AI4EIC

University of Regina

Sci Faculty of Science

Partial Wave Analysis on Neutral b_1 Meson at GlueX

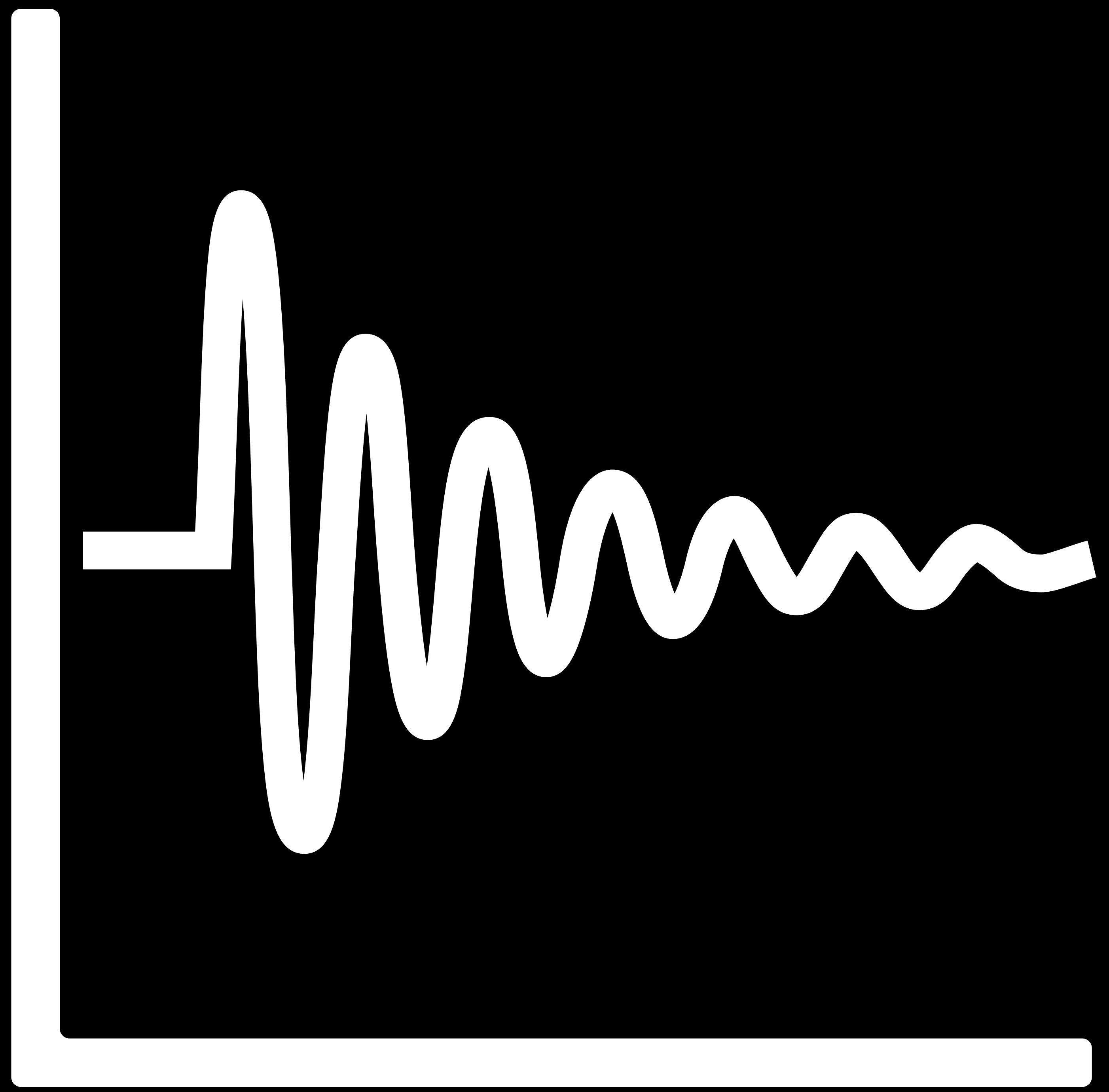
Searching for a needle in a haystack

GlueX

Karthik Suresh, JLab Thesis Prize Talk
11th June 2024

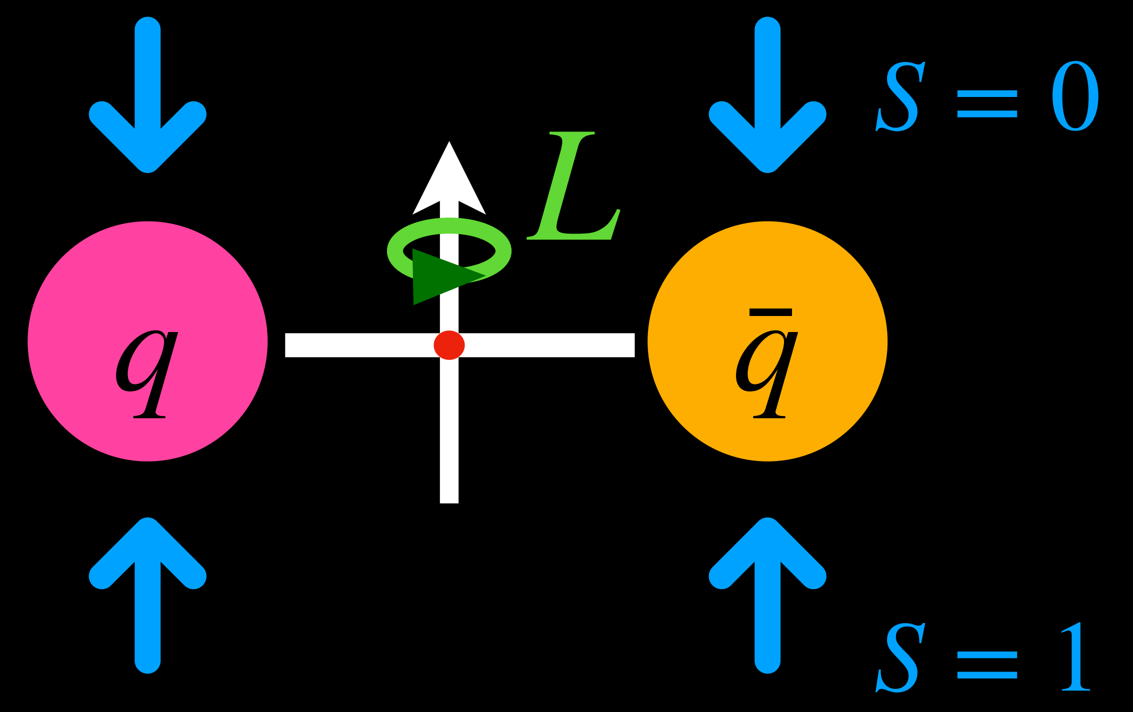
William & Mary
CHARTERED 1693

Table of Contents



Hadronic Spectrum

Periodic table of Mesons arranged by J^{PC} (I^G)

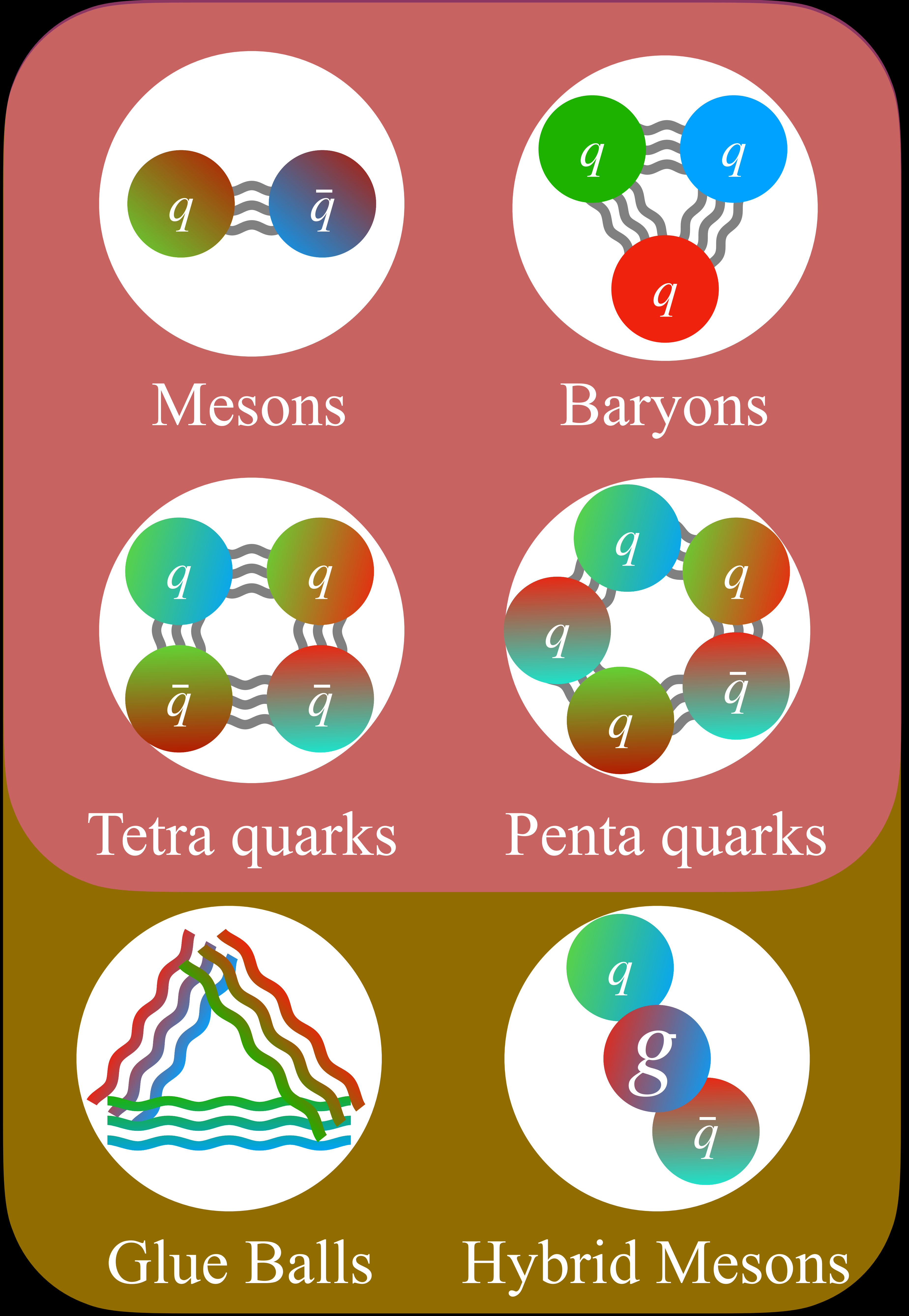


- Total Spin (J) from $|L - S|$ to $|L + S|$
- Parity (P) $= (-1)^{L+1}$
- Charge Conjugation (C) $= (-1)^{L+S}$

