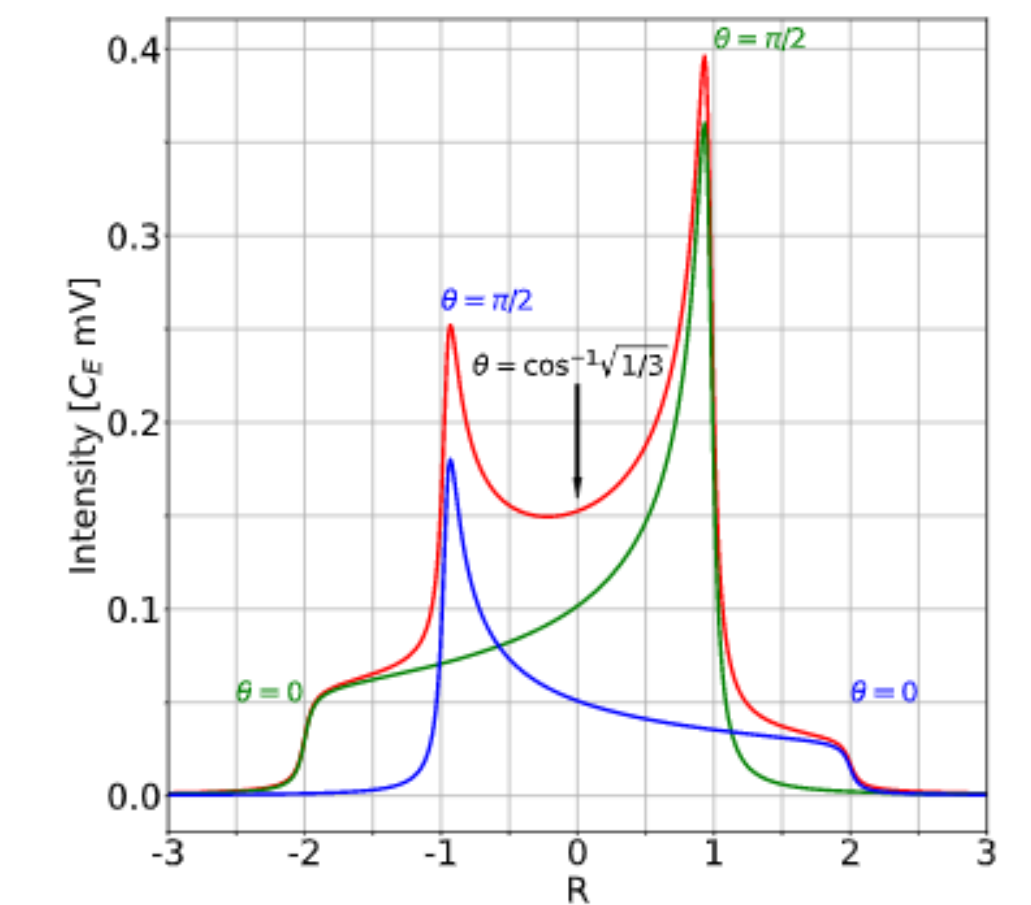
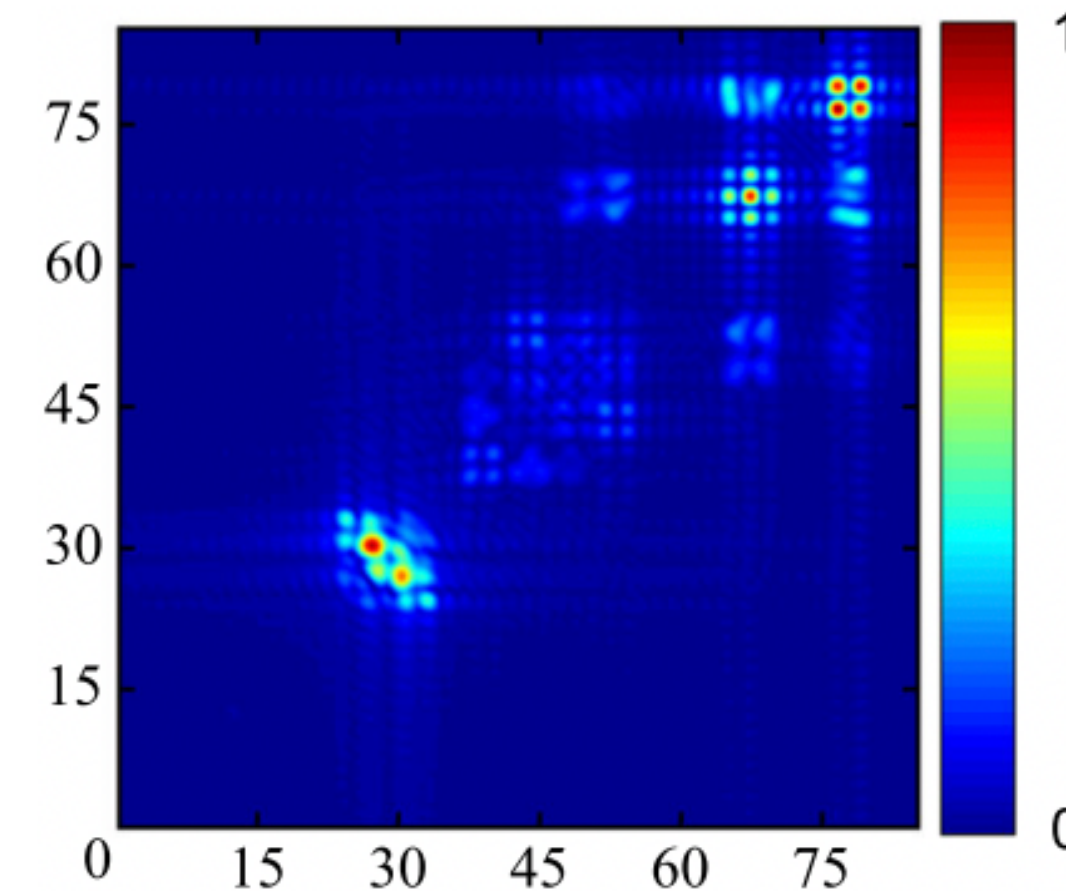
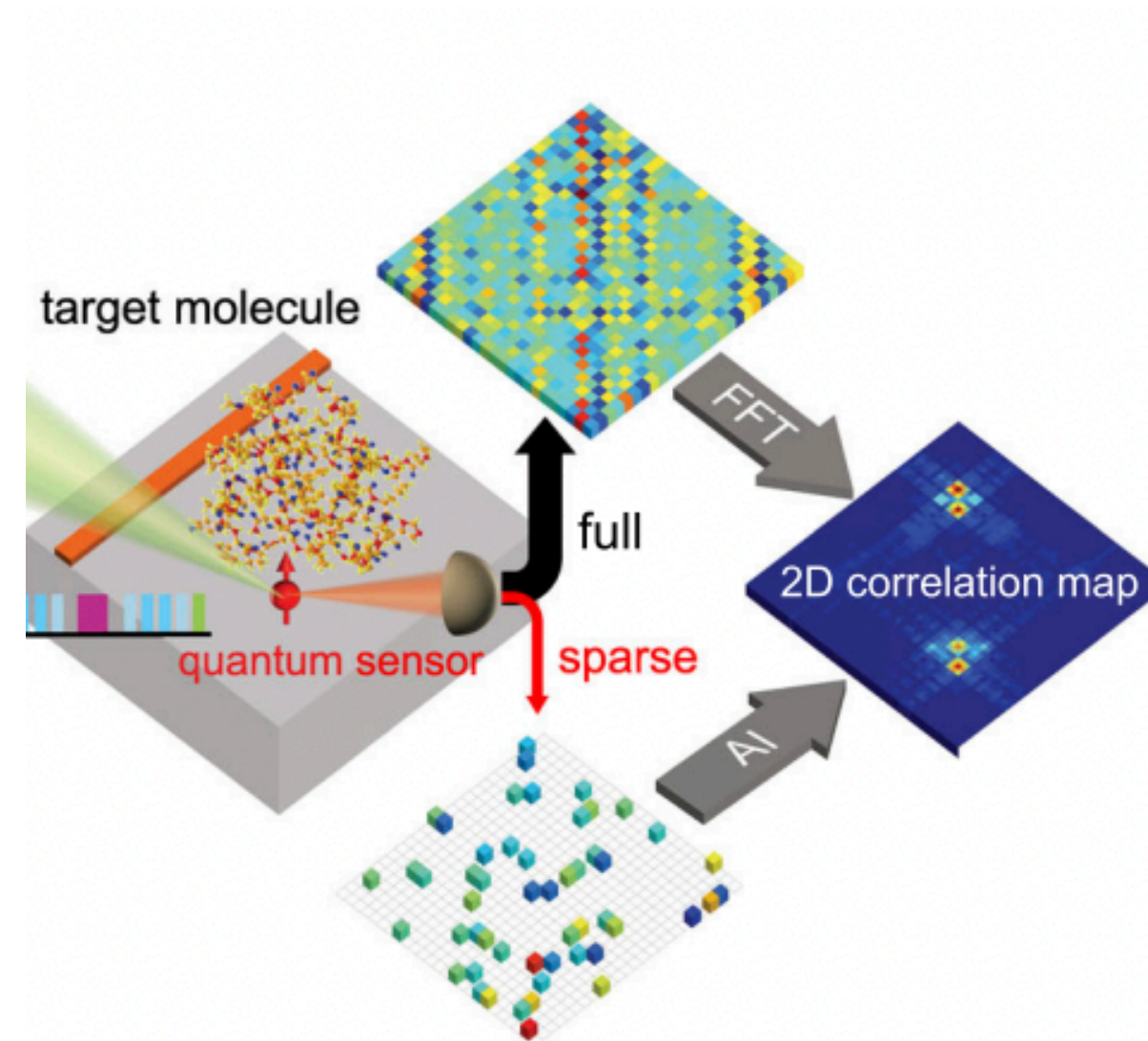
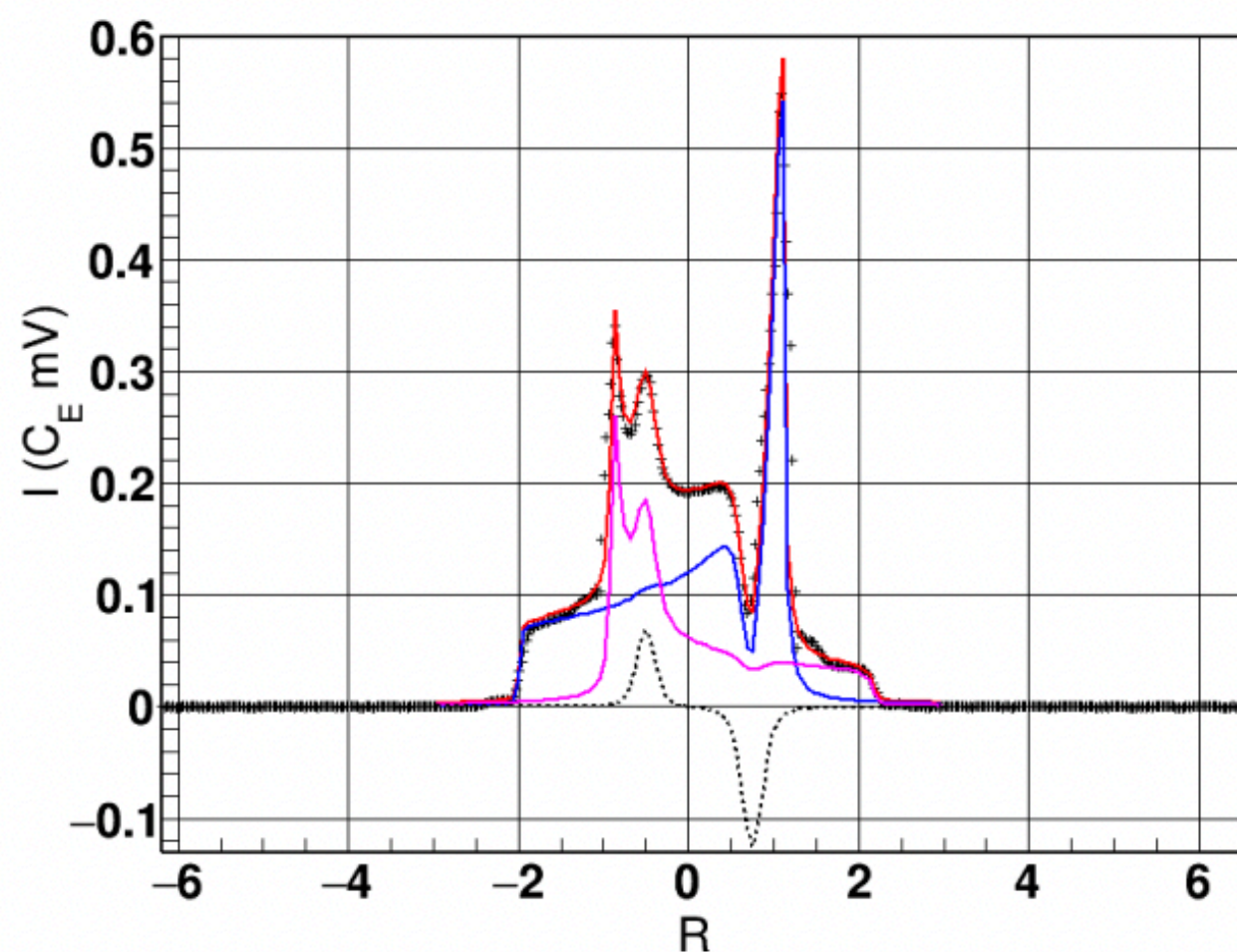
- Absorption/Dispersion
- Fast Phase Sampling
- Adjustable destructive RF
- Separation of RF range

Original Liverpool design

- Phase Sensitive detector
- Constant Current
- Non-destructive (low amplitude)
- Full spectral range

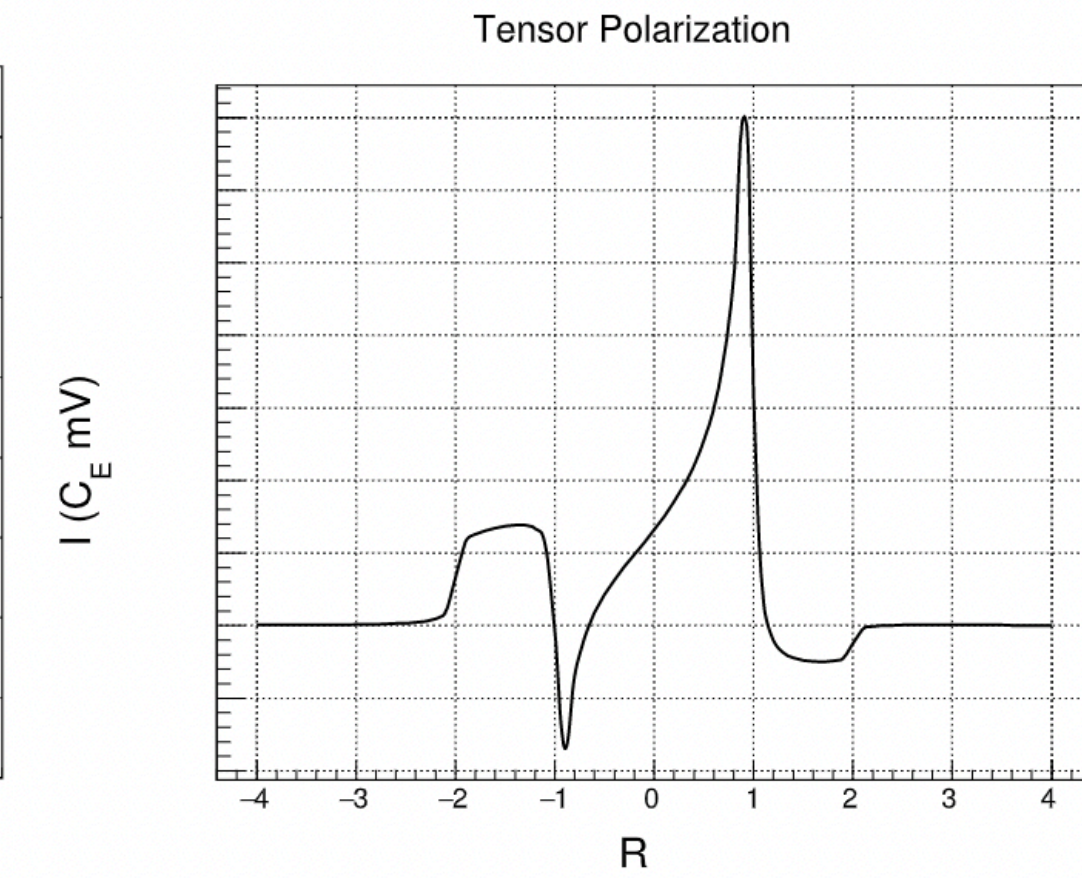
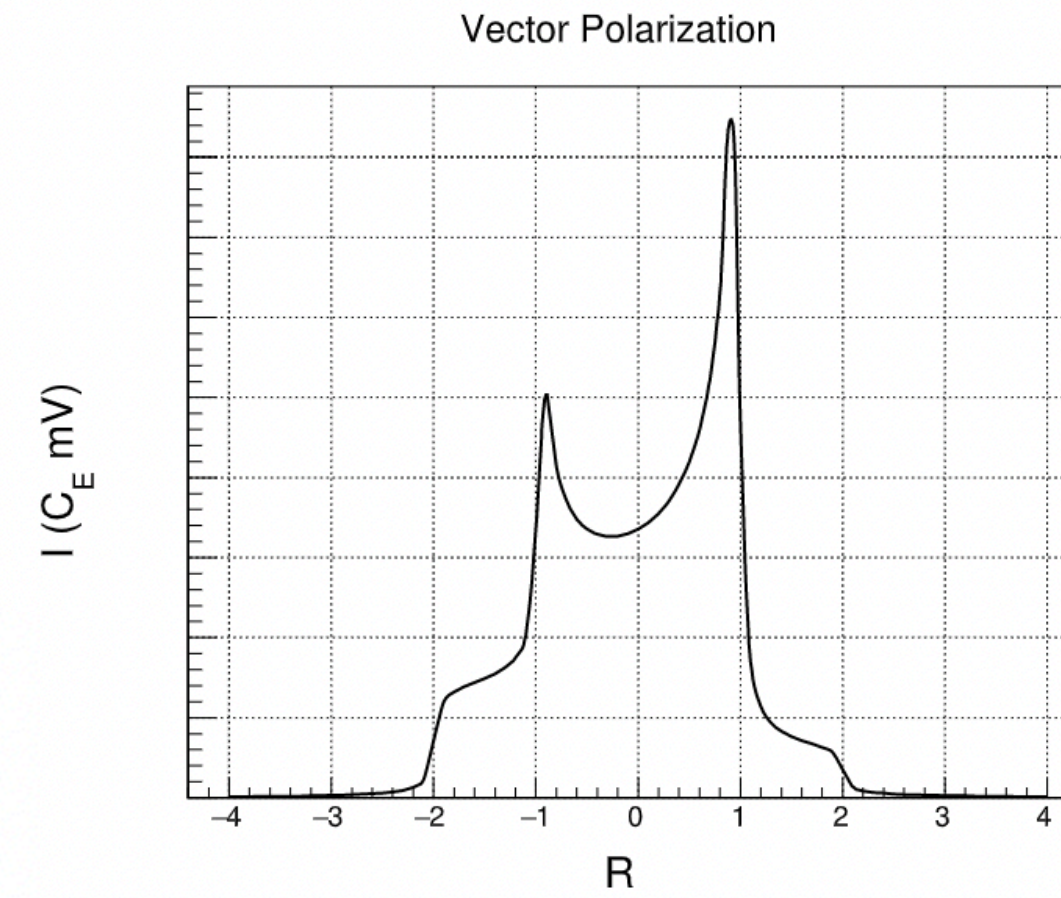
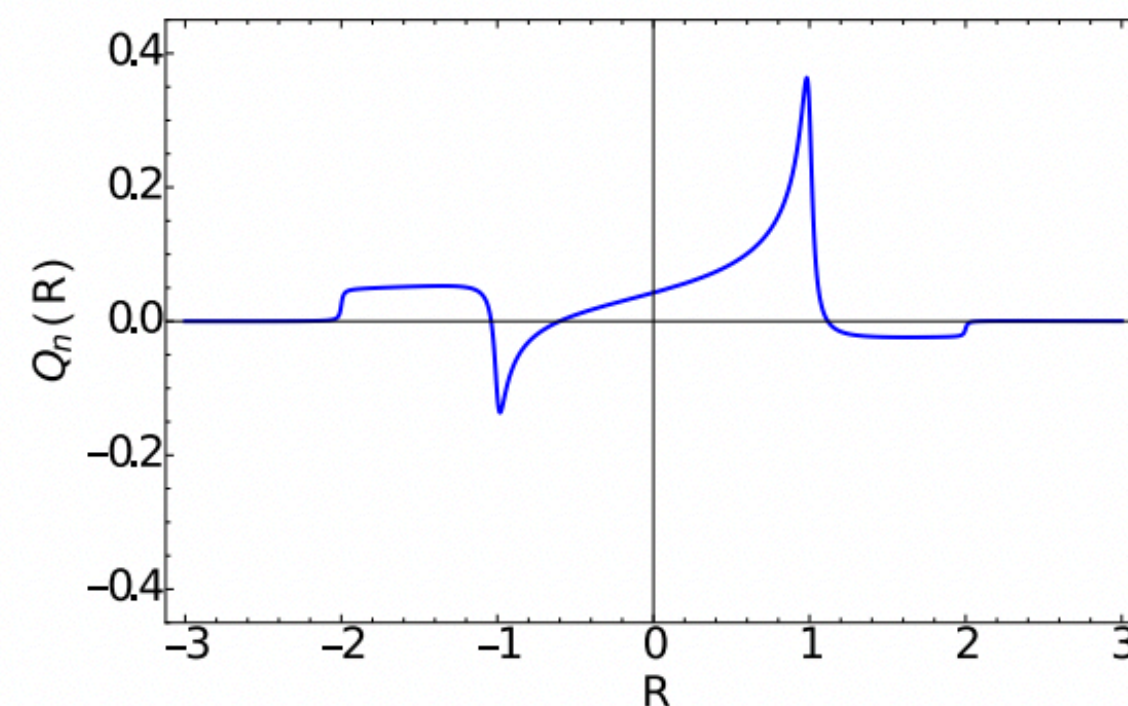
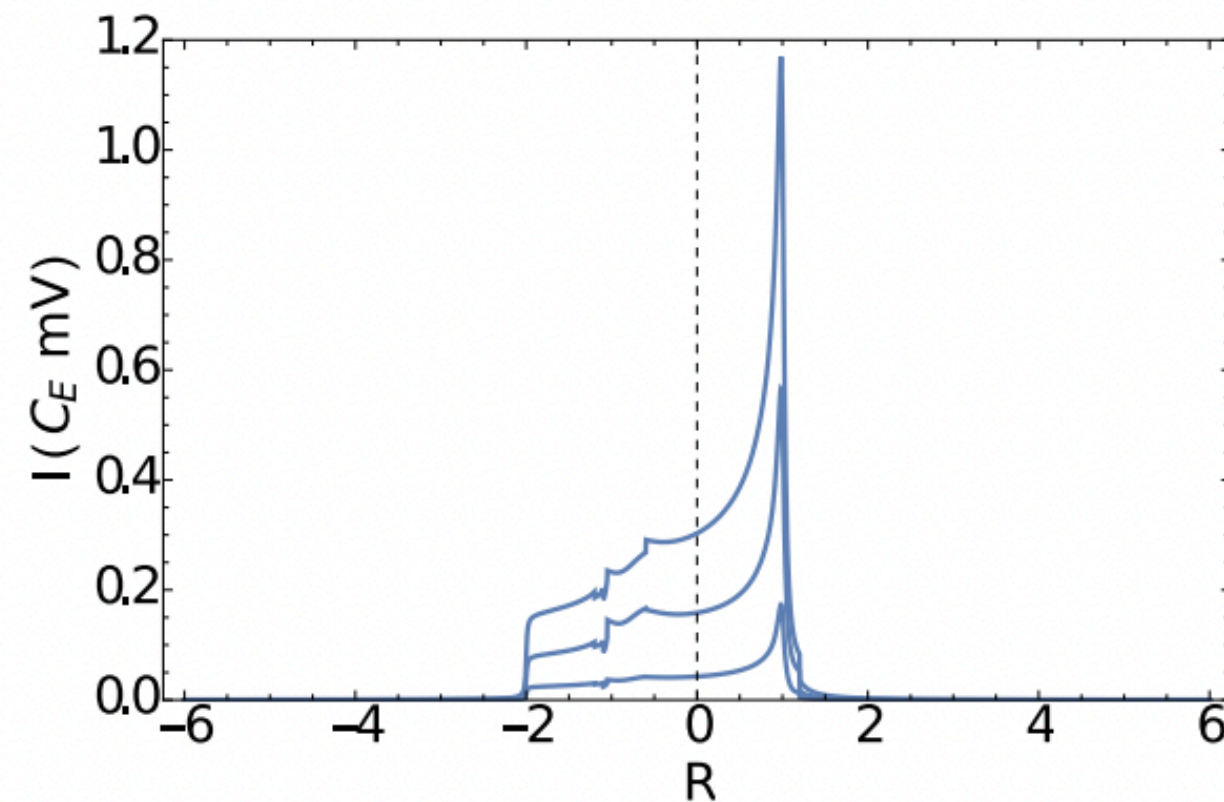
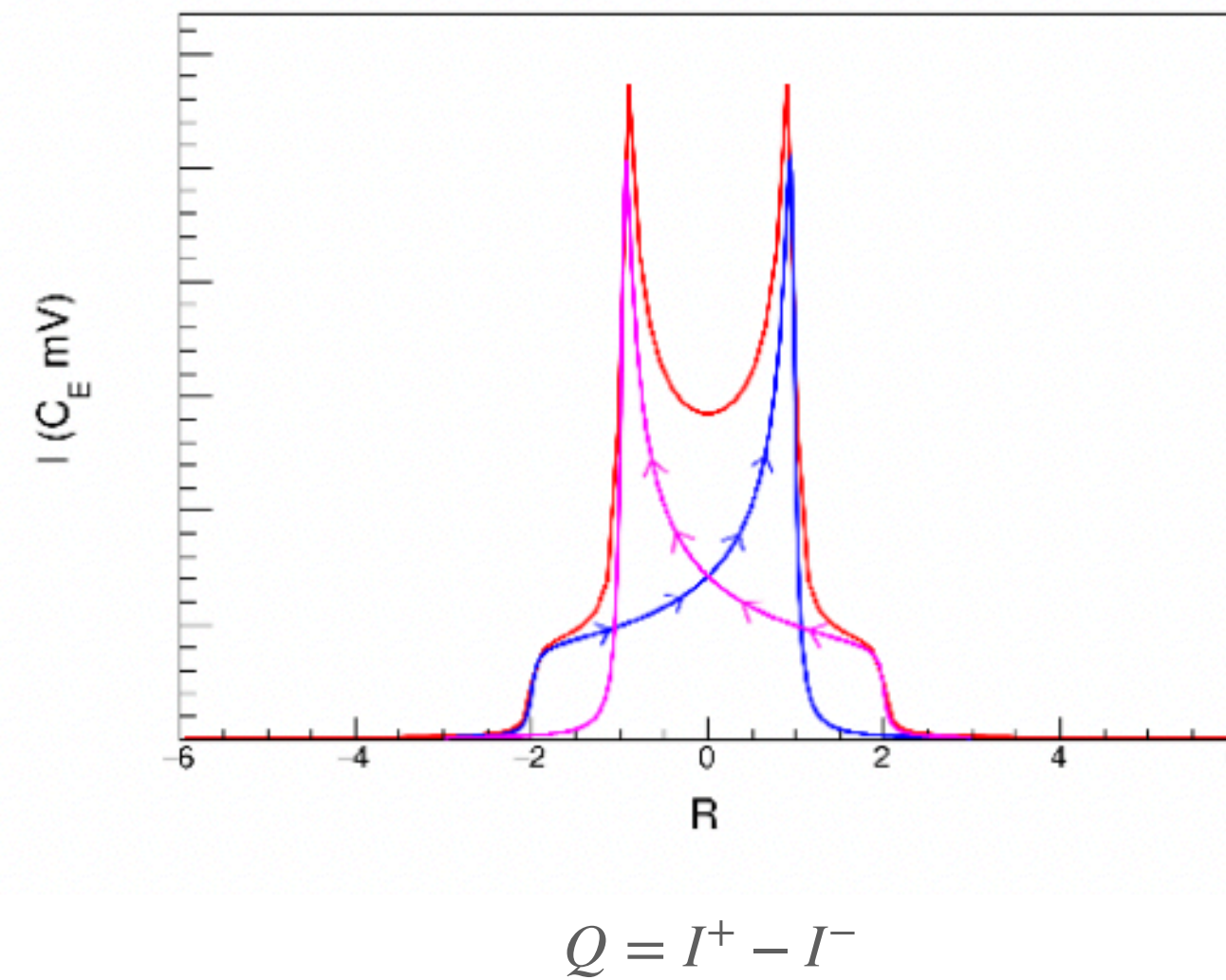
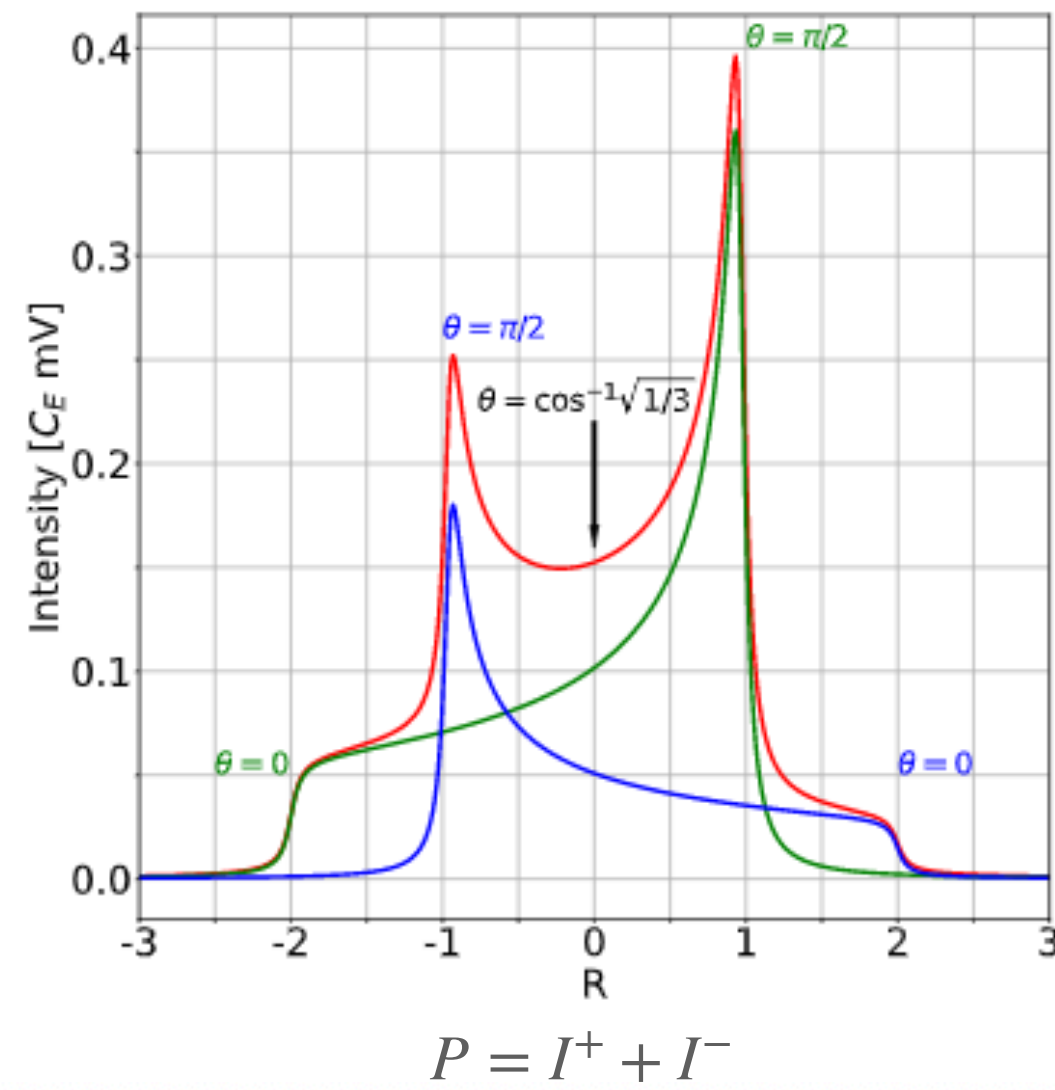


Standard Error in Experiments: 4%
Theoretical Limit: 0.8%



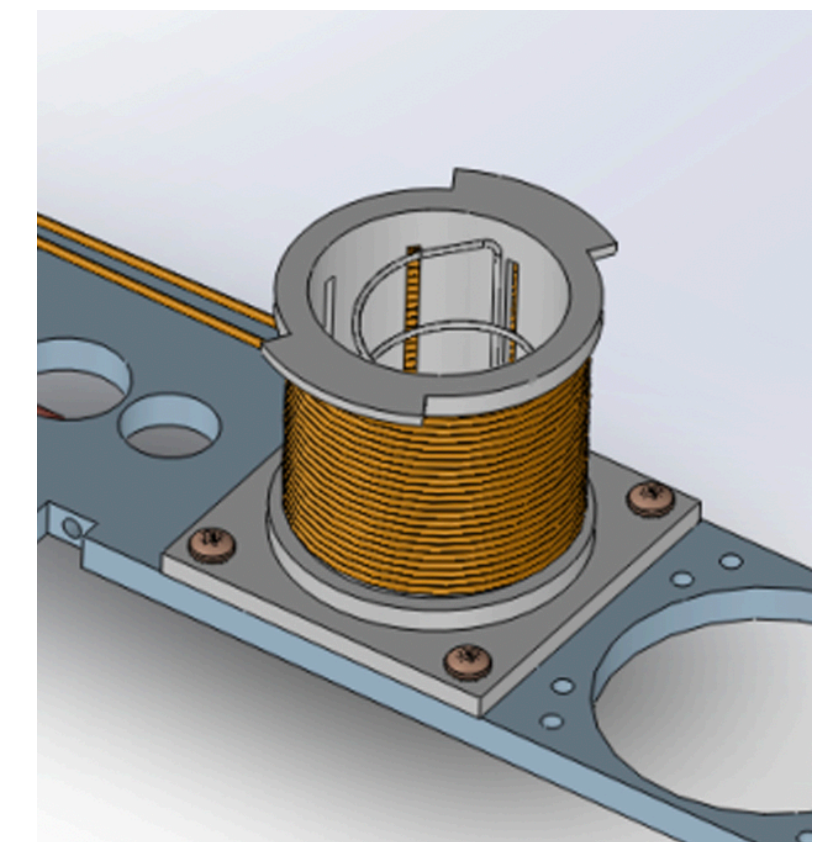
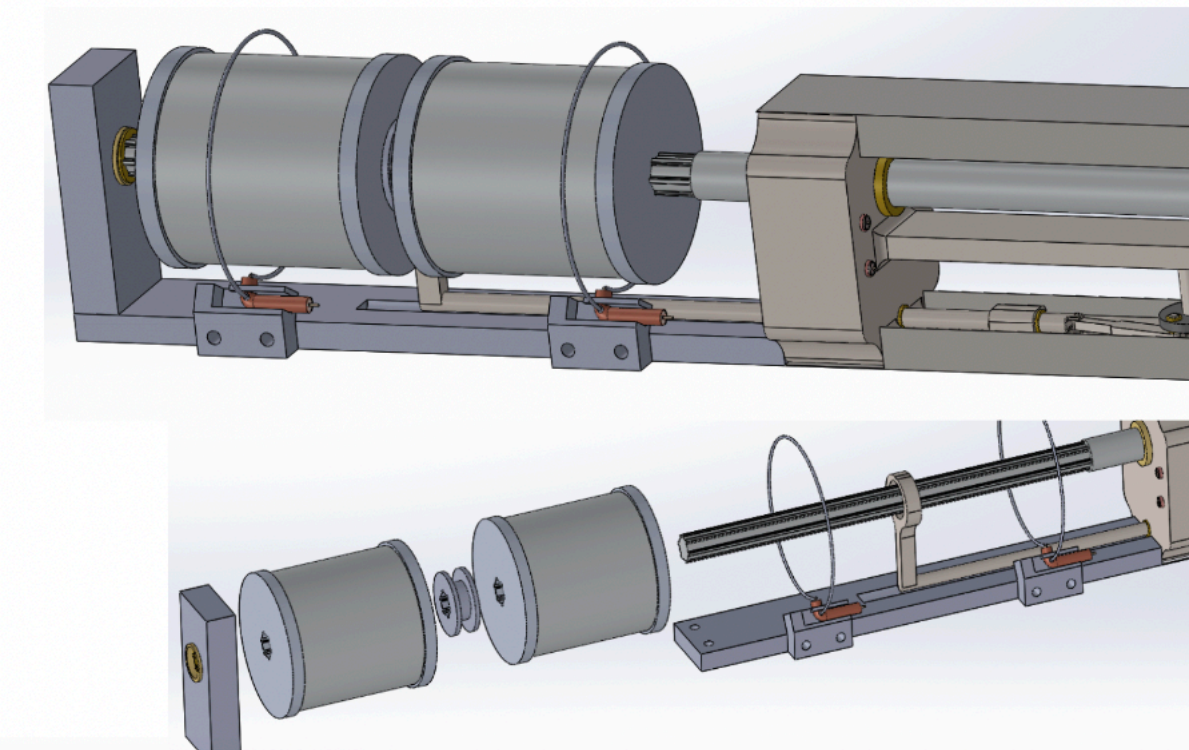
Some Examples In Polarized Targets