Quantum ChromoDynamics

- Include "gluonic" interactions to build up states
- Predicts
  - "Hybrid " mesons
  - "Exotic" States **NOT** allowed in Quark Model $J^{PC} = [0^{+\,-}, 1^{-\,+}, 2^{+\,-}, 3^{-\,+}]$

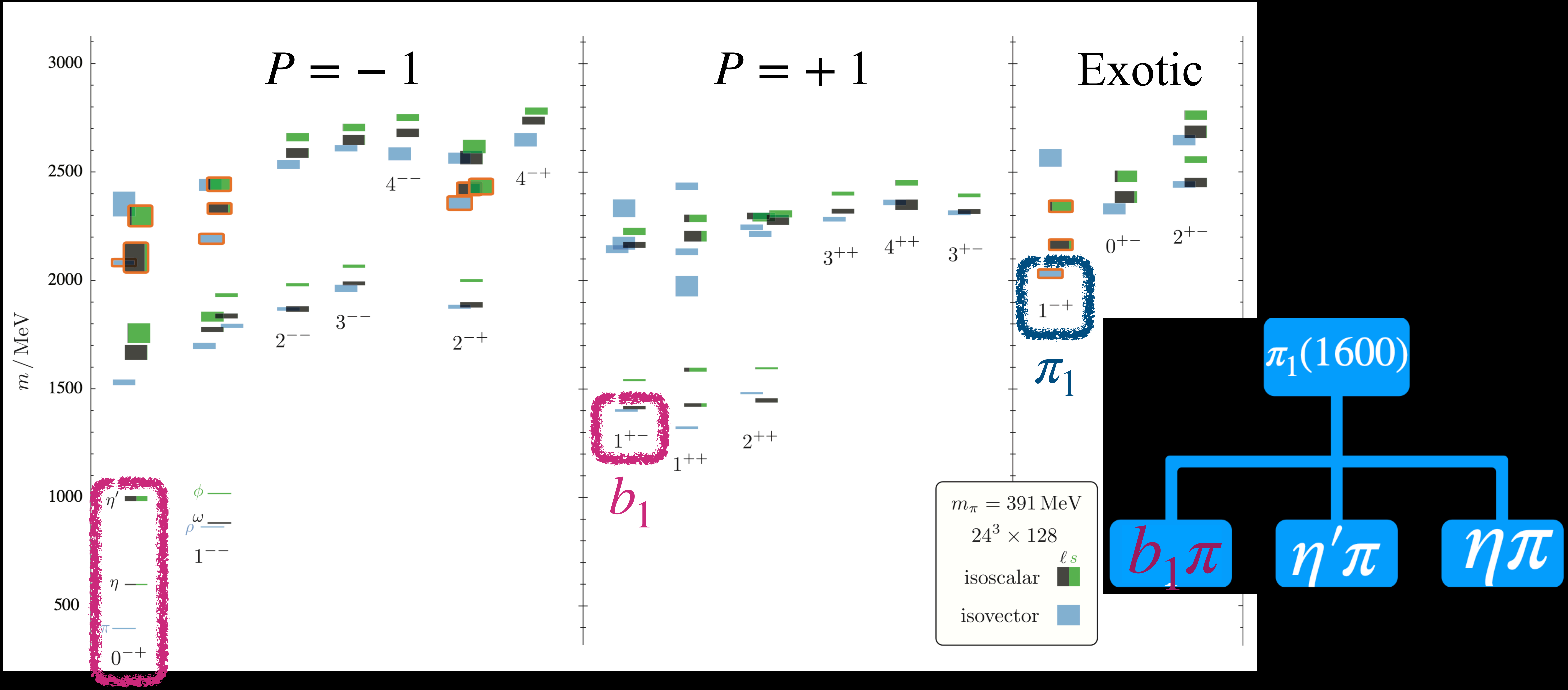
State $^{2s+1}l_J$	Name	S	L	Total Spin J^{PC}	$I = 0$	$I = 1$	$I = \frac{1}{2}$
$^1S_0$	Pseudo Scalar	0	0	0^{-+}	$\eta, \eta^{'}$	π	K
$^3S_1$	Vector	1	0	1^{--}	ω, ϕ	ρ	K^*
$^1P_1$	Axial Vector	0	1	1^{+-}	$h_1, h_1^{'}$	b_1	K_1
$^3P_0$	Scalar	1	1	0^{++}	$f_0, f_0^{'}$	a_0	K_1^*
$^3P_1$	Axial Vector	1	1	1^{++}	$f_1, f_1^{'}$	a_1	K_1
$^3P_2$	Tensor	1	1	2^{++}	$f_2, f_2^{'}$	a_2	K_2^*