EPJA 53 (2017) 7-13

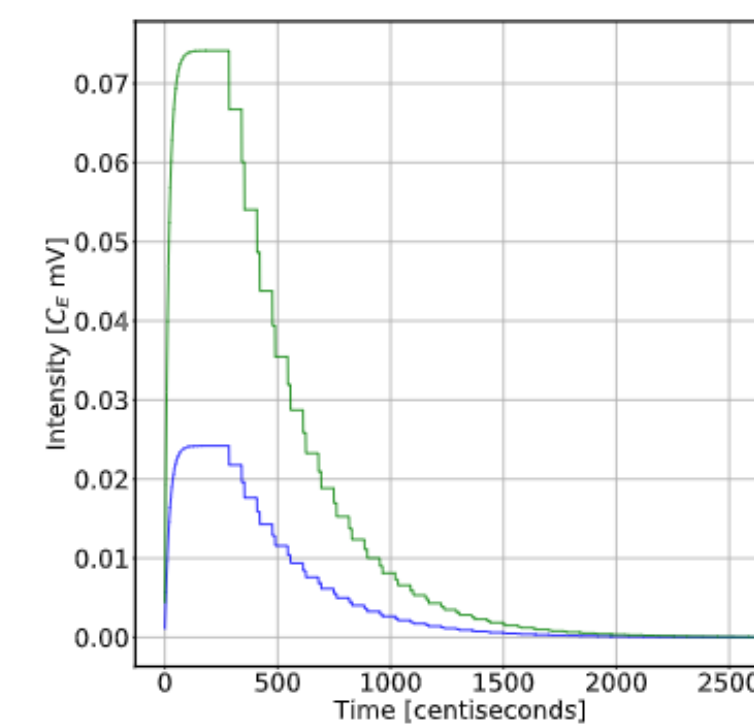
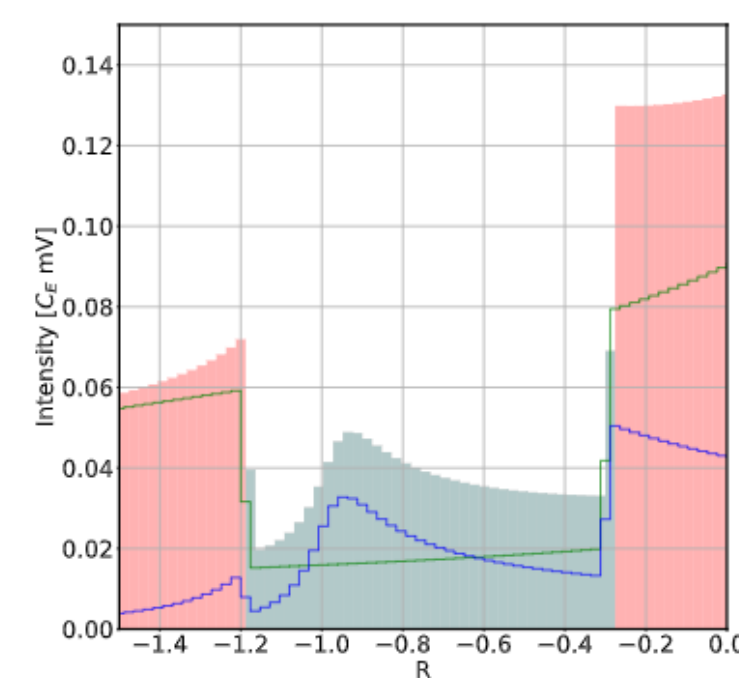
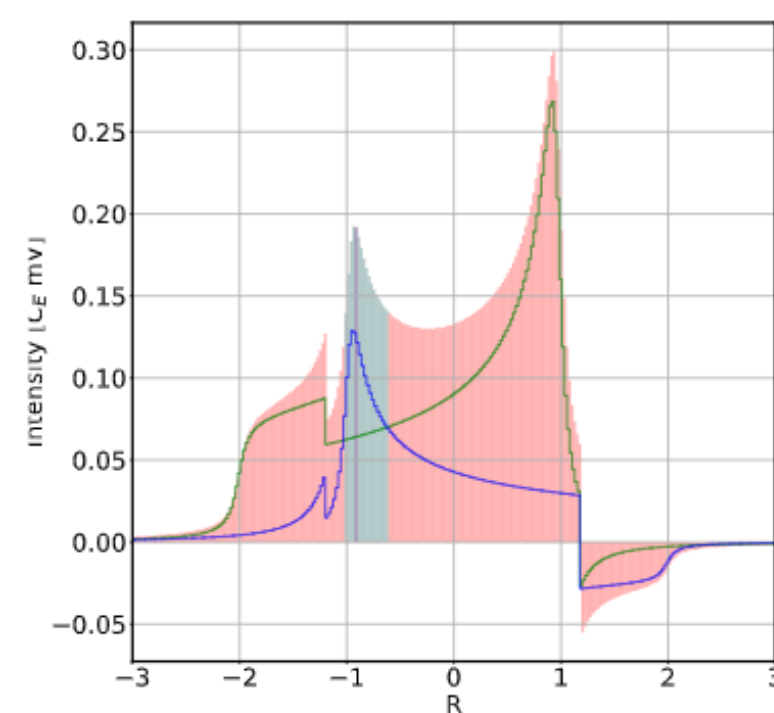
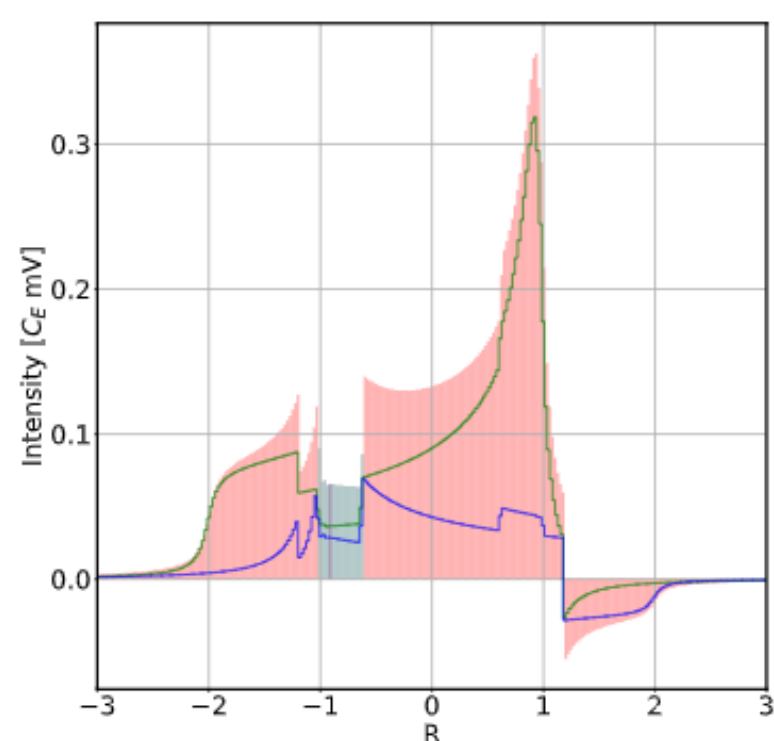
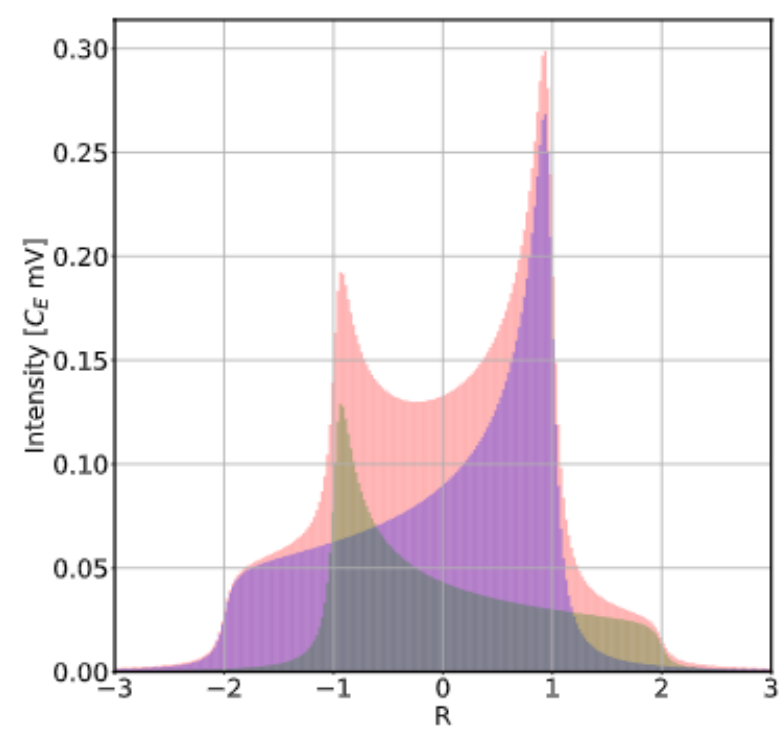
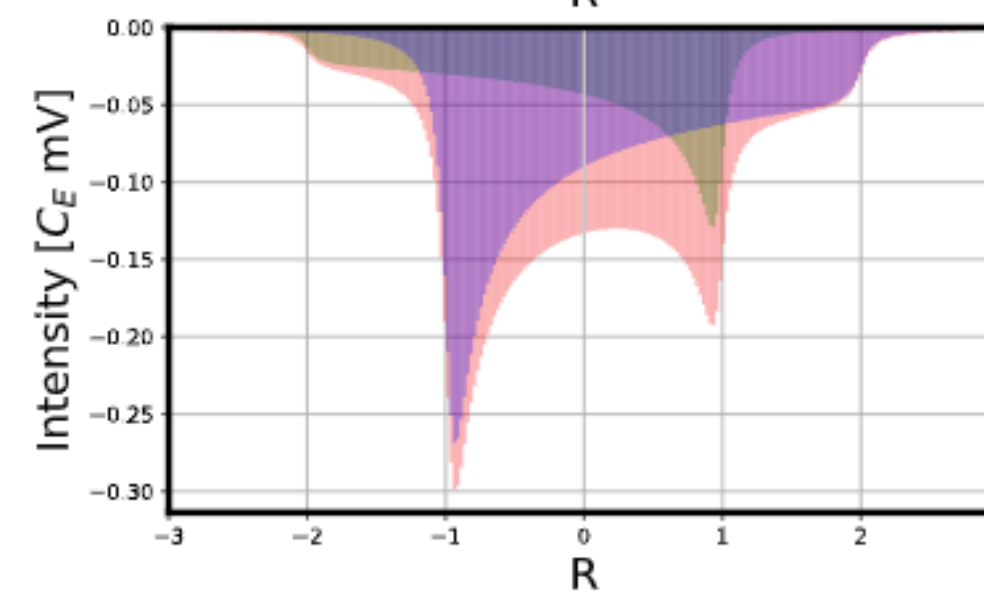
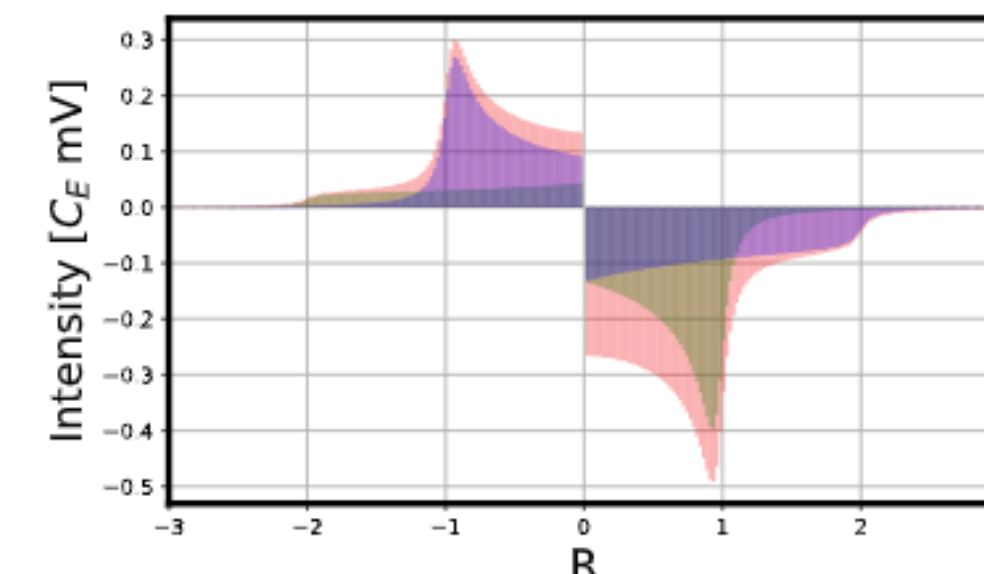
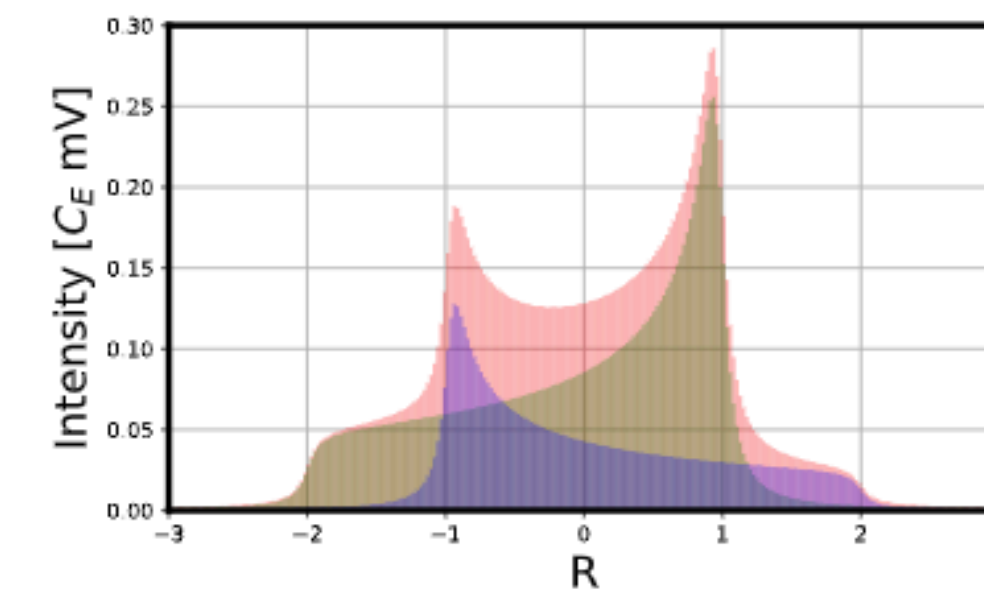
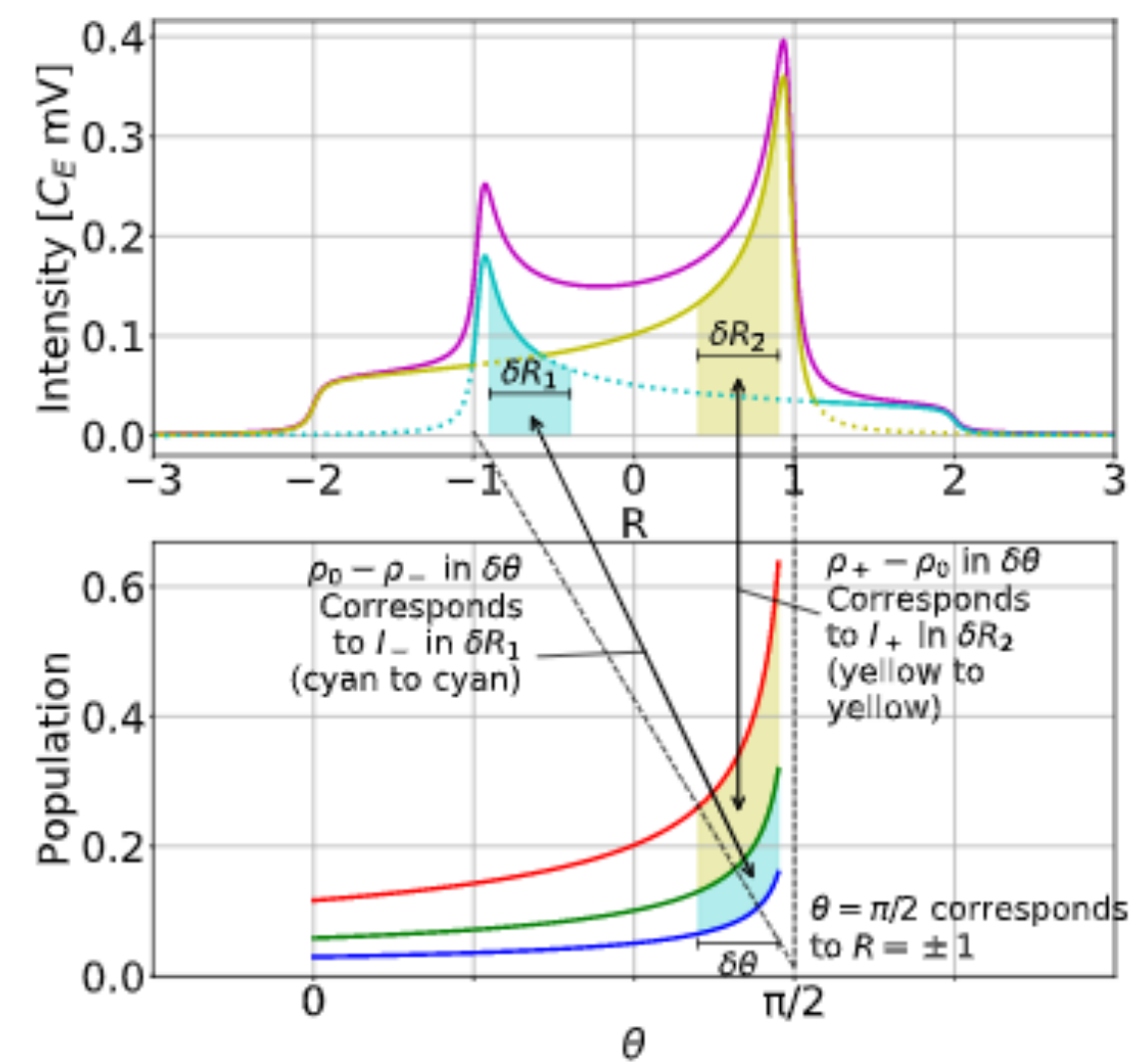
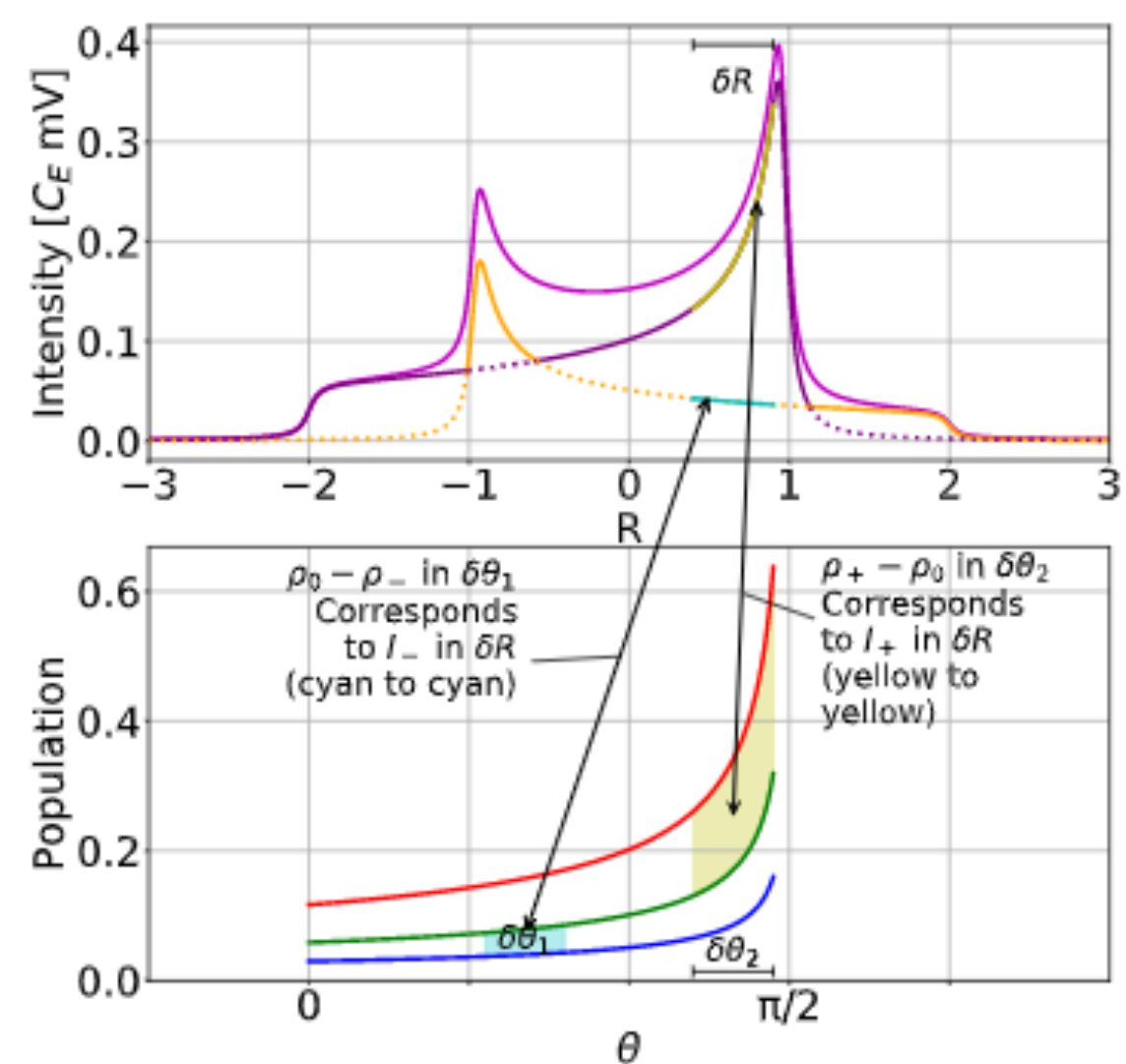
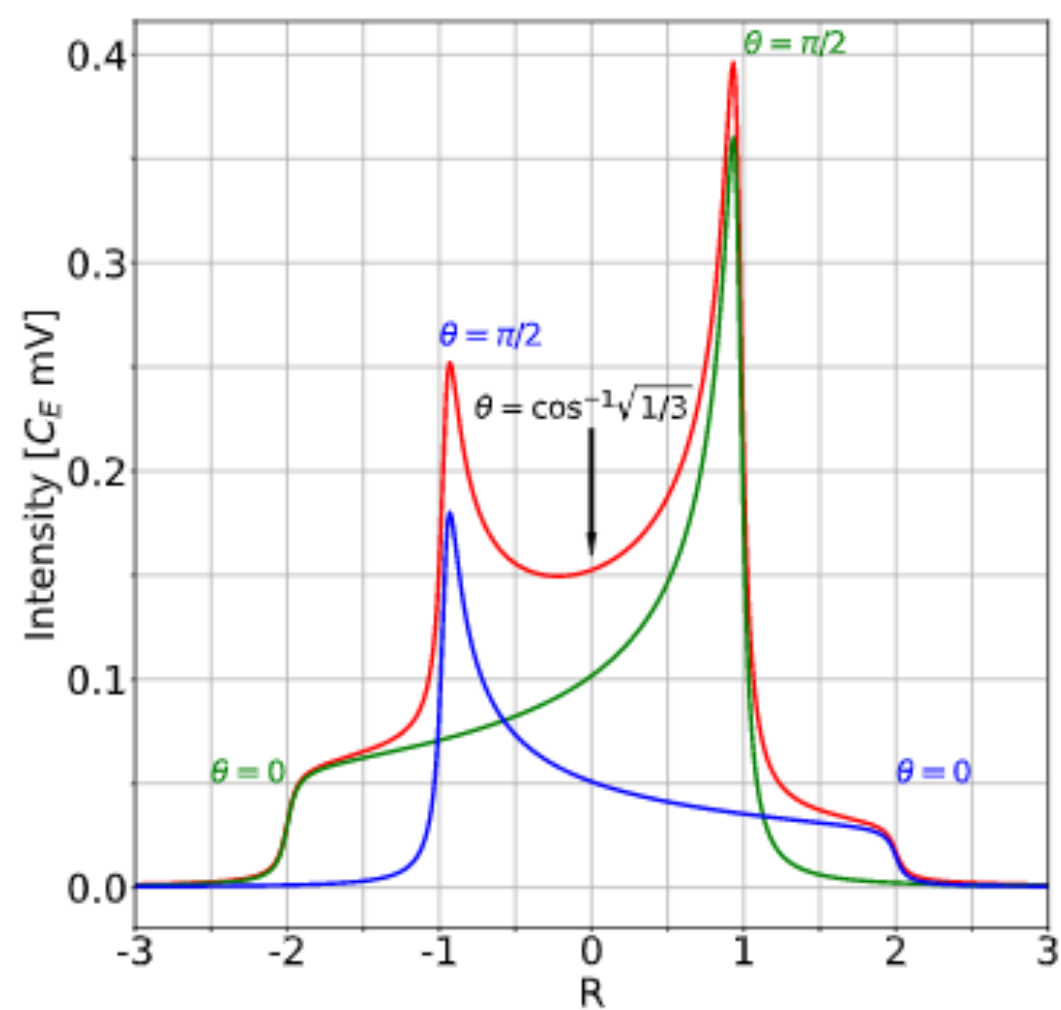