Light Meson Spectrum in LQCD

The Exotic $\pi_1(1600)$ and its decay to $b_1\pi$

Jozef J. Dudek, et al. HadronSpectrum Collaboration
Phys. Rev. D 88, 094505



$\pi_1(1600)$

$b_1\pi$

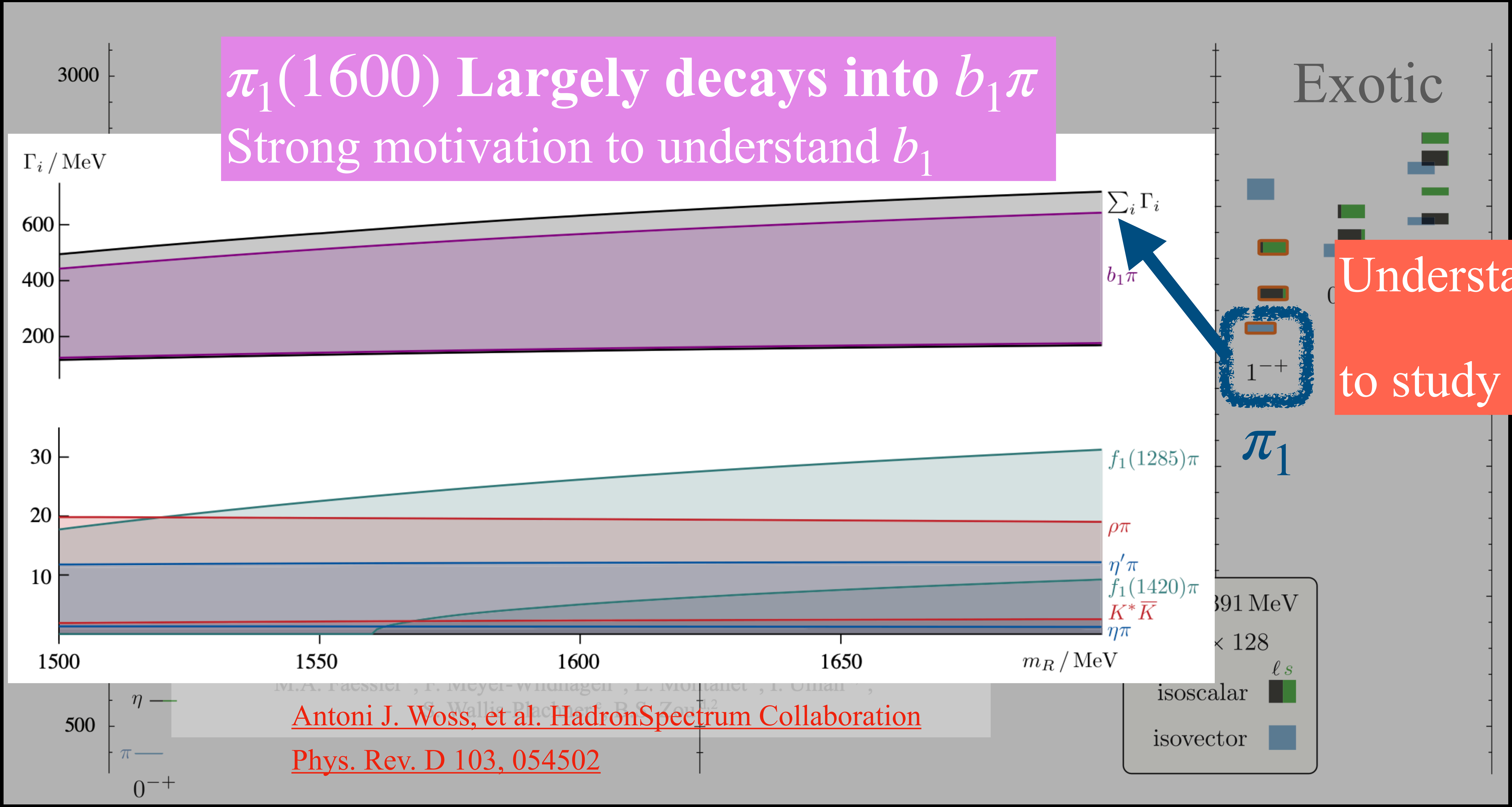
$\eta'\pi$

$\eta\pi$

Prediction of lightest Exotic decay

The Exotic $\pi_1(1600)$ and its decay to $b_1\pi$

Jozef J. Dudek, et al. HadronSpectrum Collaboration
Phys. Rev. D 88, 094505

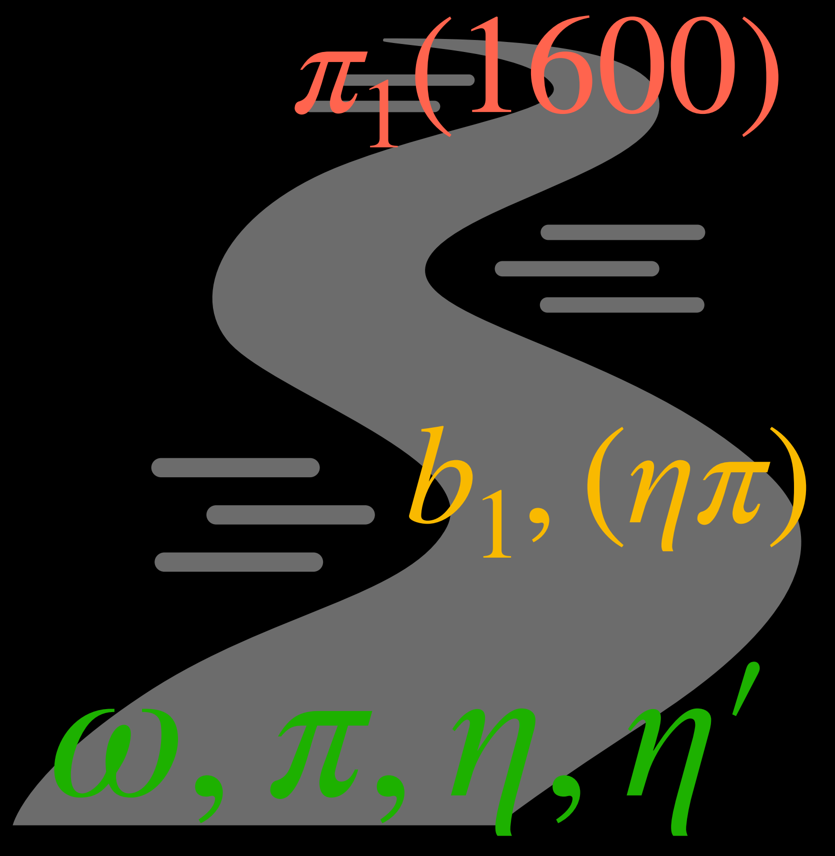


$\pi_1(1600)$ Largely decays into $b_1\pi$
Strong motivation to understand b_1

Understanding b_1 important

to study the $\pi_1(1600)$ Exotic

Antoni J. Woss, et al. HadronSpectrum Collaboration
Phys. Rev. D 103, 054502

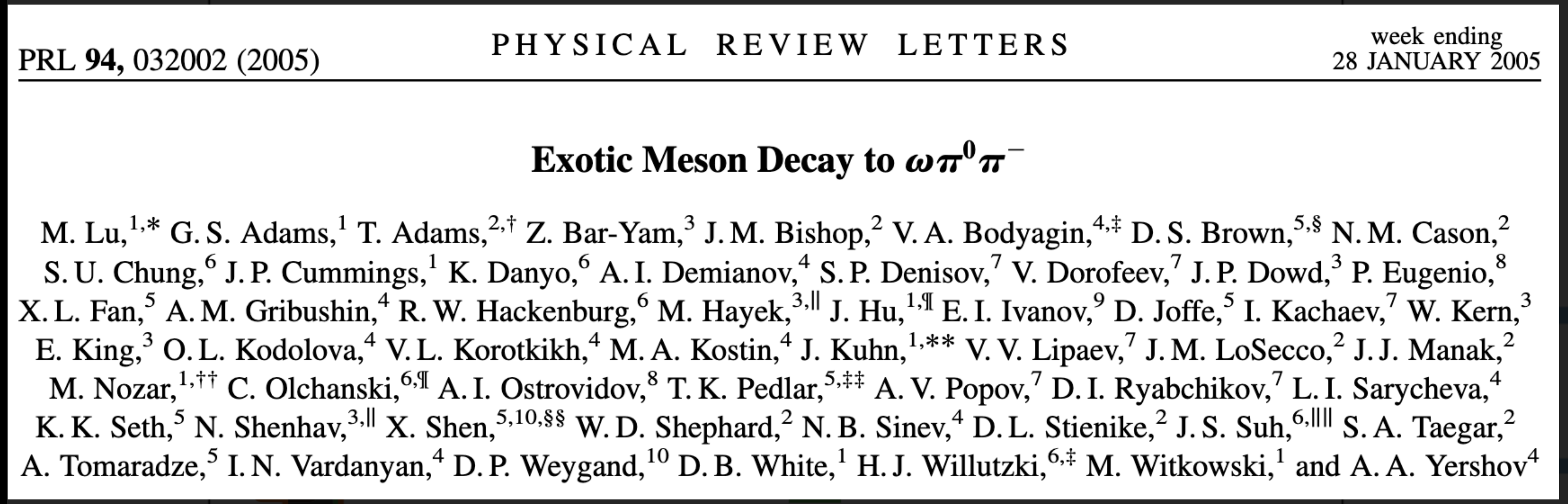


The Standard Model of Physics

Check out Talk from William Imoehl

Jozef J. Dudek, et al. HadronSpectrum Collaboration
Phys. Rev. D 88, 094505

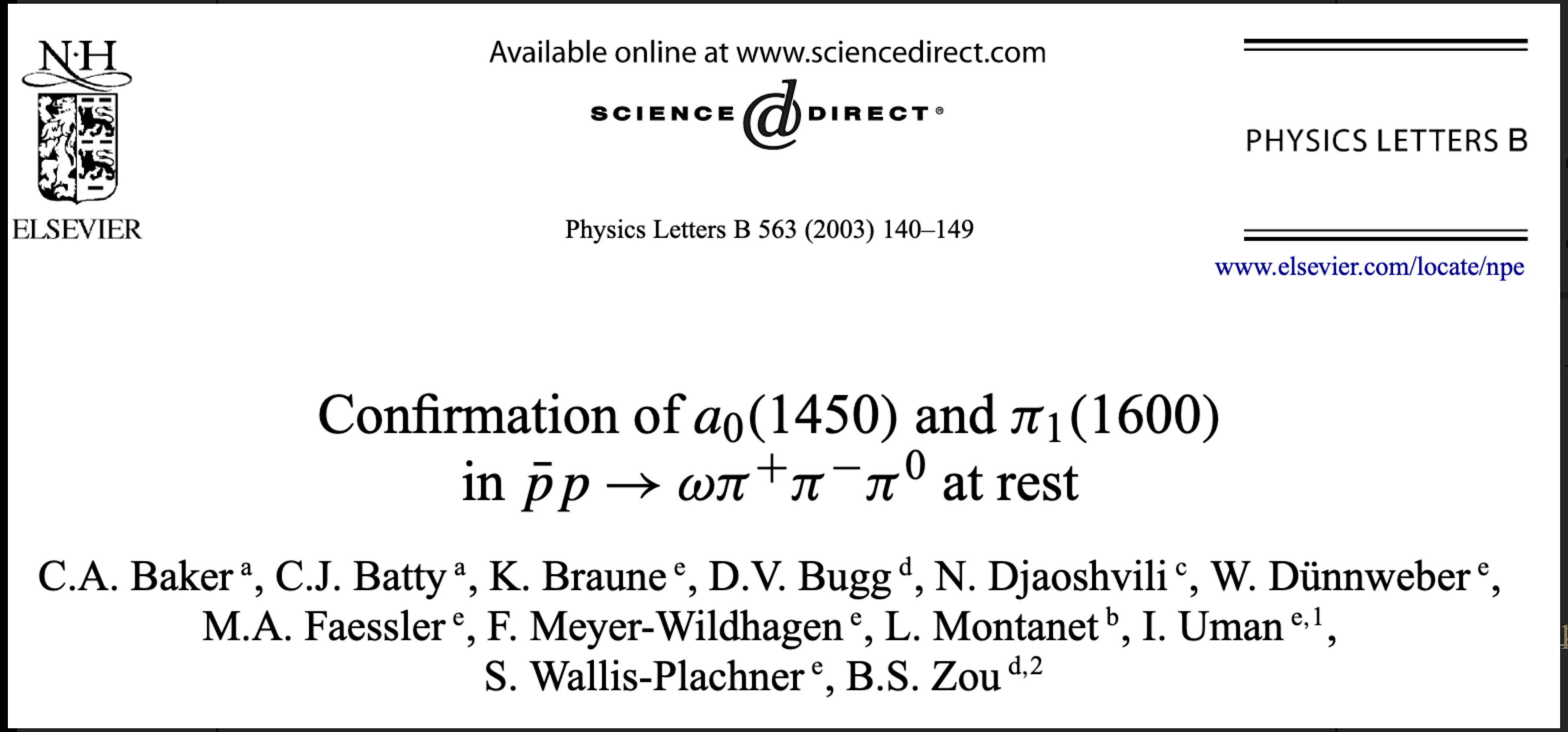
scant experimental evidence for $b_1\pi$……



PRL **94,** 032002 (2005) PHYSICAL REVIEW LETTERS week ending 28 JANUARY 2005

Exotic Meson Decay to $\omega\pi^0\pi^-$

M. Lu,[1,*] G. S. Adams,[1] T. Adams,[2,†] Z. Bar-Yam,[3] J. M. Bishop,[2] V. A. Bodyagin,[4,‡] D. S. Brown,[5,§] N. M. Cason,[2] S. U. Chung,[6] J. P. Cummings,[1] K. Danyo,[6] A. I. Demianov,[4] S. P. Denisov,[7] V. Dorofeev,[7] J. P. Dowd,[3] P. Eugenio,[8] X. L. Fan,[5] A. M. Gribushin,[4] R. W. Hackenburg,[6] M. Hayek,[3,∥] J. Hu,[1,¶] E. I. Ivanov,[9] D. Joffe,[5] I. Kachaev,[7] W. Kern,[3] E. King,[3] O. L. Kodolova,[4] V. L. Korotkikh,[4] M. A. Kostin,[4] J. Kuhn,[1,**] V. V. Lipaev,[7] J. M. LoSecco,[2] J. J. Manak,[2] M. Nozar,[1,††] C. Olchanski,[6,¶] A. I. Ostrovidov,[8] T. K. Pedlar,[5,‡‡] A. V. Popov,[7] D. I. Ryabchikov,[7] L. I. Sarycheva,[4] K. K. Seth,[5] N. Shenhav,[3,∥] X. Shen,[5,10,§§] W. D. Shephard,[2] N. B. Sinev,[4] D. L. Stienike,[2] J. S. Suh,[6,∥∥] S. A. Taegar,[2] A. Tomaradze,[5] I. N. Vardanyan,[4] D. P. Weygand,[10] D. B. White,[1] H. J. Willutzki,[6,‡] M. Witkowski,[1] and A. A. Yershov[4]