NIMA 981 (2020) 164504

- High Power RF to induce transition
- Selective Semi-saturation
- Must Optimize and Measure in real-time
- Signal Changes as a Function of Beam Dose
- NMR-AI measures and enhances Q bin by bin



Some Examples In Polarized Targets

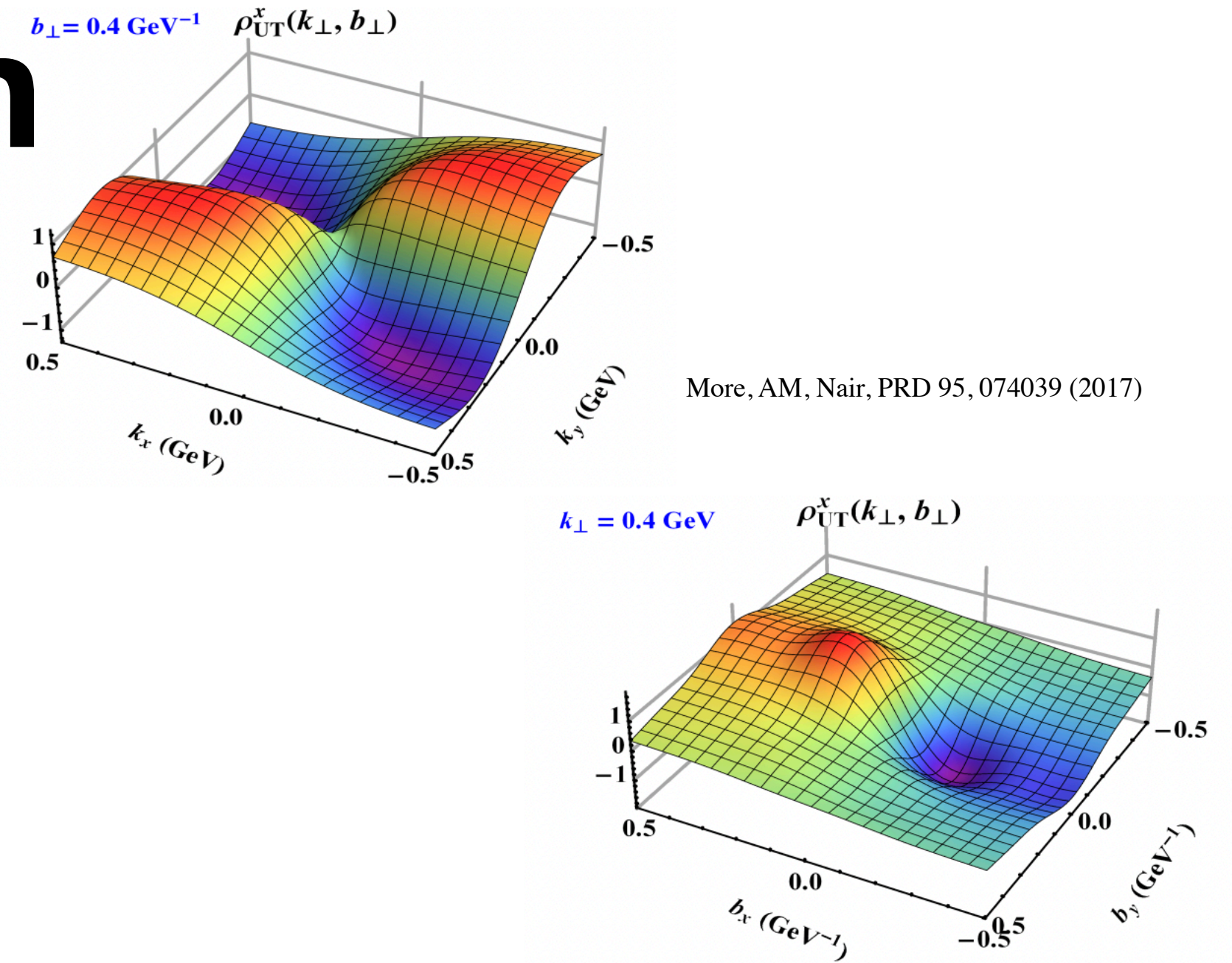
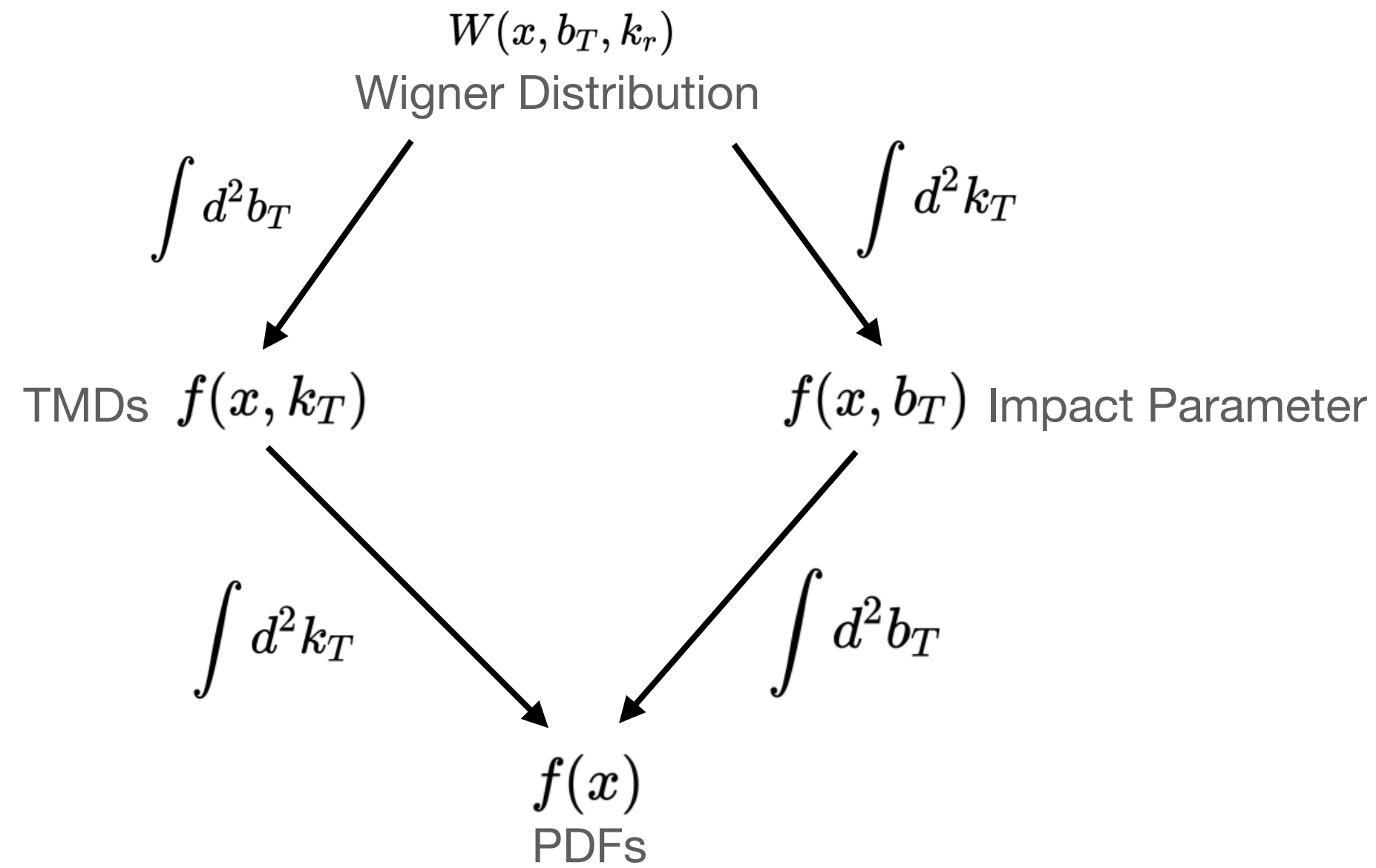
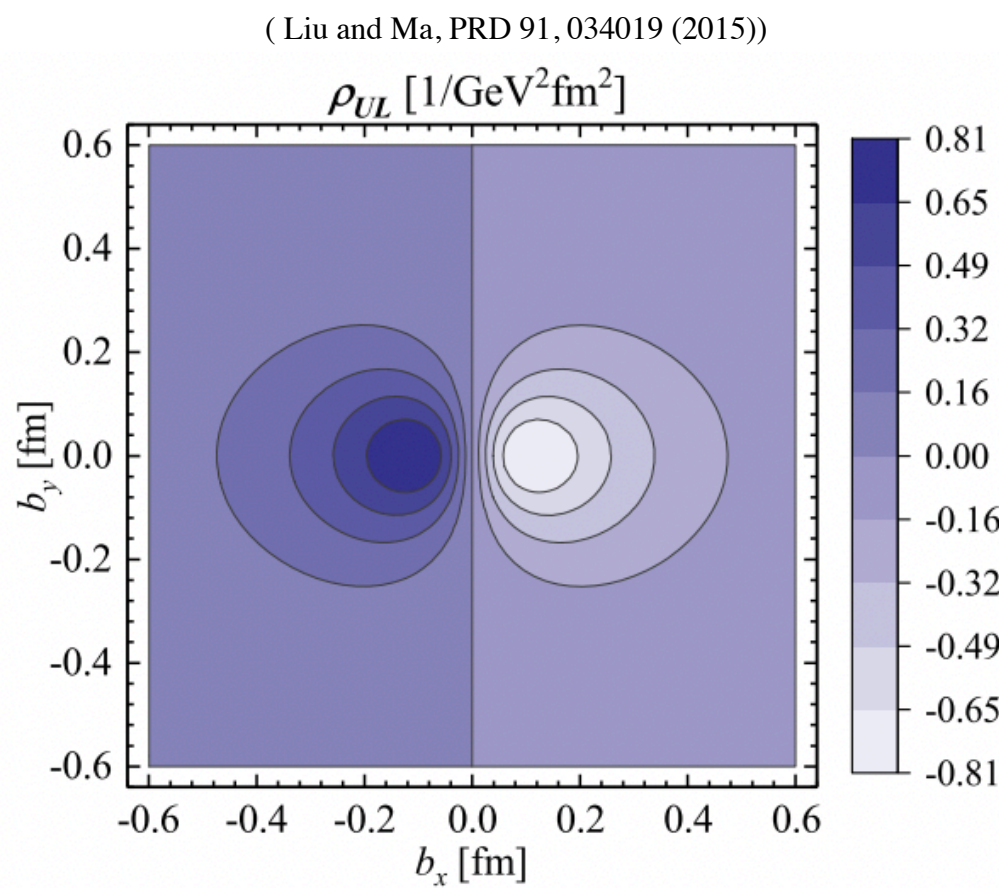


Some Examples

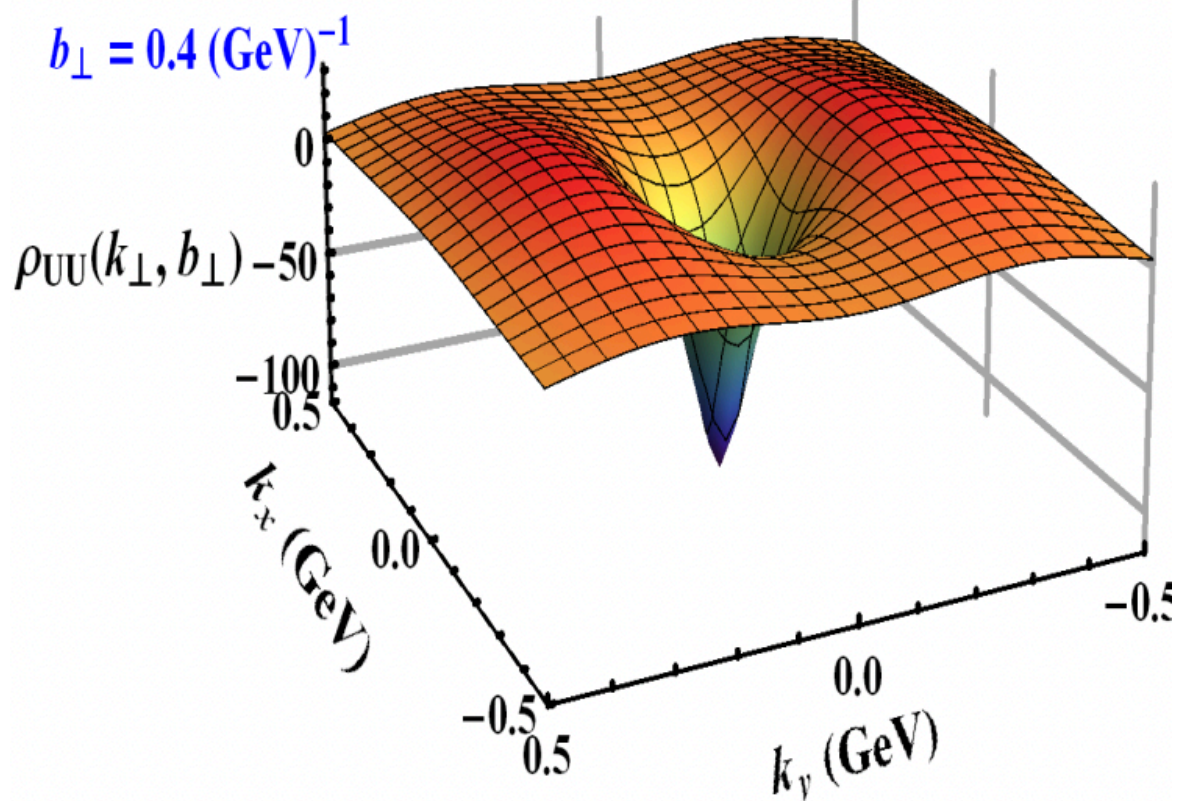
In Phenomenology (Understanding Femtoscale Dynamics)

- Inverse Problem: Determine definitive measures of proton structures using experimental information, Lattice Calculations, and Phenomenology
 - Extraction of GPDs while eliminating the reliance of model fits
 - Extraction of TMDs without assuming a Gaussian factorized form
- Curse of Dimensionality: Understanding the Mother Function (Wigner?) in terms of processes and physical observables (interpretation yields inherent sparsity)
 - How can we impose constraints at the higher-level to interpret dynamics and geometry
 - How do we best obtain information from experiments that gets us the farthest

Candidate Mother Distribution



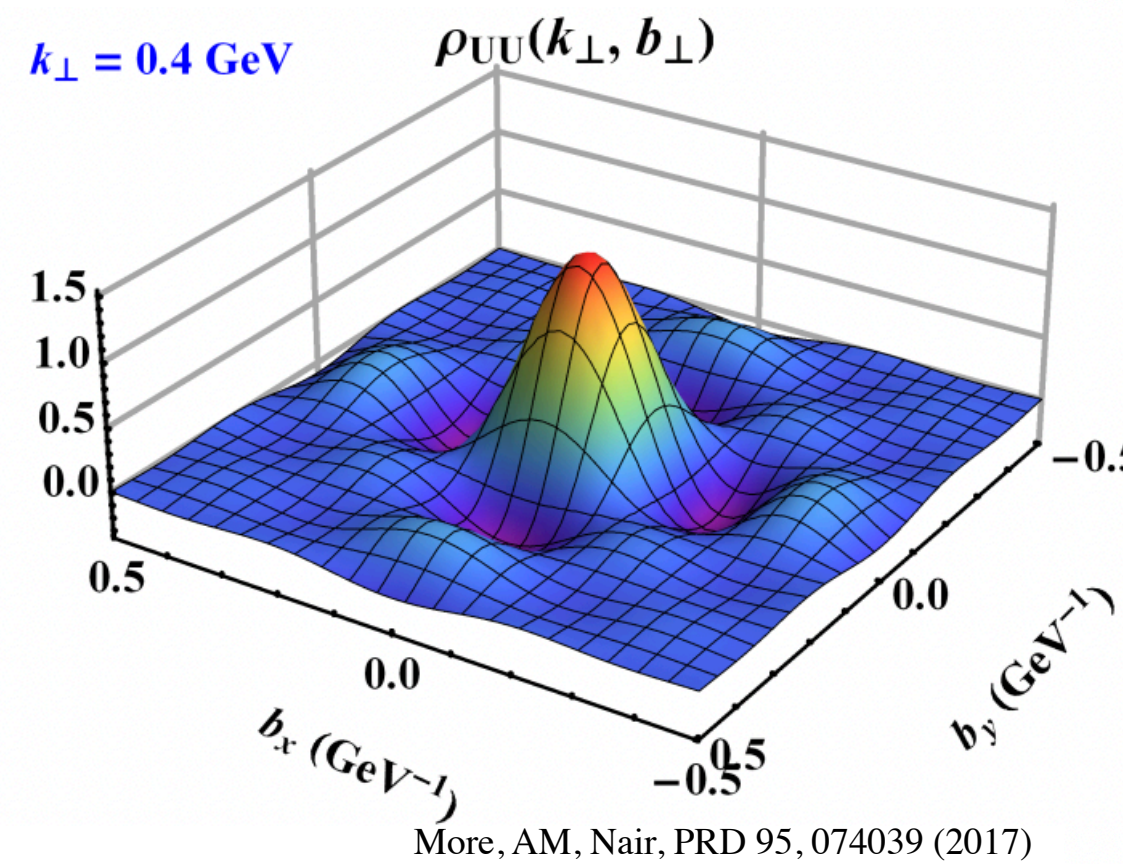
More, AM, Nair, PRD 95, 074039 (2017)