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Physics Letters B 563 (2003) 140–149

www.elsevier.com/locate/npe

Confirmation of $a_0(1450)$ and $\pi_1(1600)$ in $\bar{p}p \to \omega\pi^+\pi^-\pi^0$ at rest

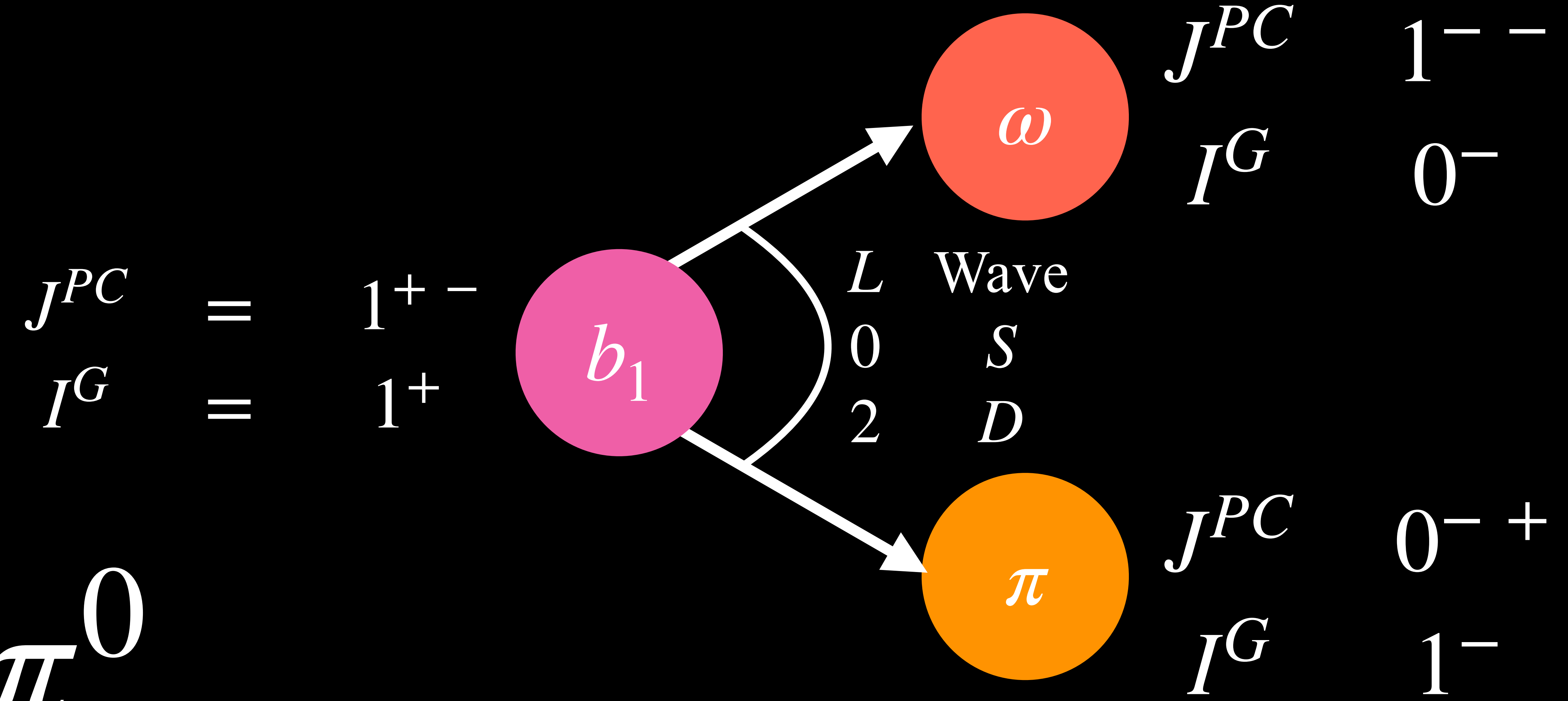
C.A. Baker[a], C.J. Batty[a], K. Braune[e], D.V. Bugg[d], N. Djaoshvili[c], W. Dünnweber[e], M.A. Faessler[e], F. Meyer-Wildhagen[e], L. Montanet[b], I. Uman[e,1], S. Wallis-Plachner[e], B.S. Zou[d,2]

- Previous efforts on decays to pseudo scalars like $\pi_1(1600) \to \eta^{(\prime)}\pi$
  - Simpler reconstruction — narrow resonances
  - Any odd L states — evidence of exotic
- $b_1\pi$ has larger end state multiplicity
- Very limited statistics until now
- Increased ambiguities of J^{PC} states

$b_1\pi$ challenging but high branching fraction — advantageous

b_1 meson

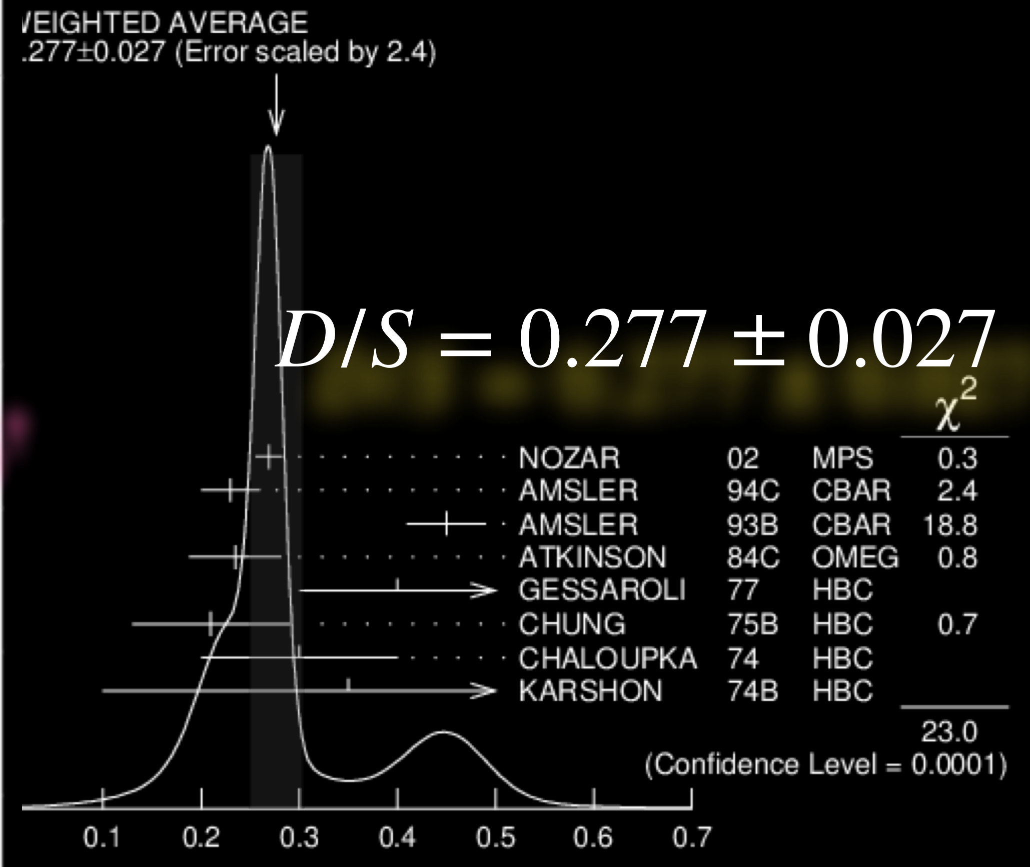
The Axial Vector



This talk's focus

$$b_1^0 \to \omega\pi^0$$

$b_1(1235)$	$I^G(J^{PC}) = 1^+(1^{+-})$
Mass	$1229.5 \pm 3.2 MeV$
Width	$142 \pm 9 MeV$
D/S Amplitude Ratio ($b_1(1235) \to \omega\pi$)	0.277 ± 0.027 $(0.27 \pm 0.2)^\dagger$
D/S Amplitude Phase Difference	$10 \pm 5°$
Dominant Decay Mode	$\omega\pi$
Other Decay Modes	$\pi^\pm\gamma$, $\eta\rho$, $K^{*\pm}K^\mp$, $KK\pi^0$, $\phi\pi$



$D/S = 0.277 \pm 0.027$

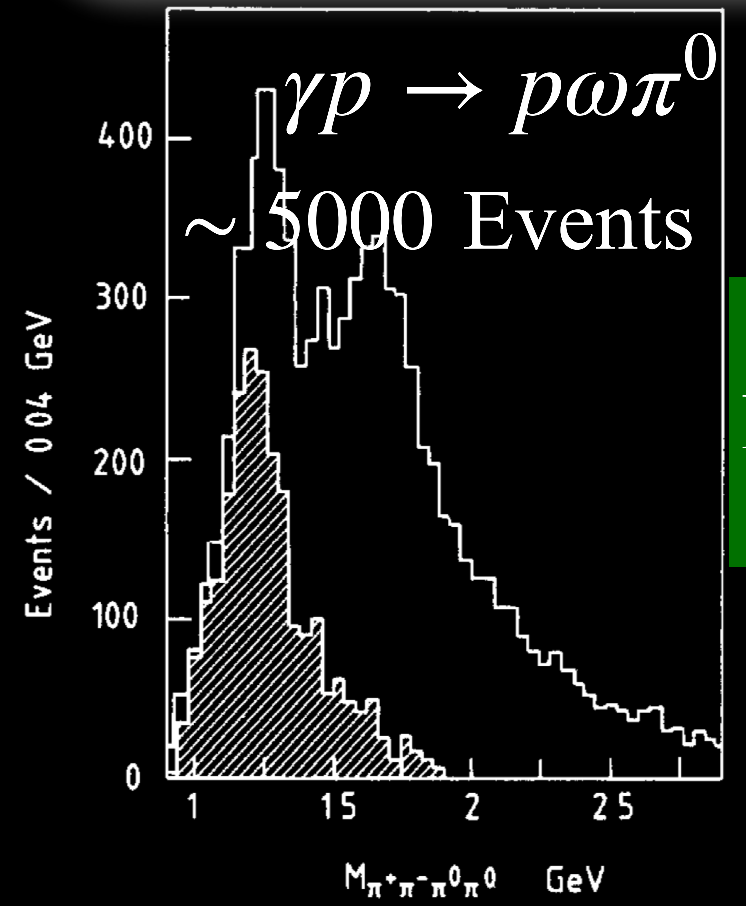
Particle Data Group Review of Particle Physics, Volume 2022, Issue 8, August 2022, 083C01.