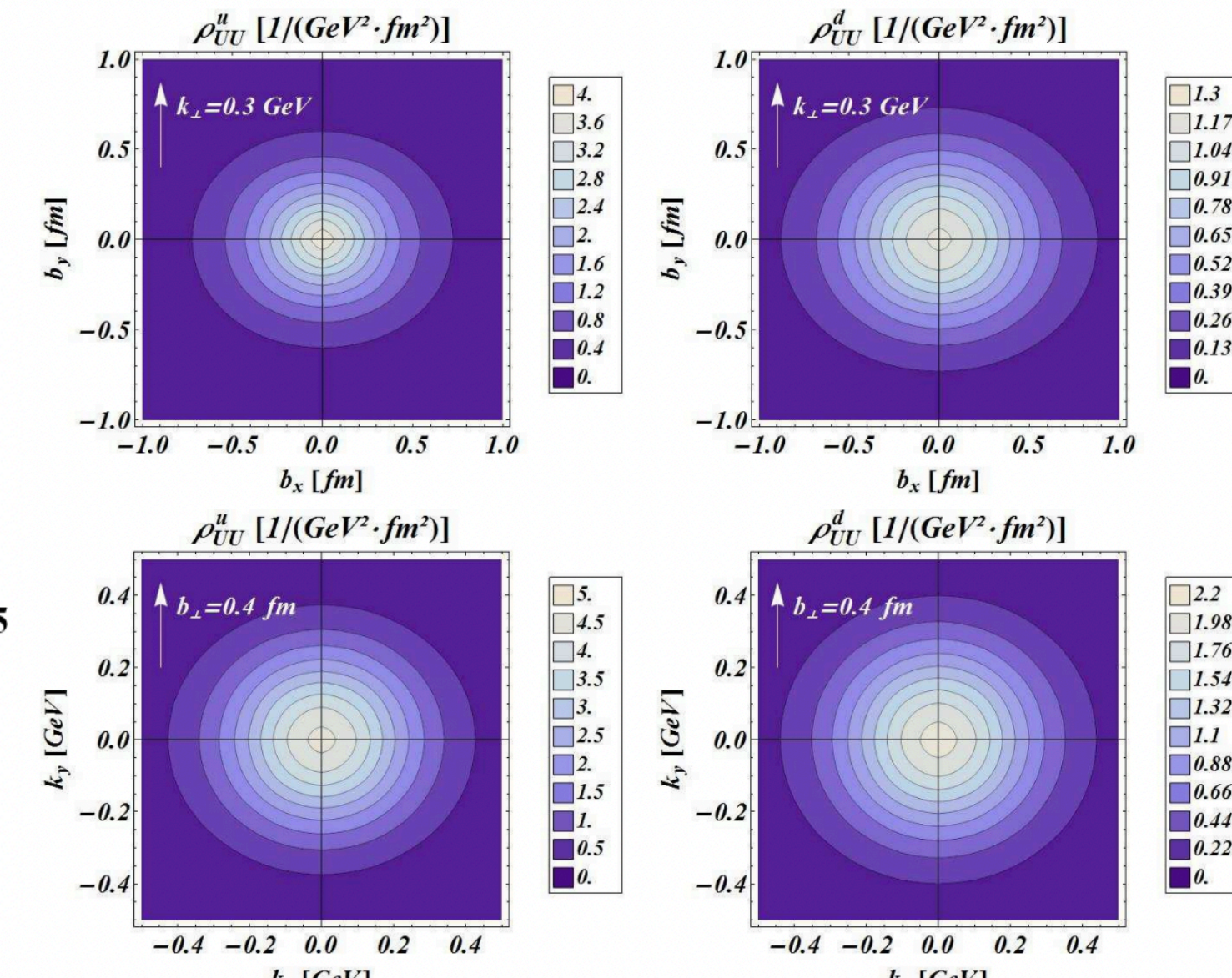
Husimi distributions have a Gaussian regularization factor in the integrand that keeps them positive in the entire range of transverse space coordinate

Zhi-Lei Ma and Zhun Lu
Phys. Rev. D 98, 054024

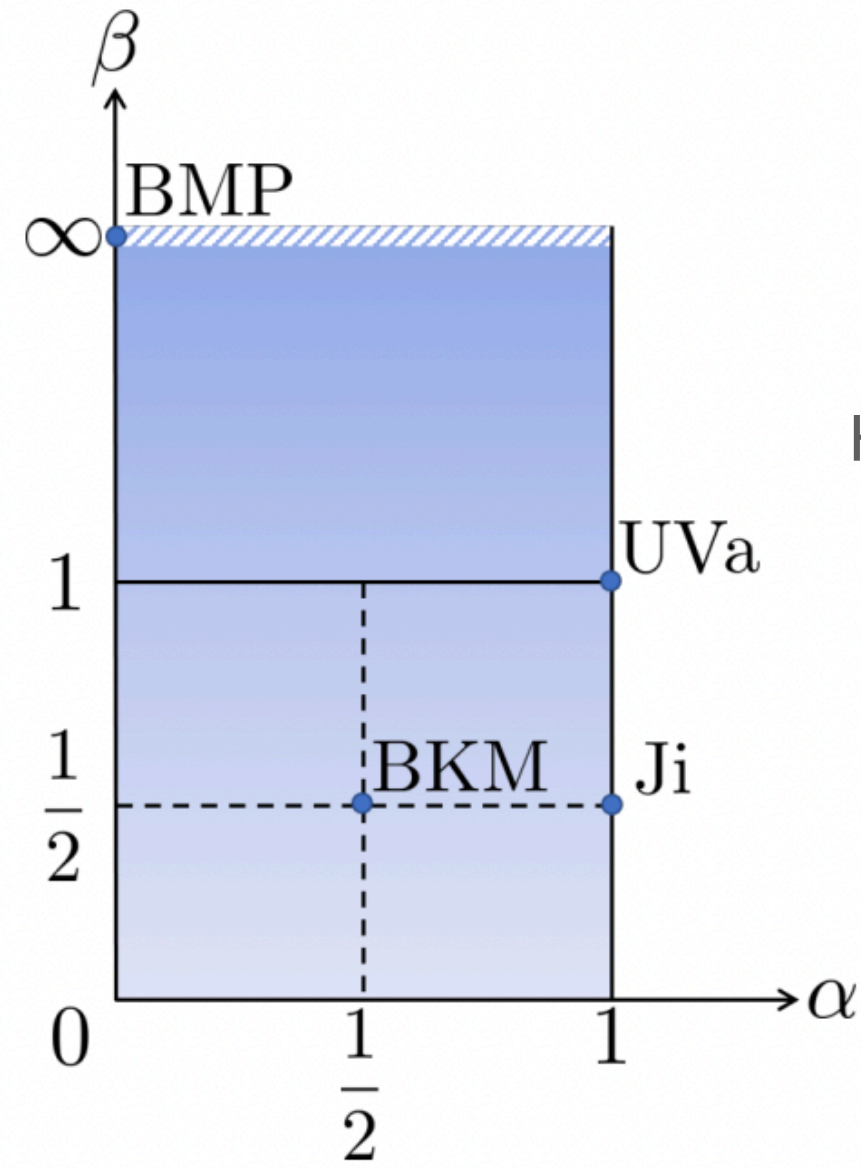
TMDs and Impact Parameters give complementary information about partons and are fundamentally connected to the Wigner Distribution



Lorce and Pasquini, PRD 84, 014015 (2011); Liu and Ma, PRD 91, 034019 (2015)



Challenges in the Interpretation



Helicity Amplitudes

Y. Guo, at el., arxiv2109.10373

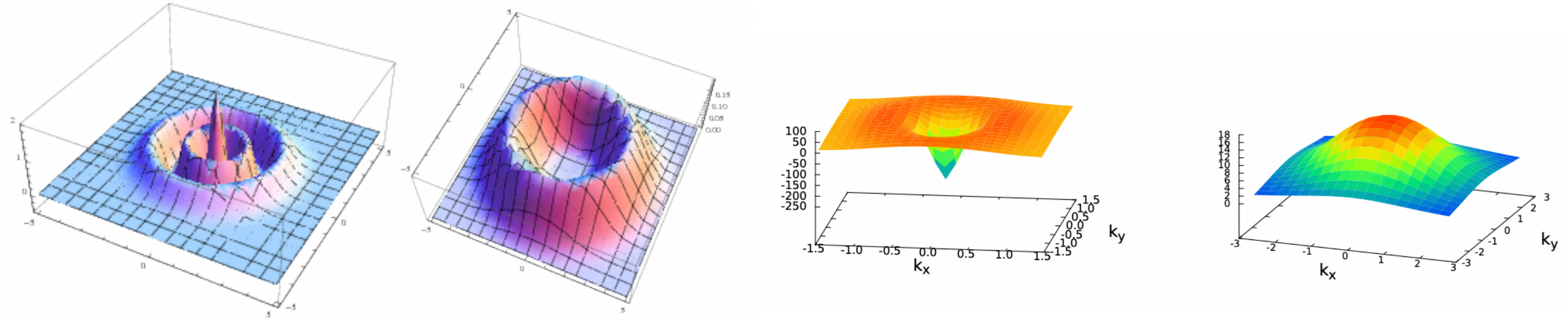
$$H(x, x, t) = \frac{nr}{1+x} \left(\frac{2x}{1+x}\right)^{-\alpha(t)} \left(\frac{1-x}{1+x}\right)^b \frac{1}{\left(1 - \frac{1-x}{1+x} \frac{t}{M^2}\right)^p} \quad \text{GPDs}$$

$$f_{q/p}(x, k_{\perp}) = f_q(x) \frac{1}{\pi \langle k_{\perp}^2 \rangle} e^{-k_{\perp}^2 / \langle k_{\perp}^2 \rangle}$$

$$\Delta^N f_{q/p^{\dagger}}(x, k_{\perp}) = 2\mathcal{N}_q(x) h(k_{\perp}) f_{q/p}(x, k_{\perp}) \quad \text{TMDs}$$

$$h(k_{\perp}) = \sqrt{2} e \frac{k_{\perp}}{M_1} e^{-k_{\perp}^2 / M_1^2}$$

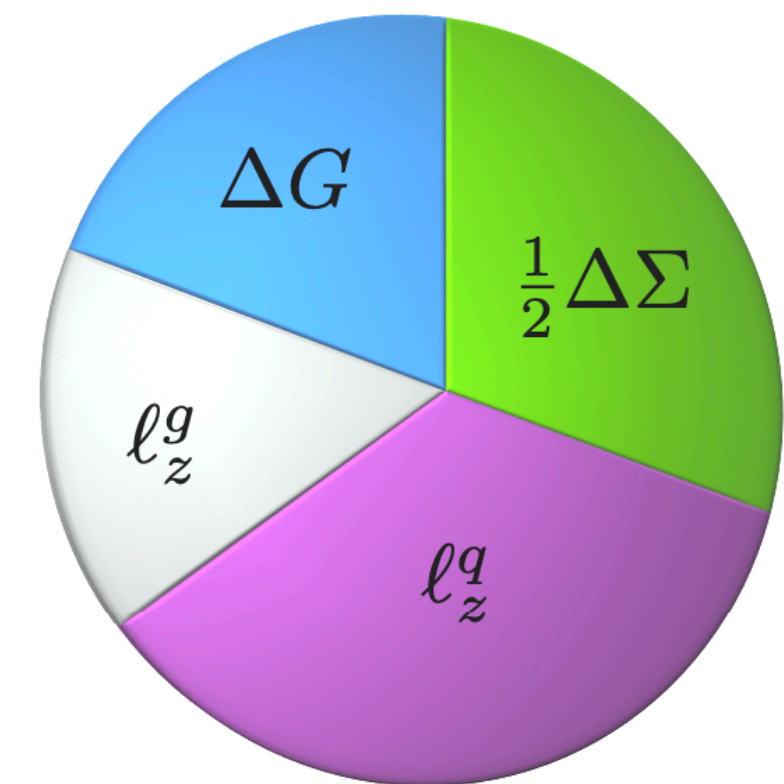
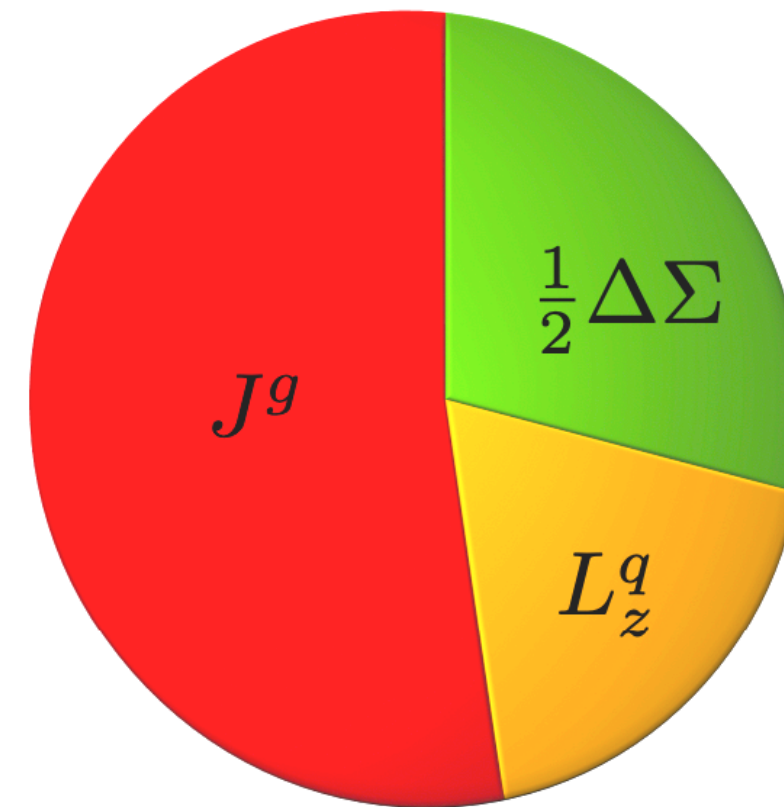
$$\mathcal{N}_q(x) = N_q x^{\alpha_q} (1-x)^{\beta_q} \frac{(\alpha_q + \beta_q)^{(\alpha_q + \beta_q)}}{\alpha_q^{\alpha_q} \beta_q^{\beta_q}} \quad \mathcal{N}_{\bar{q}}(x) = N_{\bar{q}}$$



[Hagiwara and Hattaji, nuclphysa.2015.04.005, arxiv:1412.4591](https://arxiv.org/abs/1412.4591)

$$\frac{1}{2} = \frac{1}{2} \Delta\Sigma(\mu) + L_z^q(\mu) + J^g(\mu)$$

$$\frac{1}{2} = \frac{1}{2} \Delta\Sigma(\mu) + \ell_z^q(\mu) + \ell_z^g(\mu) + \Delta G(\mu)$$



M. Engelhardt *et al.*, PRD102, 074505 (2020)

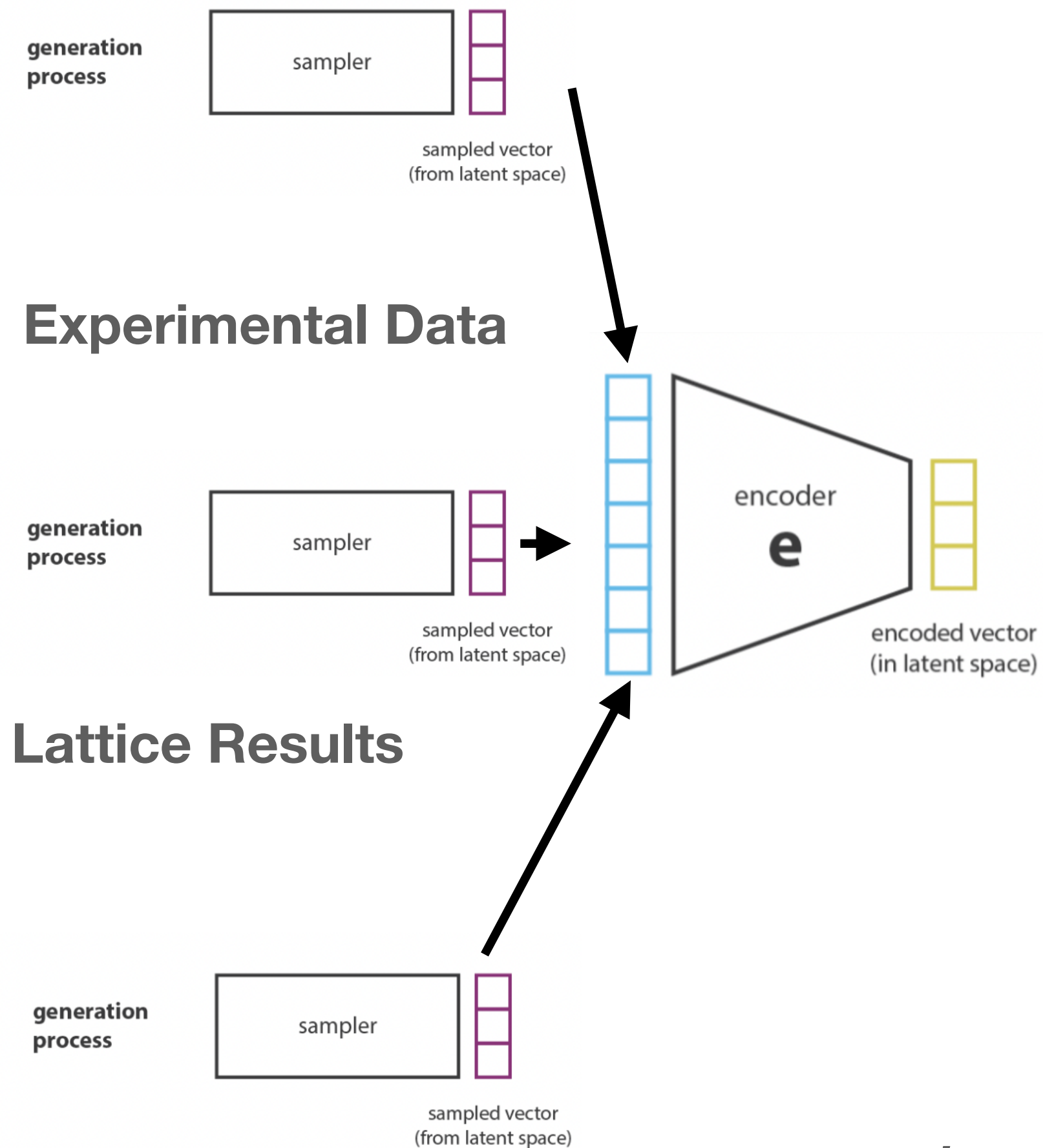
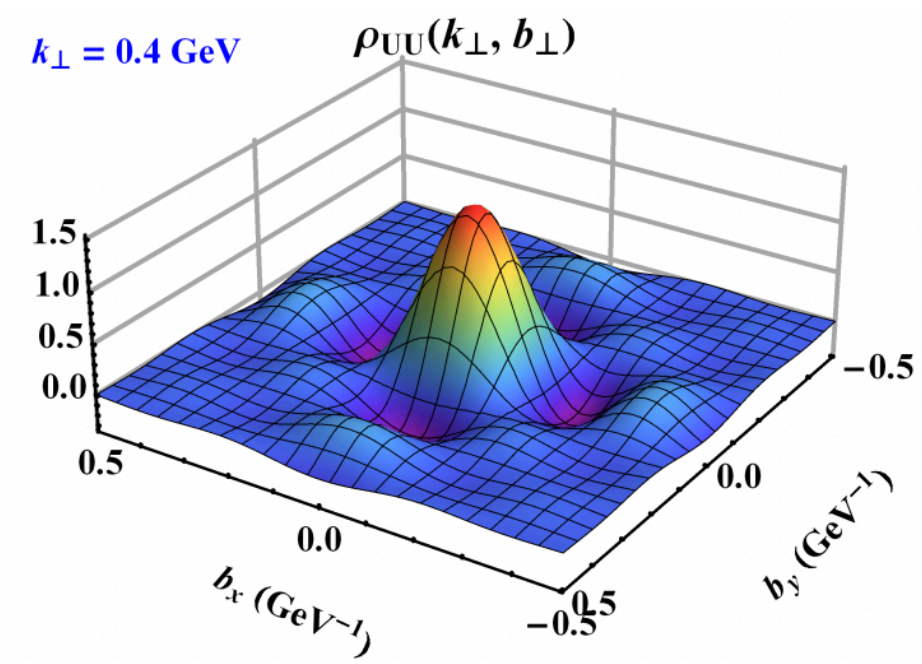
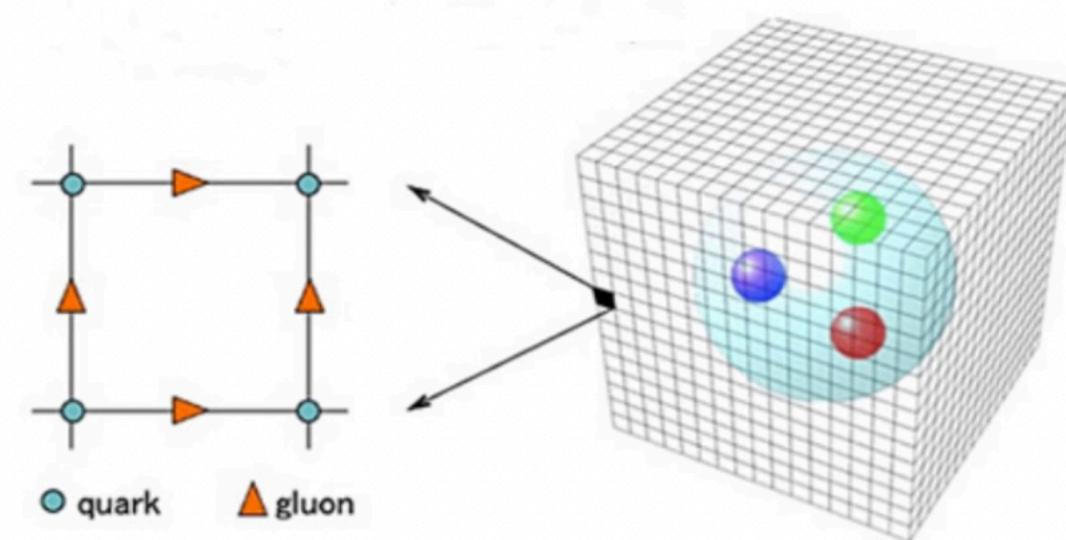
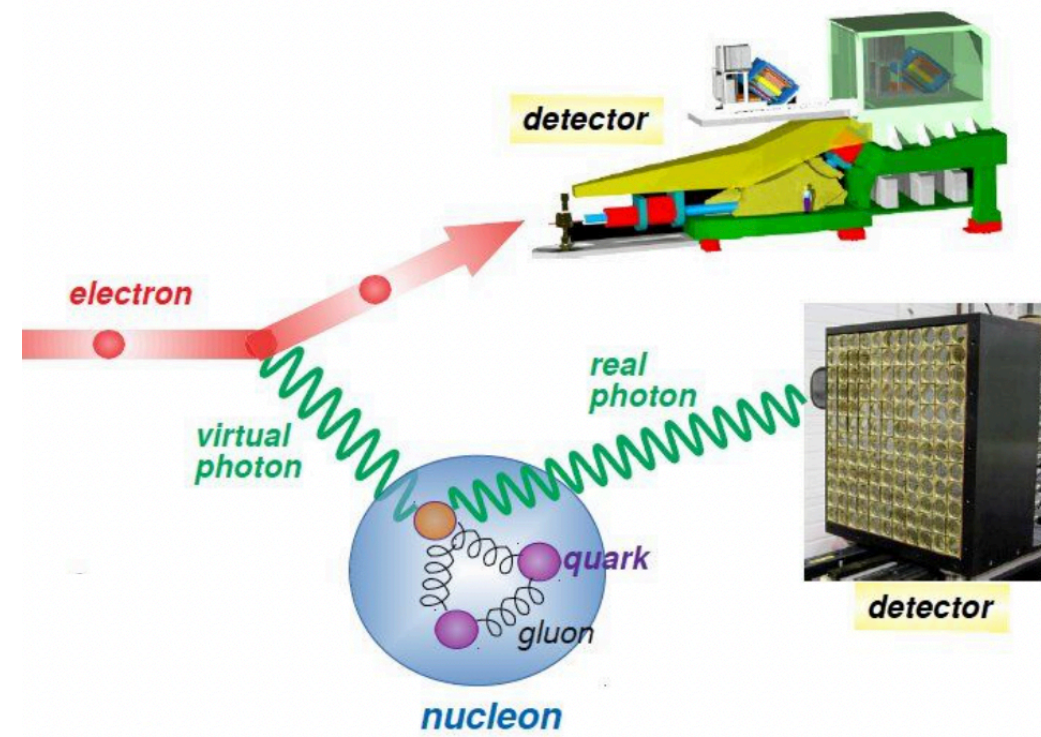
A. Adare *et al.*, PRD93, 011501 (2016)

C. Alexandrou *et al.*, PRL119,142002 (2017)

Explore the Feature Space

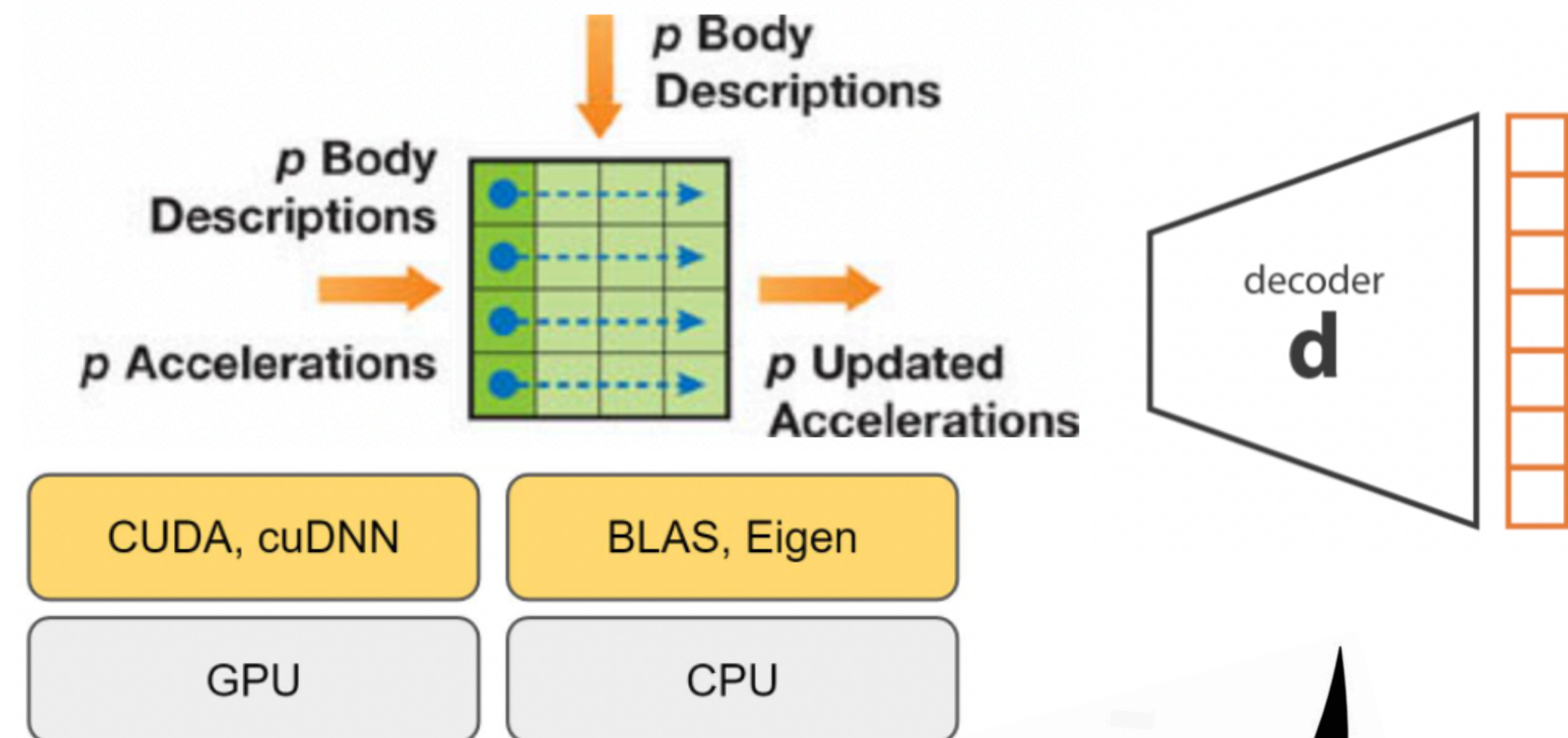
A Second Look at Multilayered Integration

- ANN Global Analysis
- Feed in Data, Constraints, Framework
- Run encoder to map to GPU n-body sims
- Output through decoder to map to observables and data visualization
- User results as training input to exploit latent space
- Front End Visualization Studio

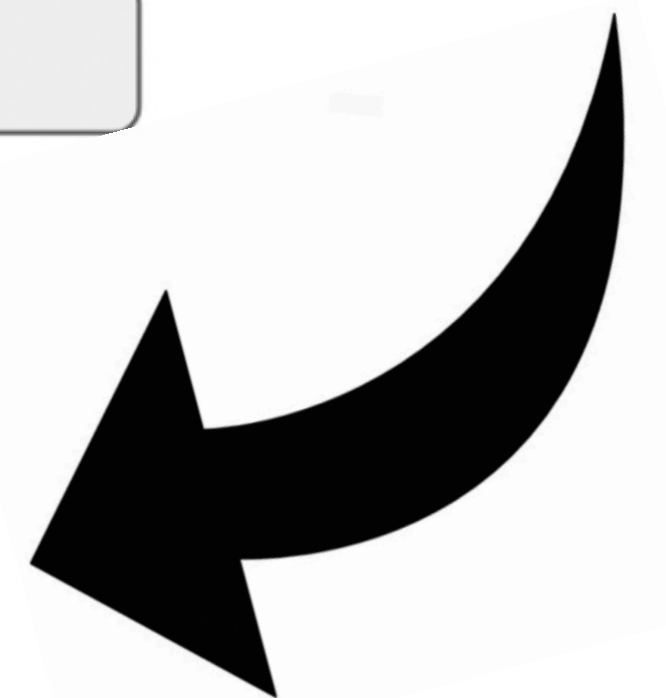


Phenomenological Framework

Piece-wise Autoencoder



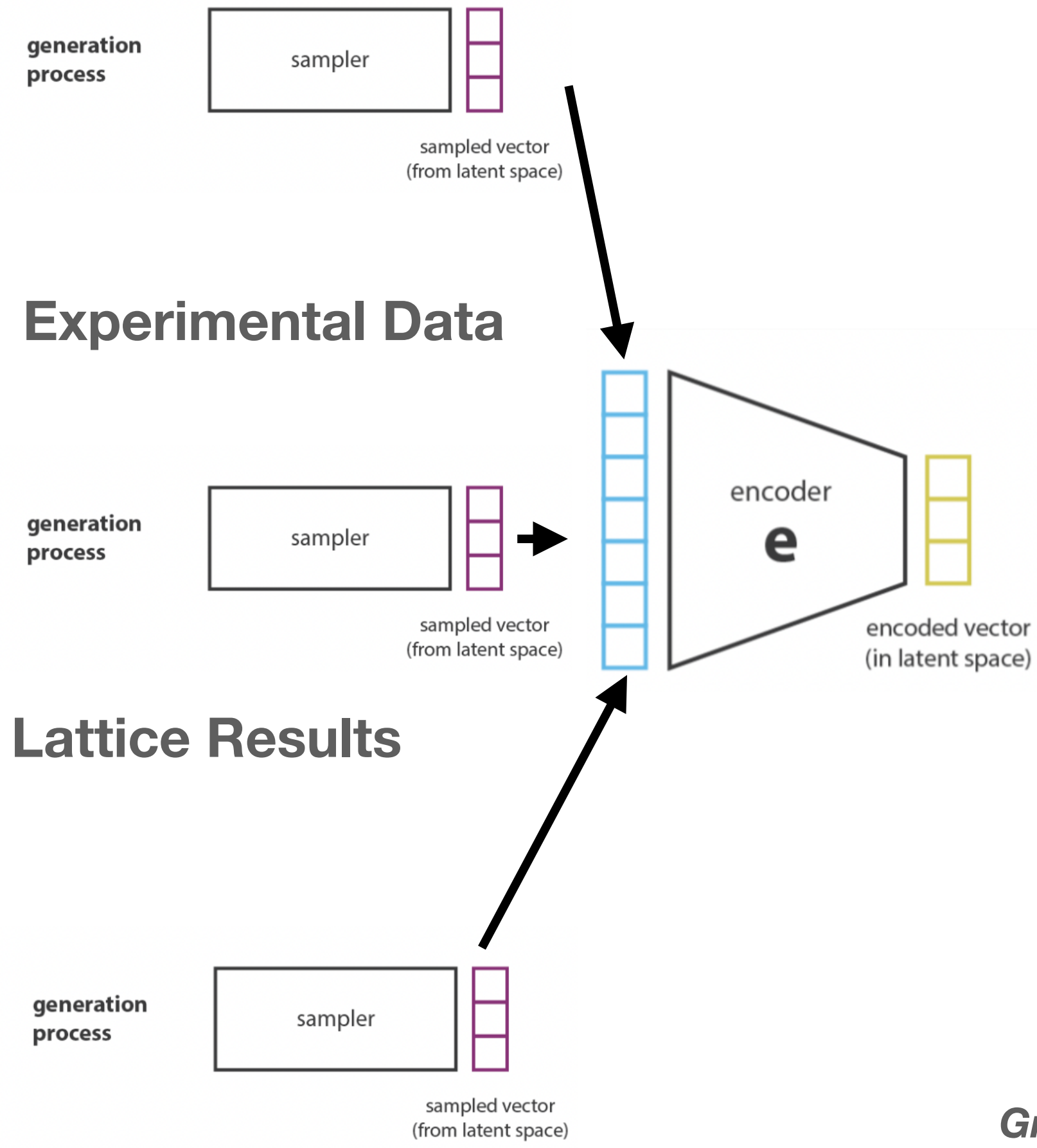
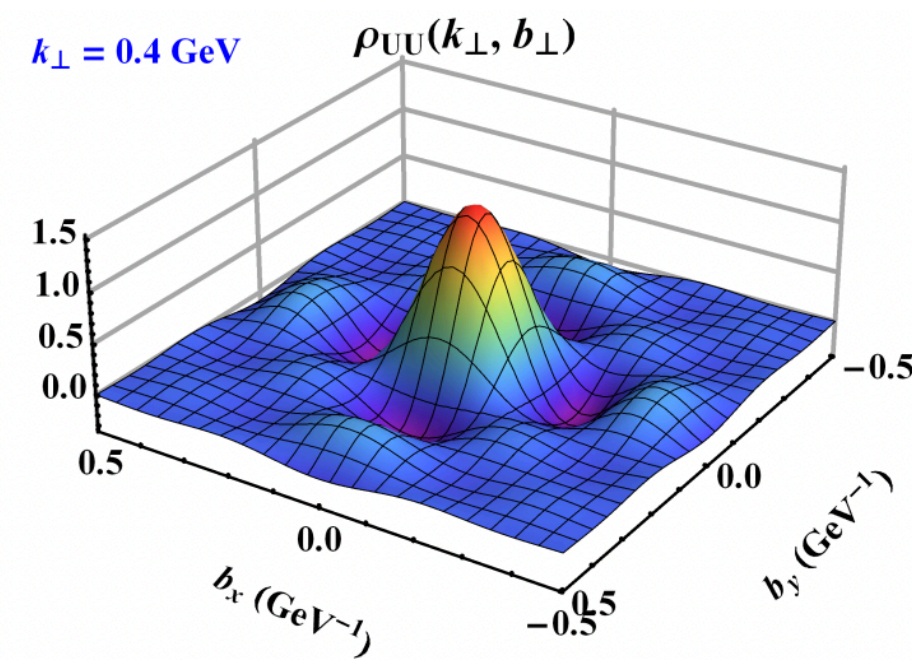
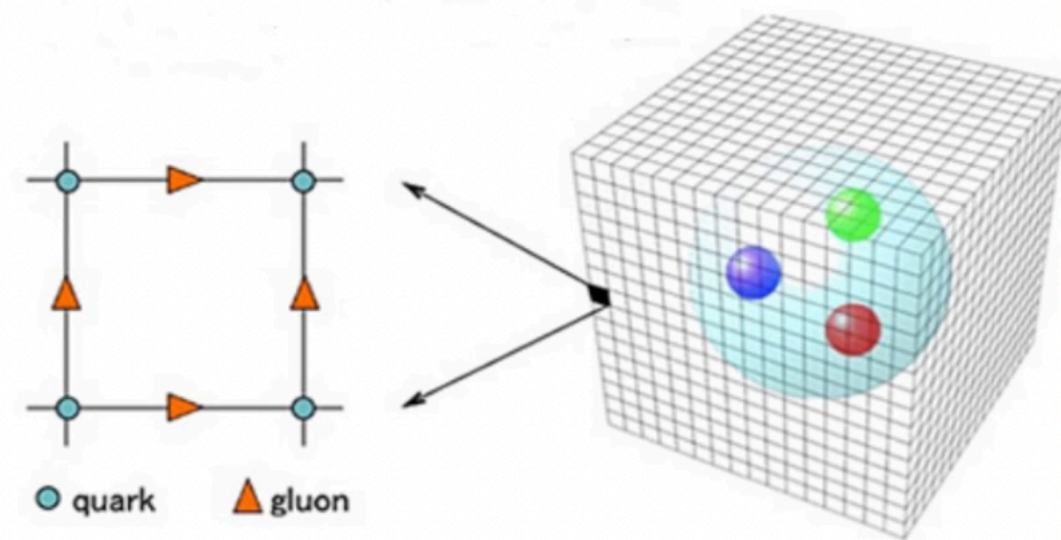
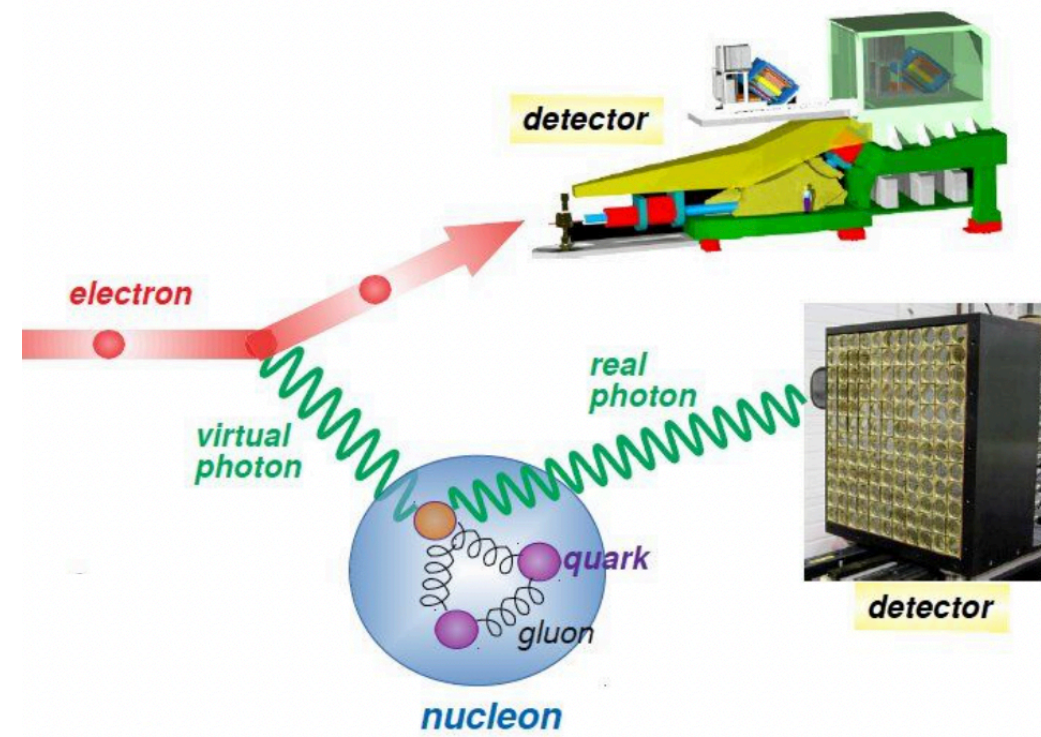
Incremental Reinforcement Learning