[†] Phys.Rev.D 100 (2019) 5, 054506

Timeline of $\omega\pi$ studies*: with focus on b_1

1984

Spin Parity Analysis
Omega Photon Collaboration



$\gamma p \rightarrow p\omega\pi^0$

~ 5000 Events

10.1016/0550-3213(84)90382-1

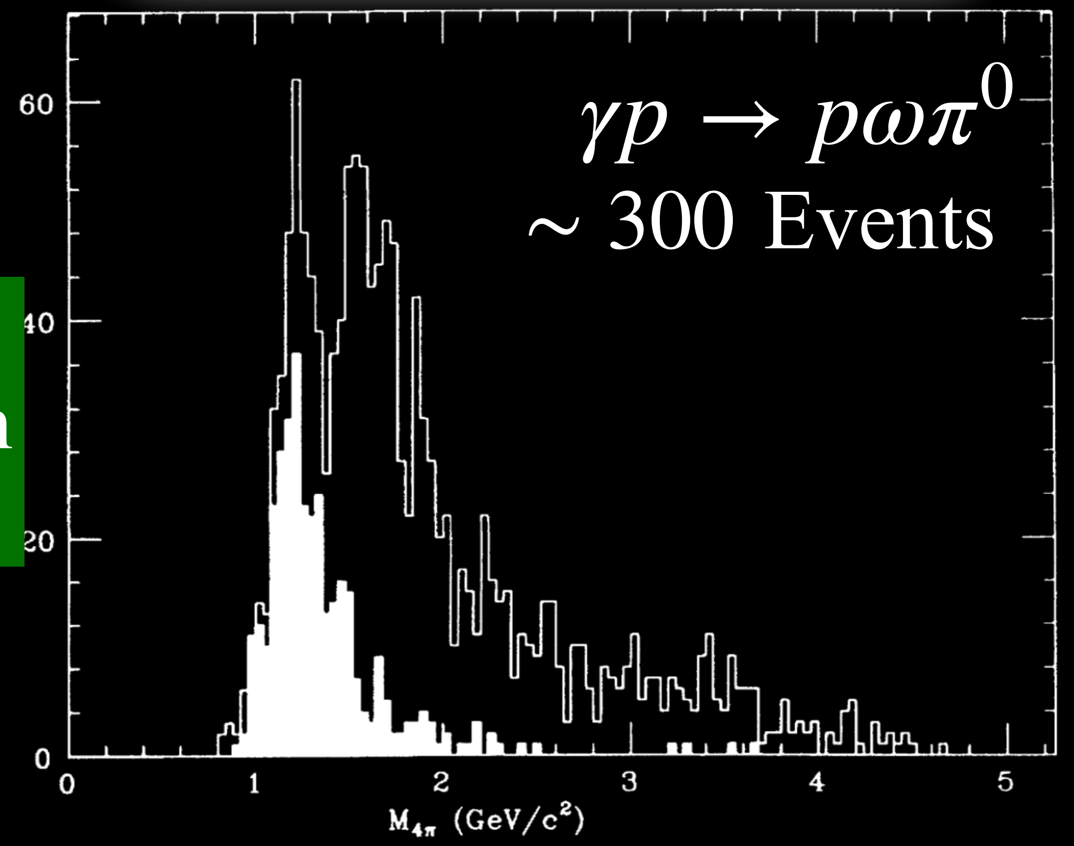
1987

Diffractive Photoproduction of
$b_1\pi$ Omega Photon Collaboration

Only known Photoproduction Experiments

1988

Production and decay of b_1
SLAC S.H.F.P Collaboration



$\gamma p \rightarrow p\omega\pi^0$

~ 300 Events

J.E Brau et al. Phys. Rev. D 37, 2379

1991

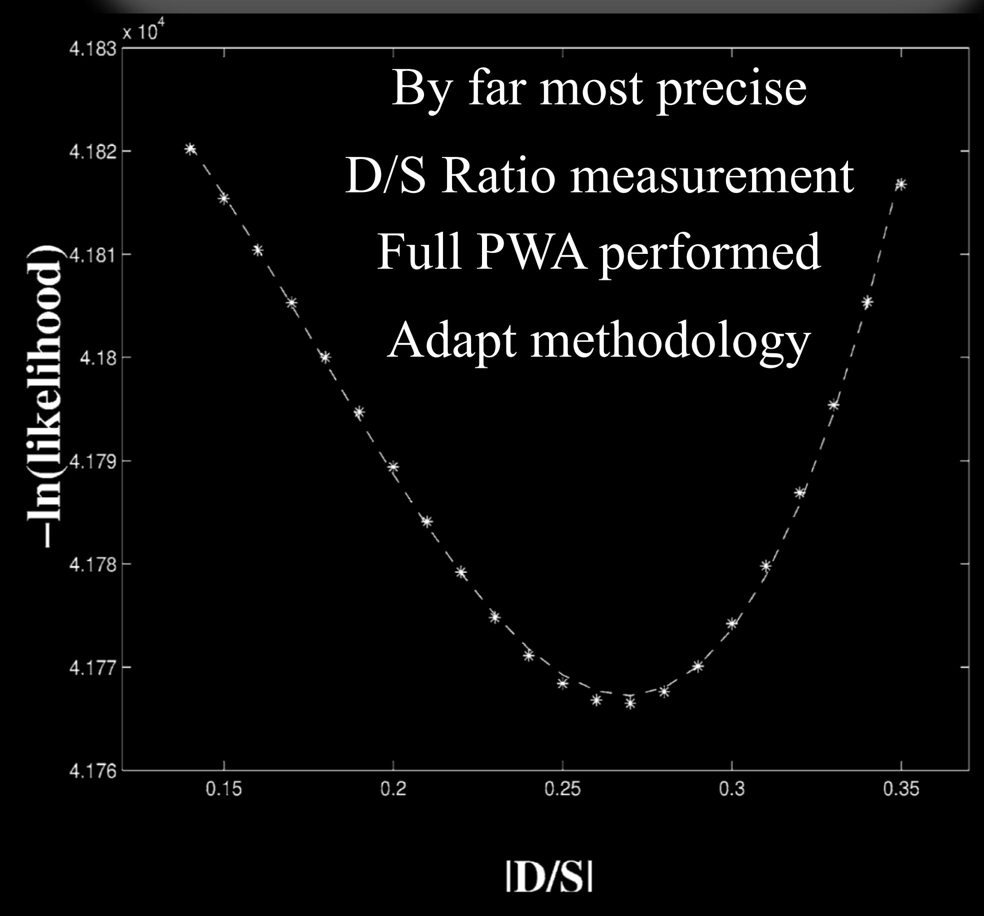
$\pi^- p \rightarrow \omega\pi^0 n$
BENKEI, KEK

1993

$\bar{p}p$ at rest to $\omega\pi^0\pi^0$
Crystal Barrel Collaboration

2002

$\pi^- p \rightarrow \omega\pi^-$ using MPS
E852 Collaboration



By far most precise
D/S Ratio measurement
Full PWA performed
Adapt methodology

10.1016/S0370-2693(02)02194-9

2017

GLUEX

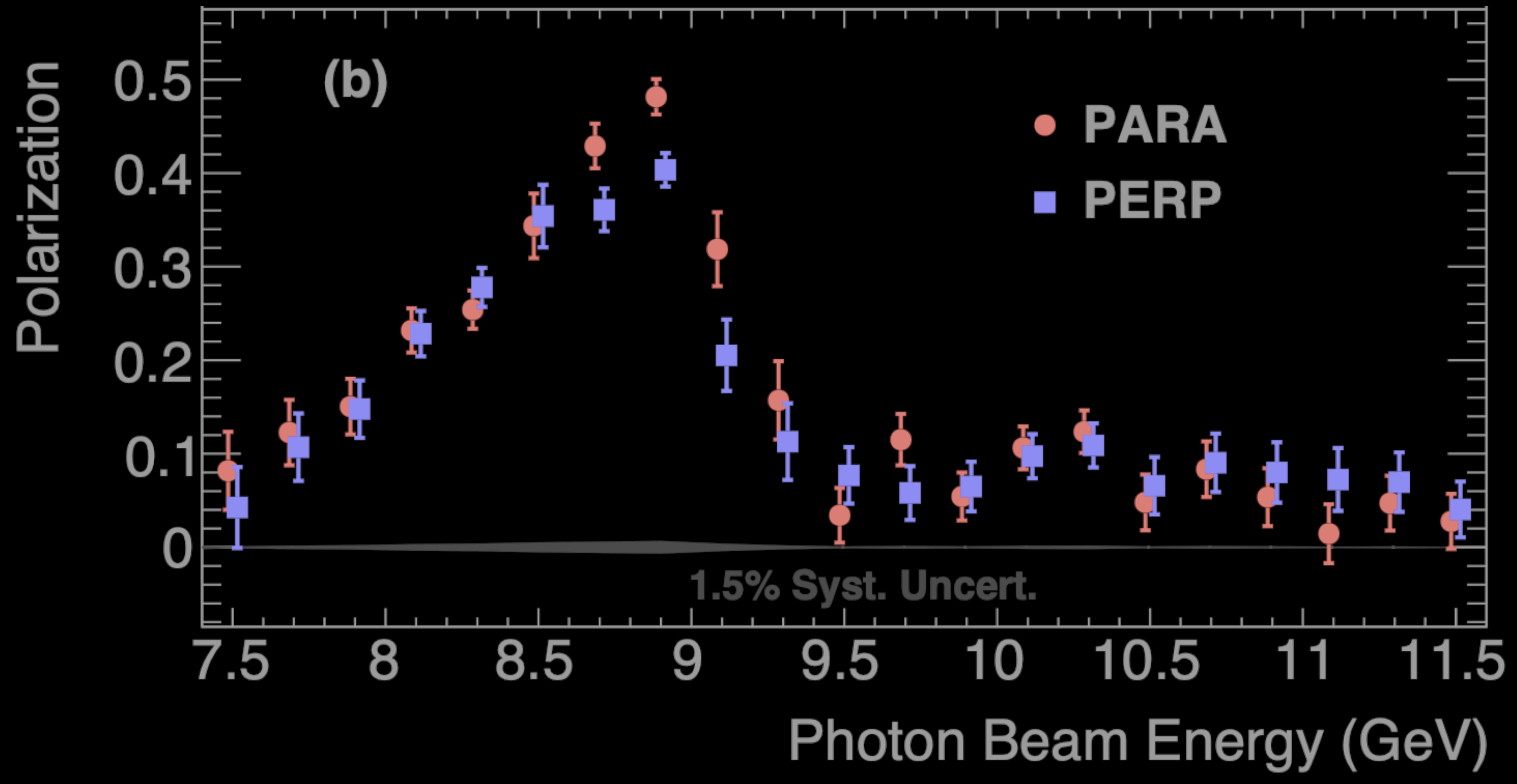
2019

Significant LQCD predictions from theory…..

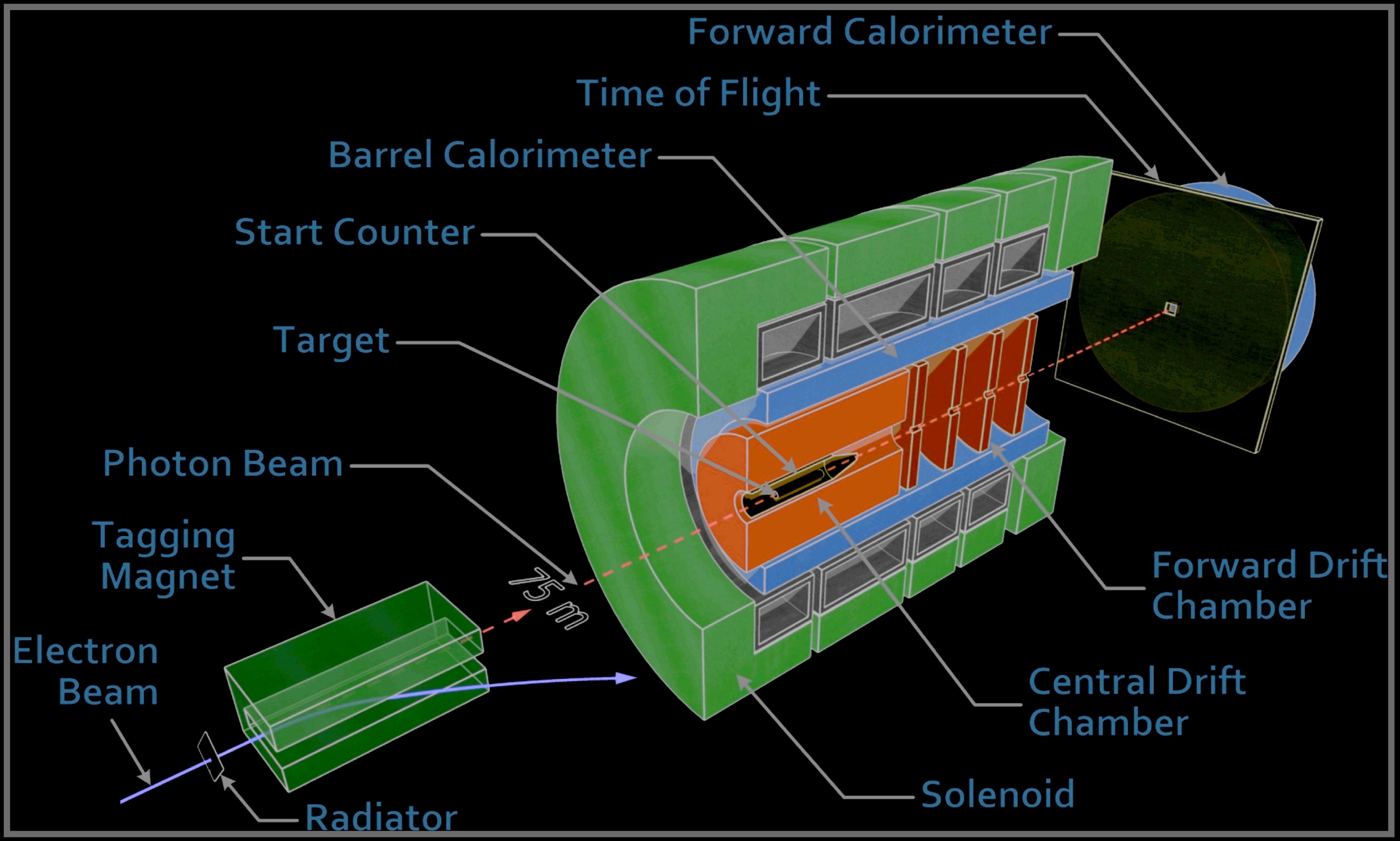
Now

*Selected experiments/studies that has the most impact for this dissertation

The Experiment



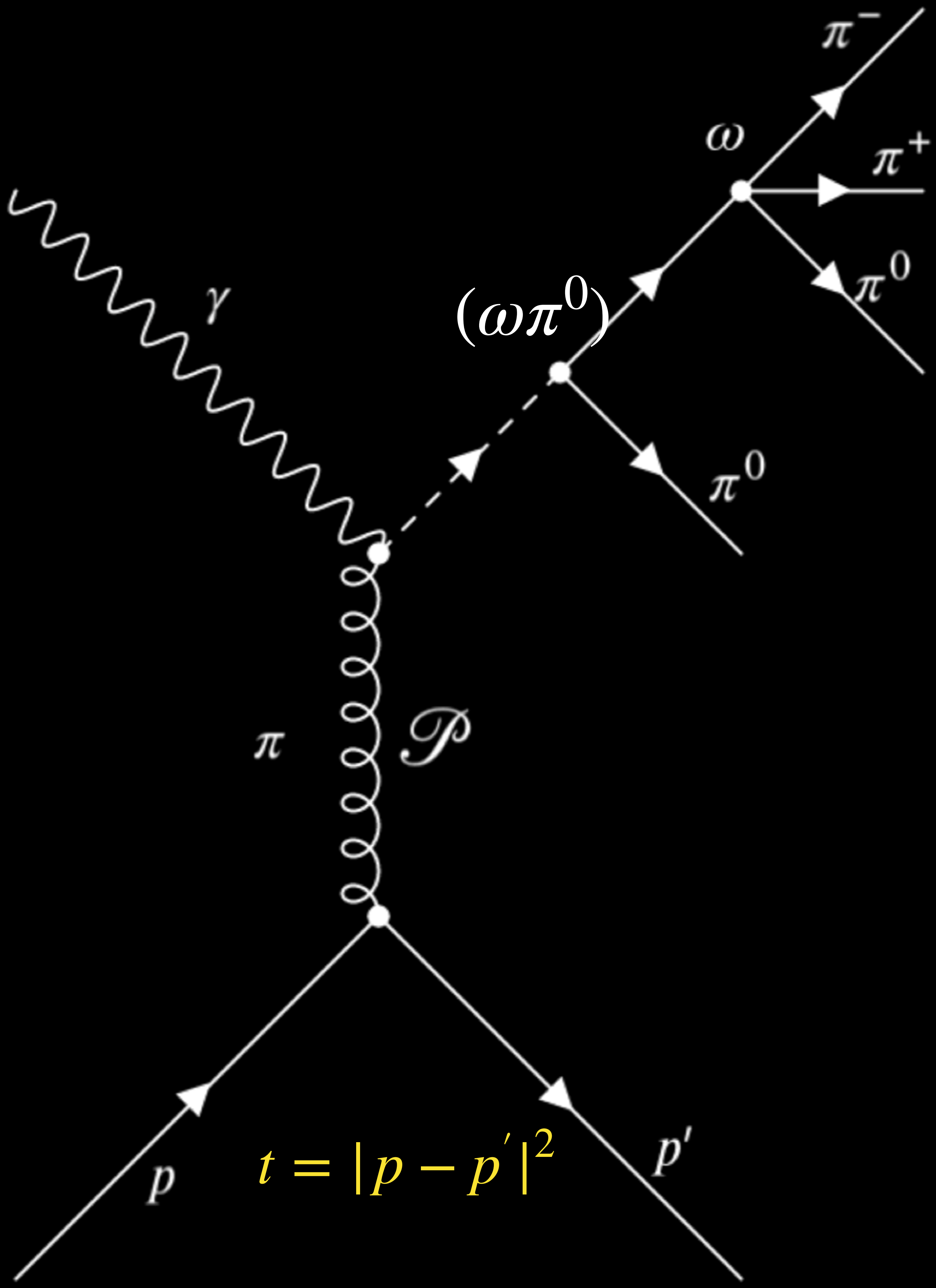
- Polarized photons through coherent bremsstrahlung
- Peak Polarization $\sim 35\ \%$ @ 8.8 GeV



- Photo-production experiment @ Jlab
- Goal : Map light meson spectrum
- Nearly 4π detection using hermetic setup
- Phase-I Data ($\sim 120\text{pb}^{-1}$)