Explore the Feature Space

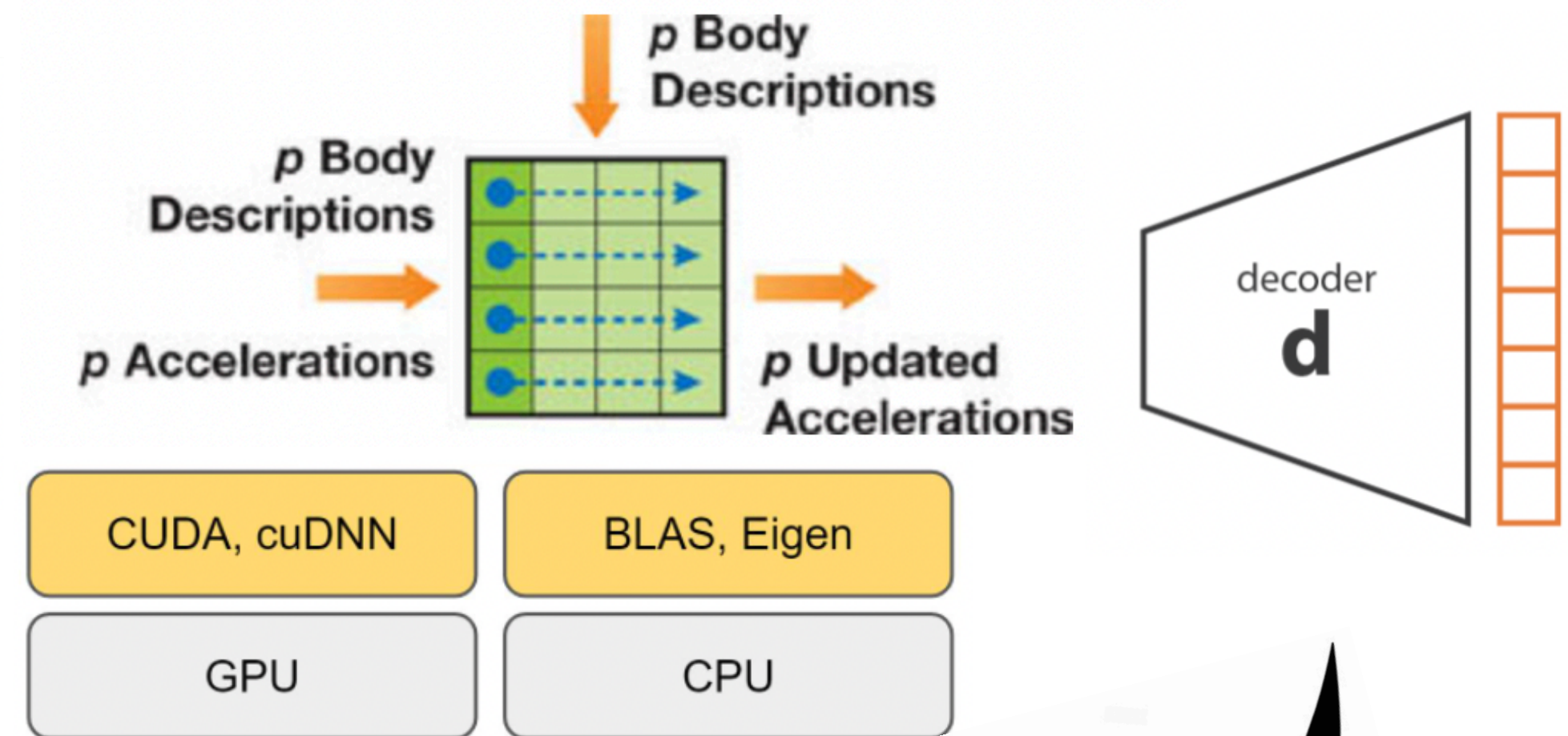
A Second Look at Multilayered Integration

- ANN Global Analysis
- Feed in Data, Constraints, Framework
- Run encoder to map to GPU n-body sims
- Output through decoder to map to observables and data visualization
- User results as training input to exploit latent space
- Front End Visualization Studio

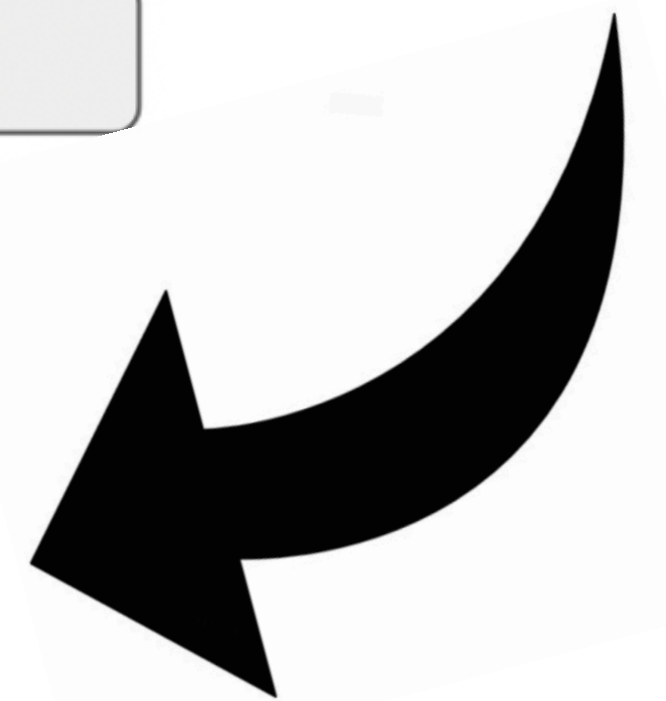


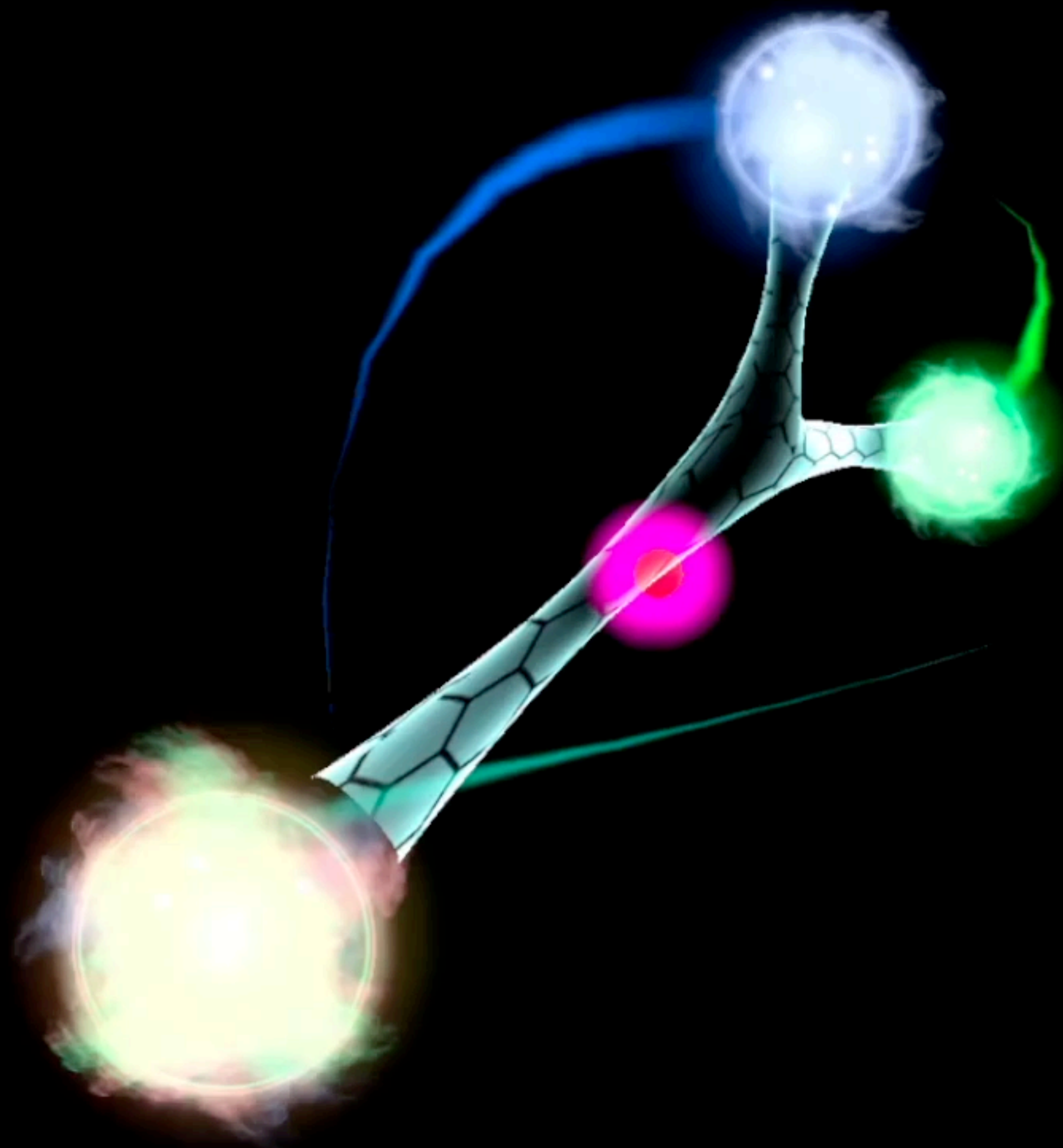
Phenomenological Framework

Piece-wise Autoencoder



Graduate Student **Samuel Liu**
Front End Visualization in Next Slide

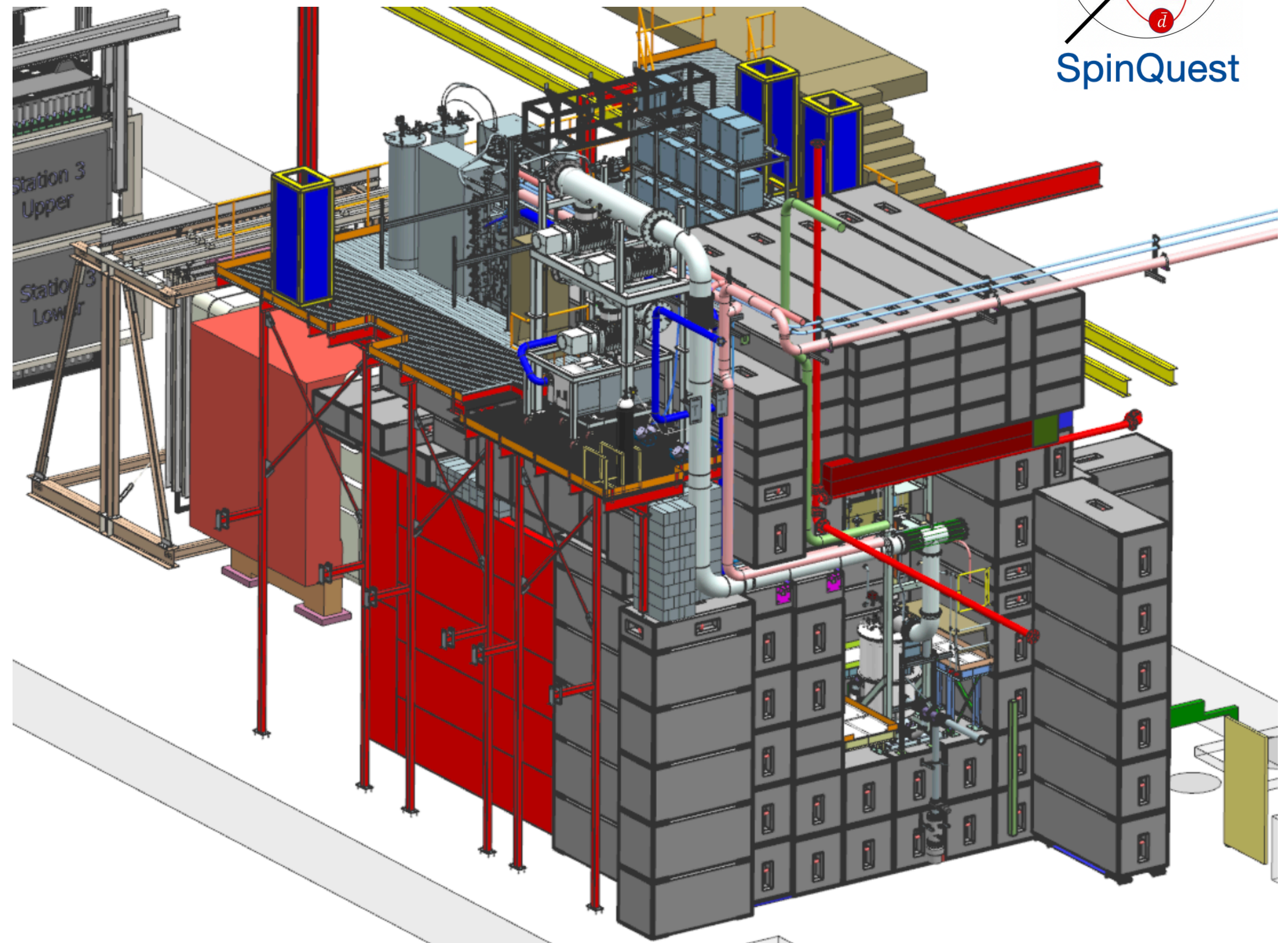
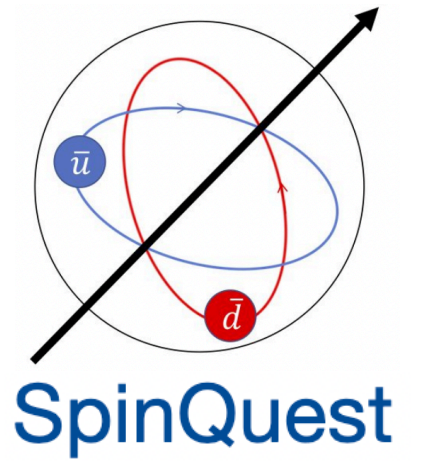




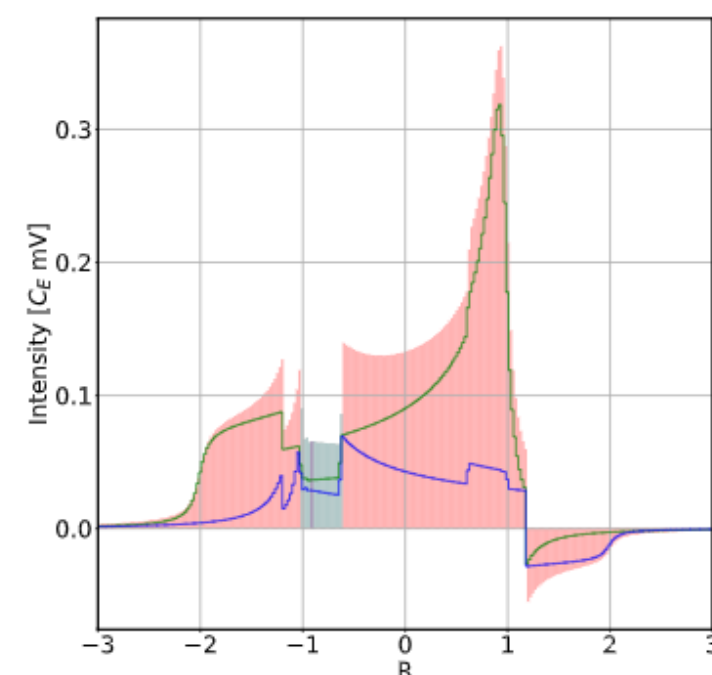
AI in Future Experiments

And the Future of Fermilab Spin

- 120 GeV proton beam
- $\sqrt{s} = 15.5$ GeV
- 1×10^{12} pro/sec for 4.4 sec/min