Photoproduction of $\omega\pi^0$ at GlueX

$$\gamma p \to \omega\pi^0 p \to (\pi^+\pi^-\pi^0)\pi^0 p$$



Selection Cuts

"Hard" Cut Selection

Particle Hypothesis

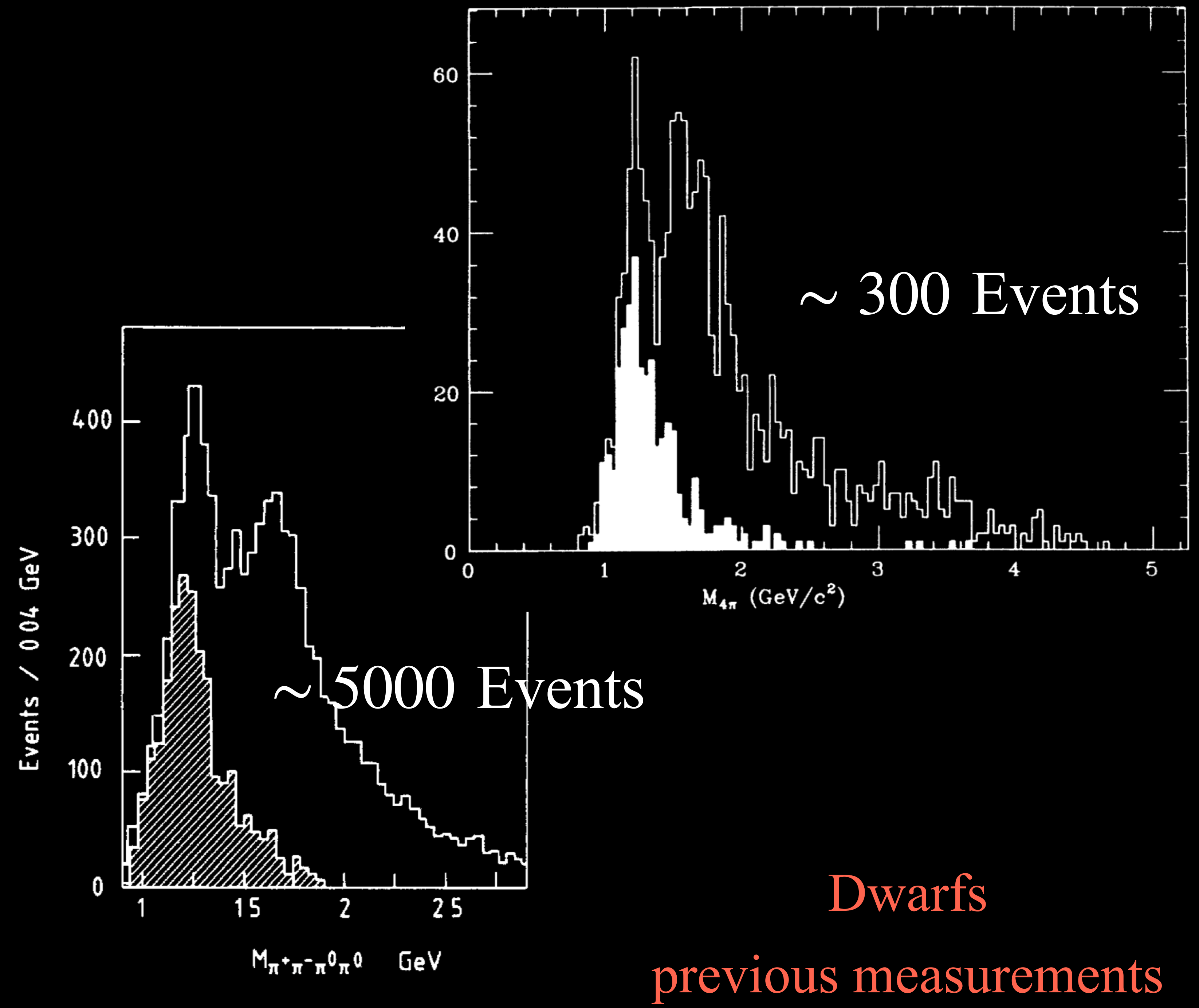
Detector response cuts

Phasespace cuts

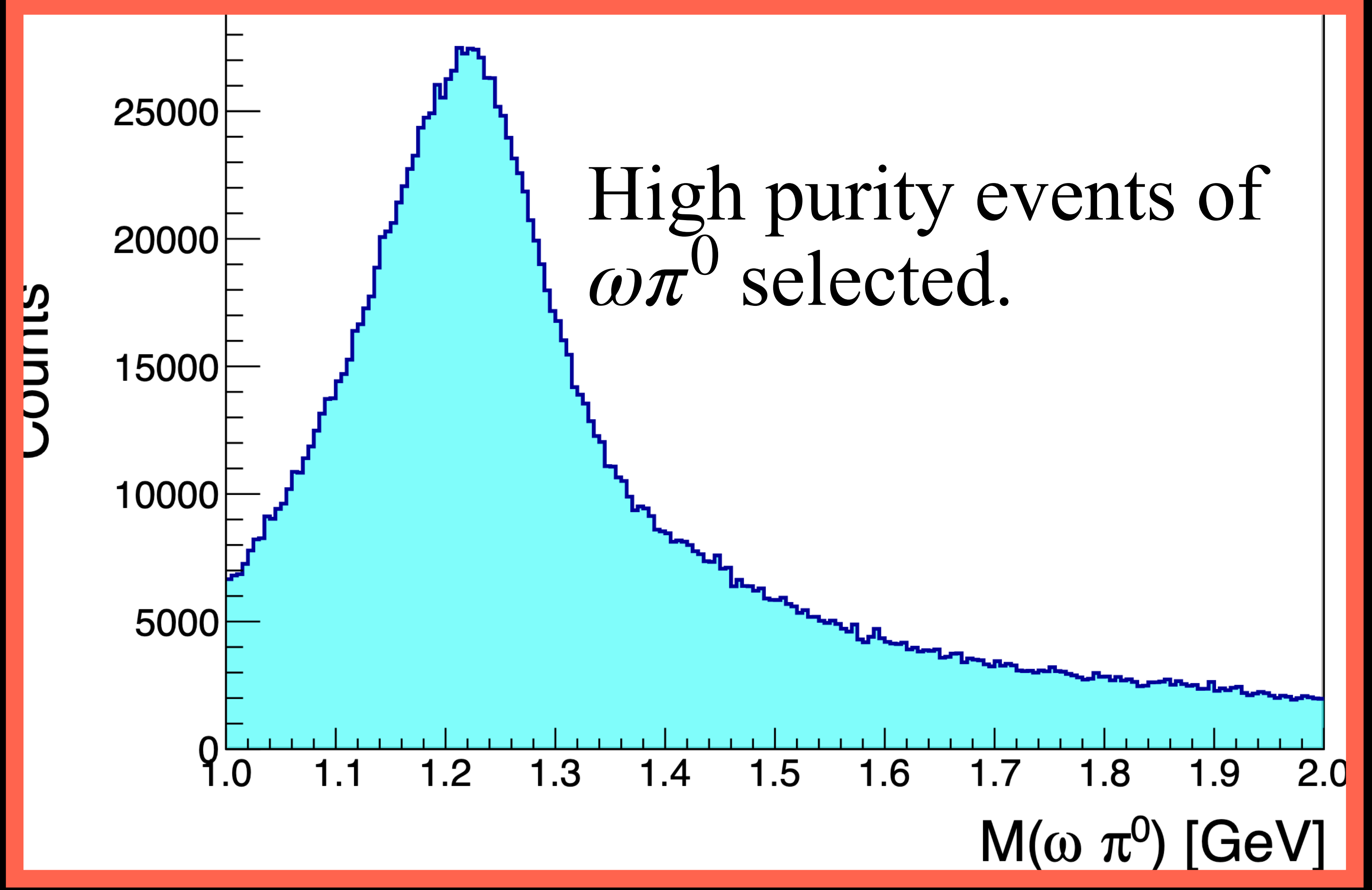
Weighted events

Accidental Side band subtraction

2D-ω side band subtraction



Dwarfs previous measurements