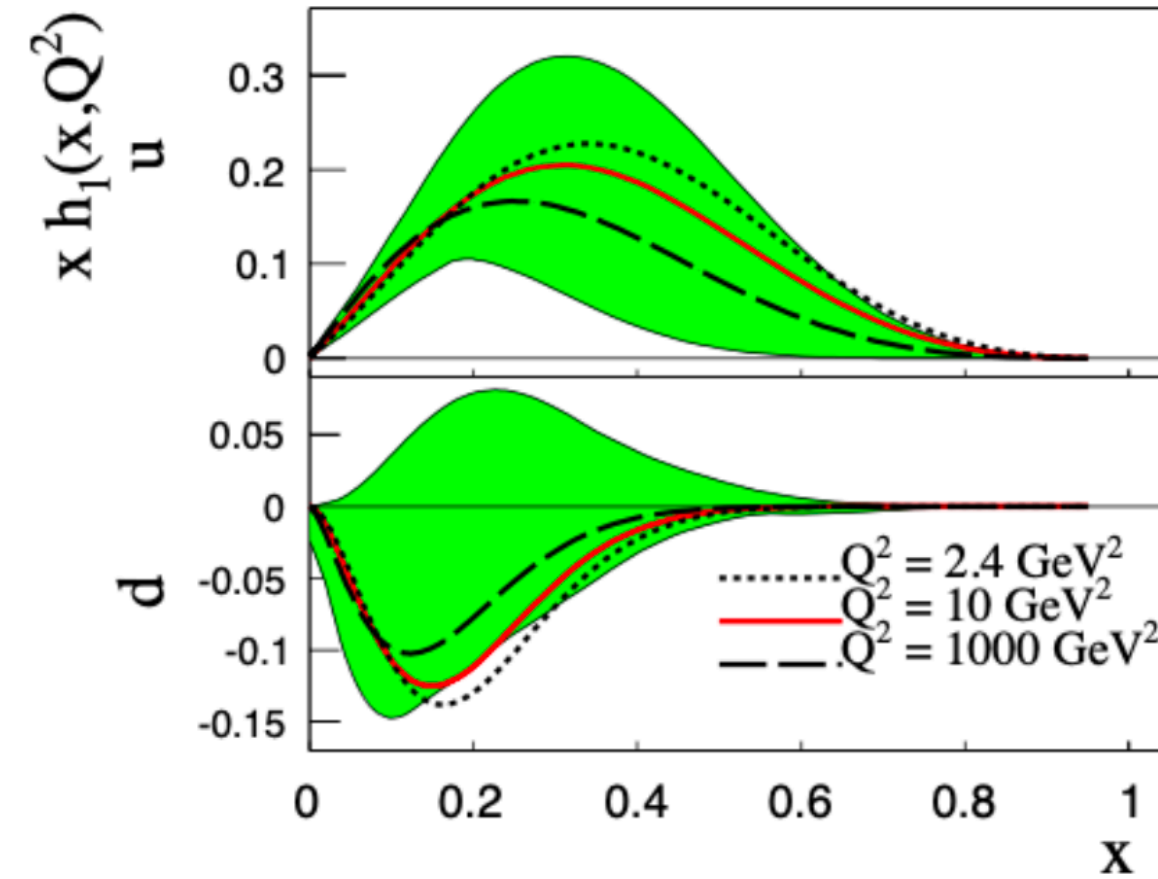
Applications in AI-NMR



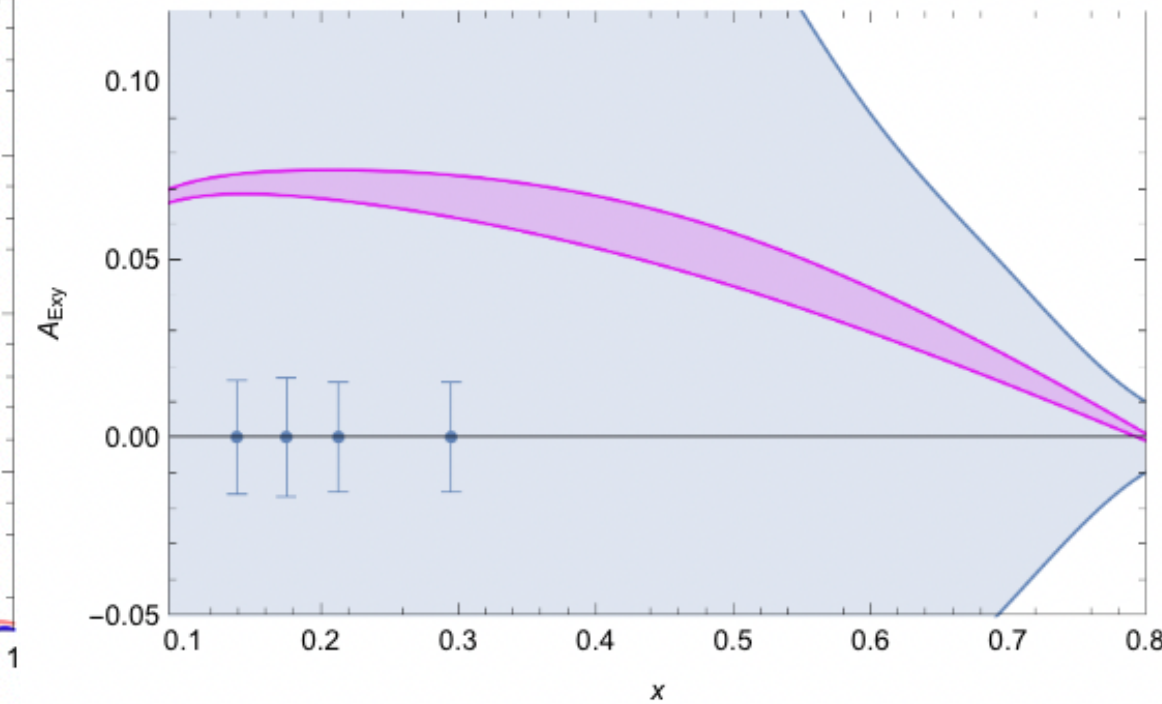
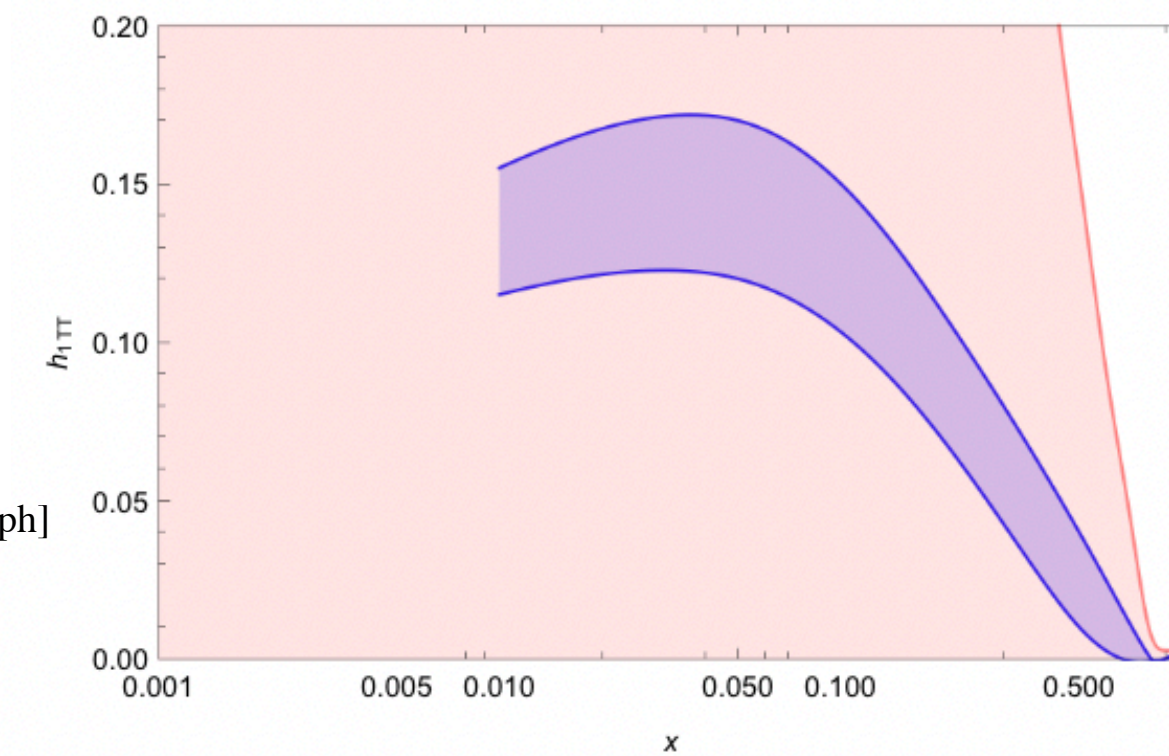
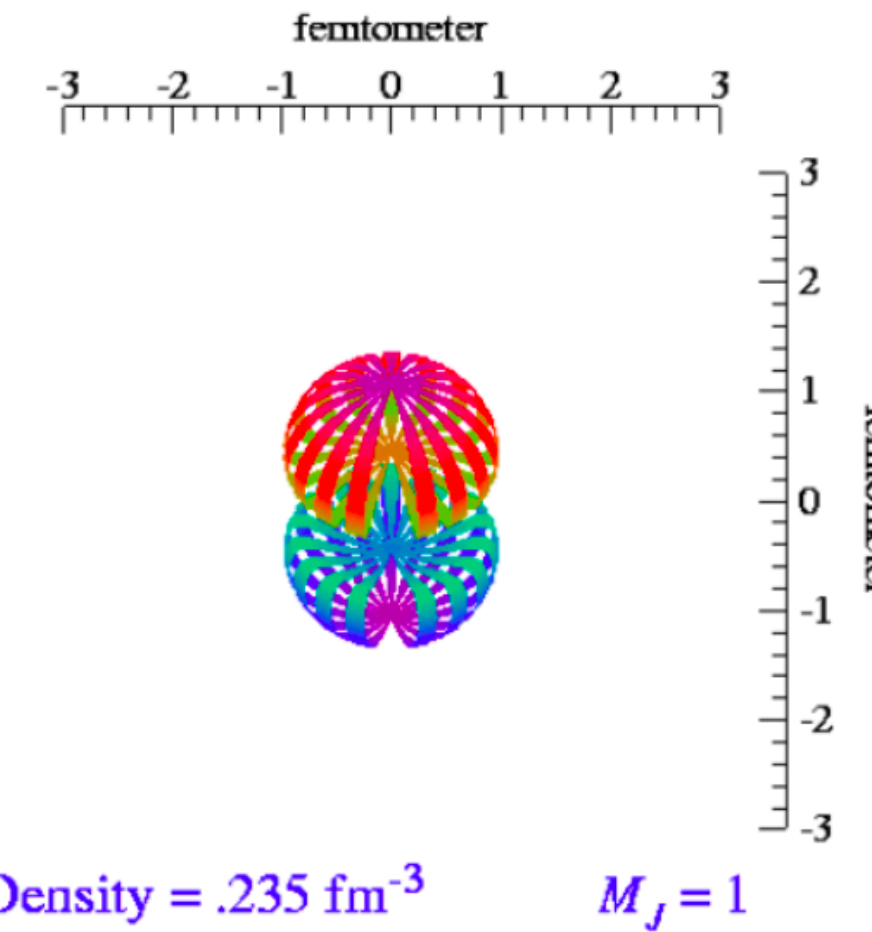
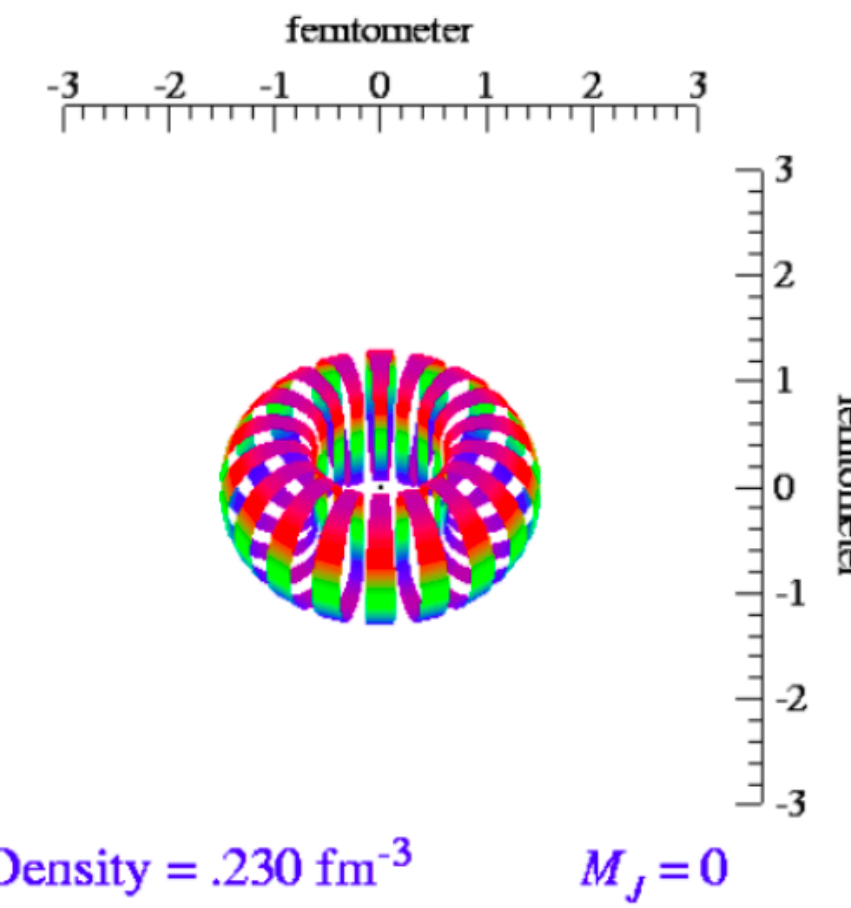
AI in Future Experiments

And the Future of Fermilab Spin

		quark operator		
		unpolarized [U]	longitudinal [L]	transverse [T]
target polarization	U	$f_1 = \odot$ unpolarized		$h_1^\perp = \odot - \ominus$ Boer-Mulders
	L		$g_1 = \odot \rightarrow \ominus \rightarrow$ helicity	$h_{1L}^\perp = \odot \rightarrow \ominus \rightarrow$ worm gear 1
	T	$f_{1T}^\perp = \odot - \ominus$ Sivers	$g_{1T} = \odot \rightarrow \ominus \rightarrow$ worm gear 2	$h_1 = \odot - \ominus$ transversity $h_{1T}^\perp = \odot \rightarrow \ominus \rightarrow$ pretzelosity
	TENSOR	$f_{1LL}(x, k_T^2)$ $f_{1LT}(x, k_T^2)$ $f_{1TT}(x, k_T^2)$	$g_{1TT}(x, k_T^2)$ $g_{1LT}(x, k_T^2)$	$h_{1LL}^\perp(x, k_T^2)$ h_{1TT}, h_{1TT}^\perp h_{1LT}, h_{1LT}^\perp

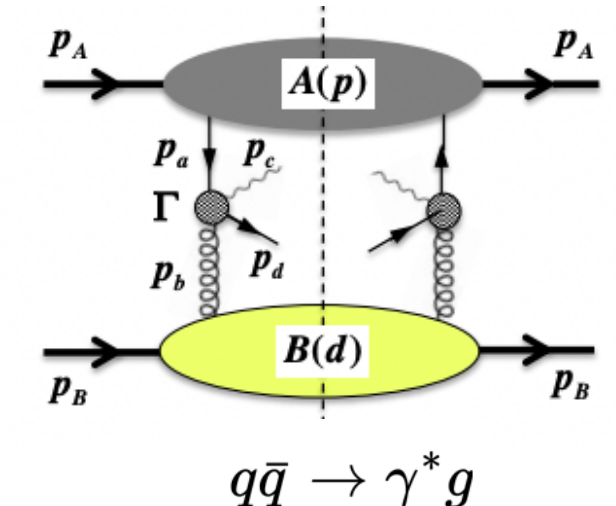
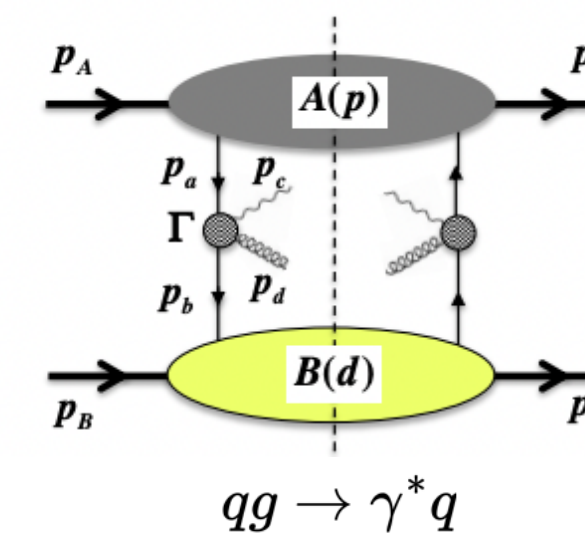
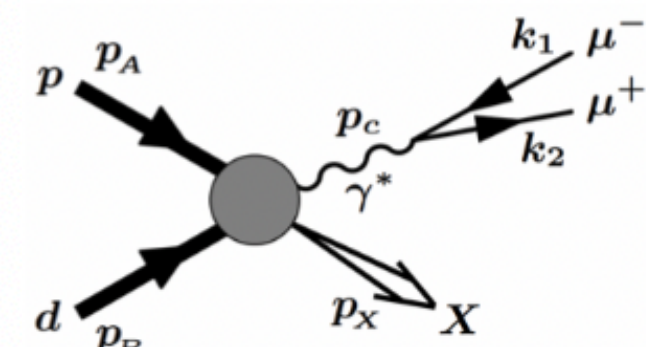
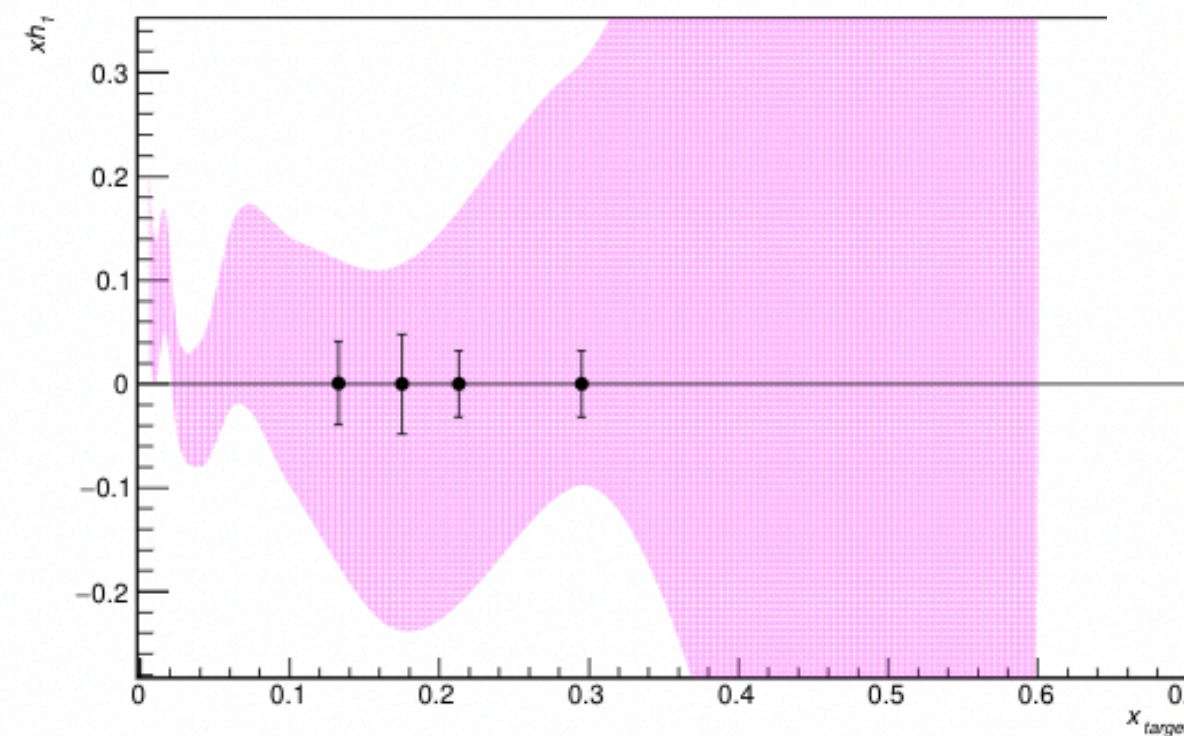


Zhong-Bo Kang, et al. JLAB-THY-15-2044, arXiv:1505.05589v1 [hep-ph]



Gluon Operator

		Unpolarized	Circular	Linear
Target Polarization	Vector Polarized			
	U	f_1		h_1^\perp
	L		g_1	h_{1L}^\perp
T	f_{1T}^\perp		g_{1T}	h_1, h_{1T}^\perp
Tensor Polarized	LL	f_{1LL}		h_{1LL}^\perp
	LT	f_{1LT}	g_{1LT}	h_{1LT}, h_{1LT}^\perp
	TT	f_{1TT}	g_{1TT}	h_{1TT}, h_{1TT}^\perp h_{1TT}^\perp



S. Kumano and Qin-Tao Song DIS2021

S. Kumano and Qin-Tao Song, Phys. Rev. D 101 (2020) 054011 & 094013.

AI in (Possible) Future Experiments

And the Future of Fermilab Spin

Transversely Polarized Target

- | | |
|--|--|
| • Tensor/Vector Polarized (ND3 Target) | <i>Quark/Gluon Transversity</i> |
| • Proton vs Deuteron (Mixed ND3-NH3) | <i>Spin Dependent Flavor Asymmetry</i> |
| • Li-7, F | <i>Polarized EMC Study</i> |
| • N14(spin-1), N15(spin-1/2) | <i>Nuclei TMDs and gluon structure</i> |

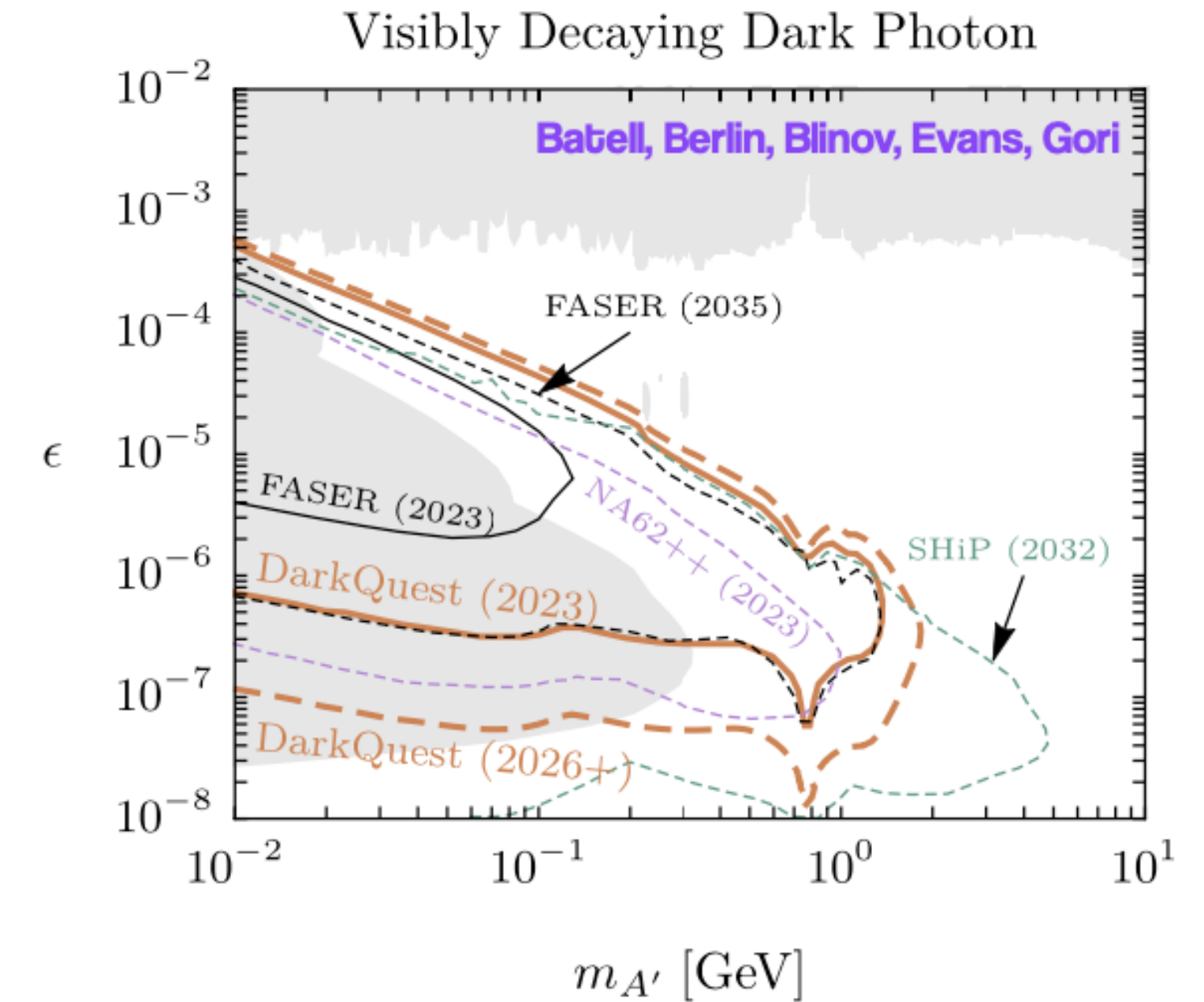
Longitudinally Polarized Target

- | | |
|--------------------------------------|--|
| • Polarized (NH3 Target) | <i>Helicity</i> |
| • Proton vs Deuteron (Mixed ND3-NH3) | <i>Spin Dependent Flavor Asymmetry</i> |
| • ND3 | <i>Tensor Pol SF</i> |

Dark Sector Physics at SpinQuest

A Unified Effort

- SpinQuest has unique potential for dark sector searches
 - Large dark sector production cross section, 120 GeV p beam
 - Geometry sensitive to unique lifetime baseline, covers open phase space
 - KMAG provides good momentum measurement for forward decays
 - EMCal upgrade opens up new final states distinct from muon backgrounds
- Wide array of signatures in electron, muon, photon, and pion final states
 - Testing many dark sector signatures: dark photon, SIMPs, inelastic DM, heavy neutrino, ALPs, g-2, etc.
 - New personpower joining SpinQuest collaboration to build this program!





Thank You

Thinking of Joining SpinQuest or Future Projects: (dustin@virginia.edu)

<https://spinqest.fnal.gov/>

<http://twist.phys.virginia.edu/E1039/>