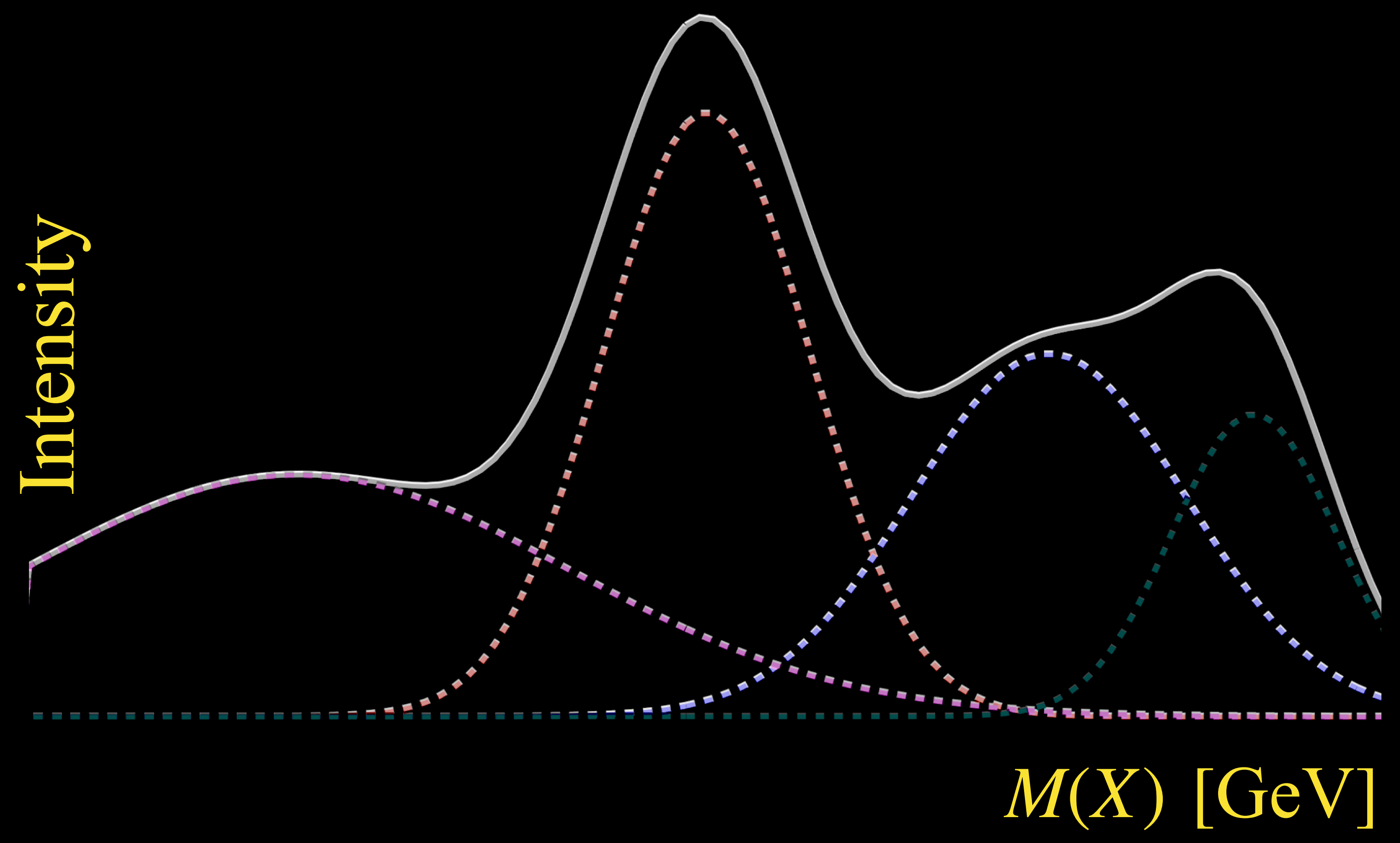


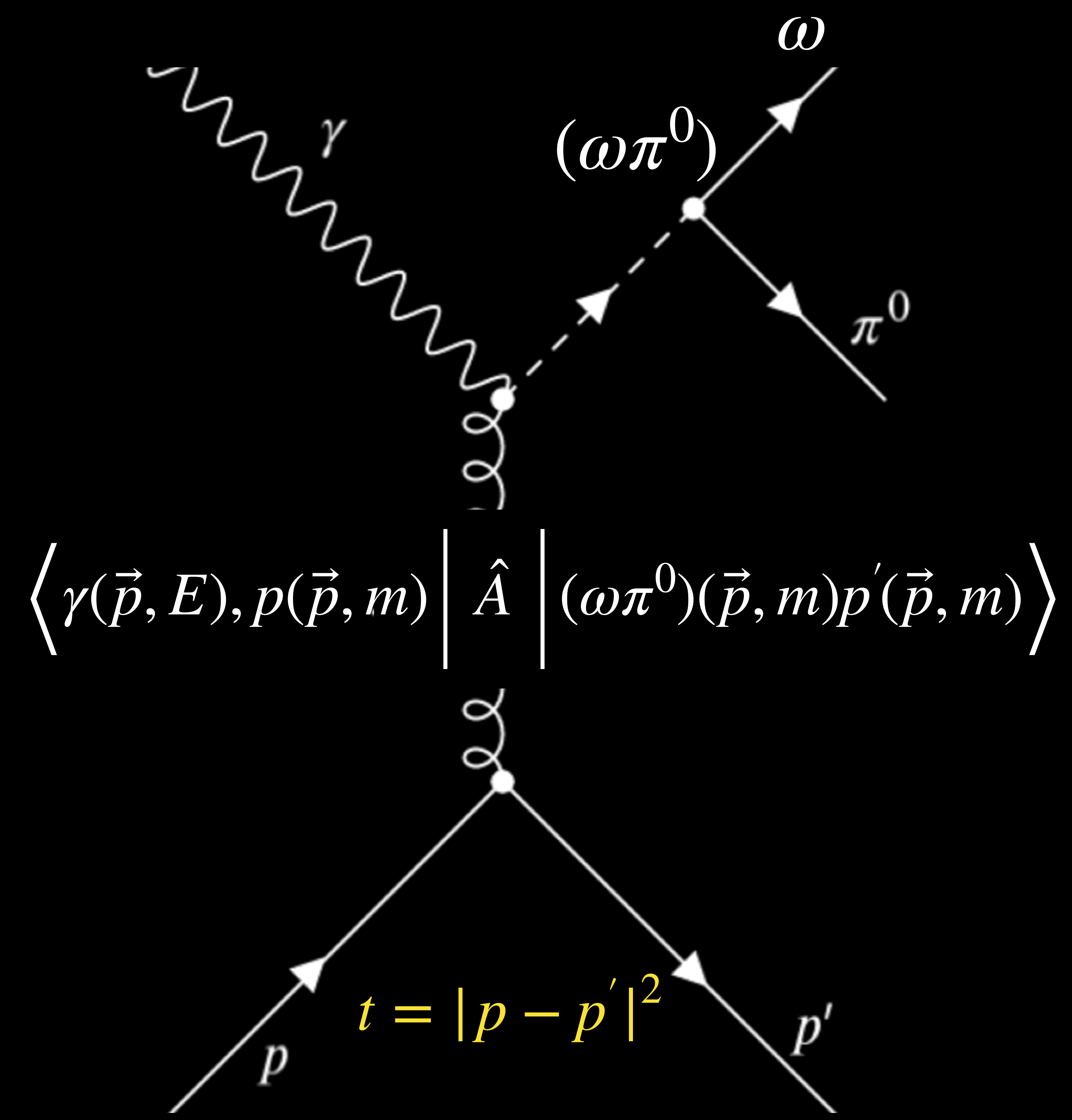
High purity events of $\omega\pi^0$ selected.

*Only Fa

Partial Wave Analysis

Intensity Model: analyzing intensity beyond "Mass Spectrum"





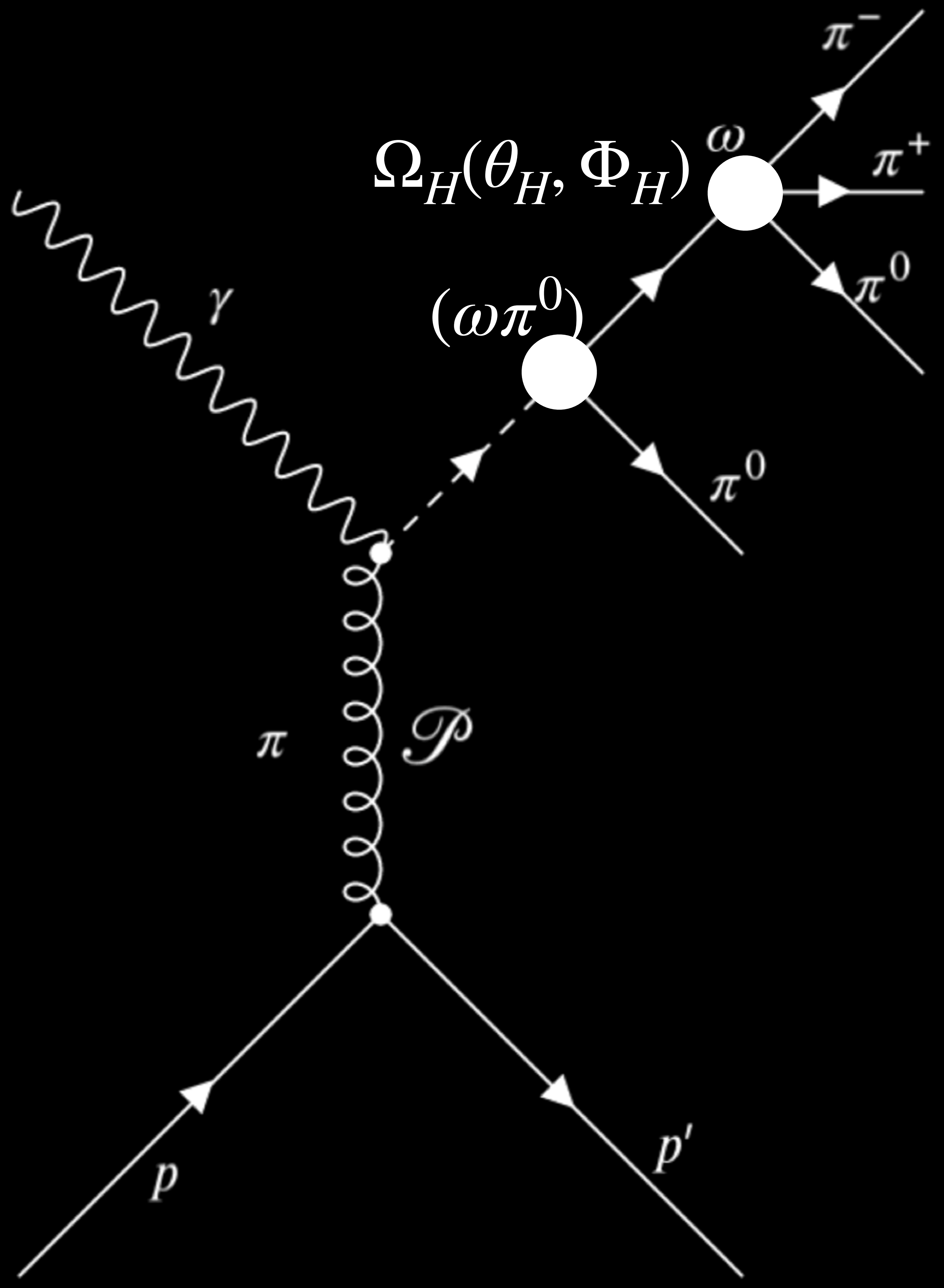
$$\mathrm{I}(\omega\pi^0) \equiv \underset{\uparrow}{\kappa} |\hat{A}|^2 \equiv \kappa A \underset{\uparrow}{\rho} A^*$$

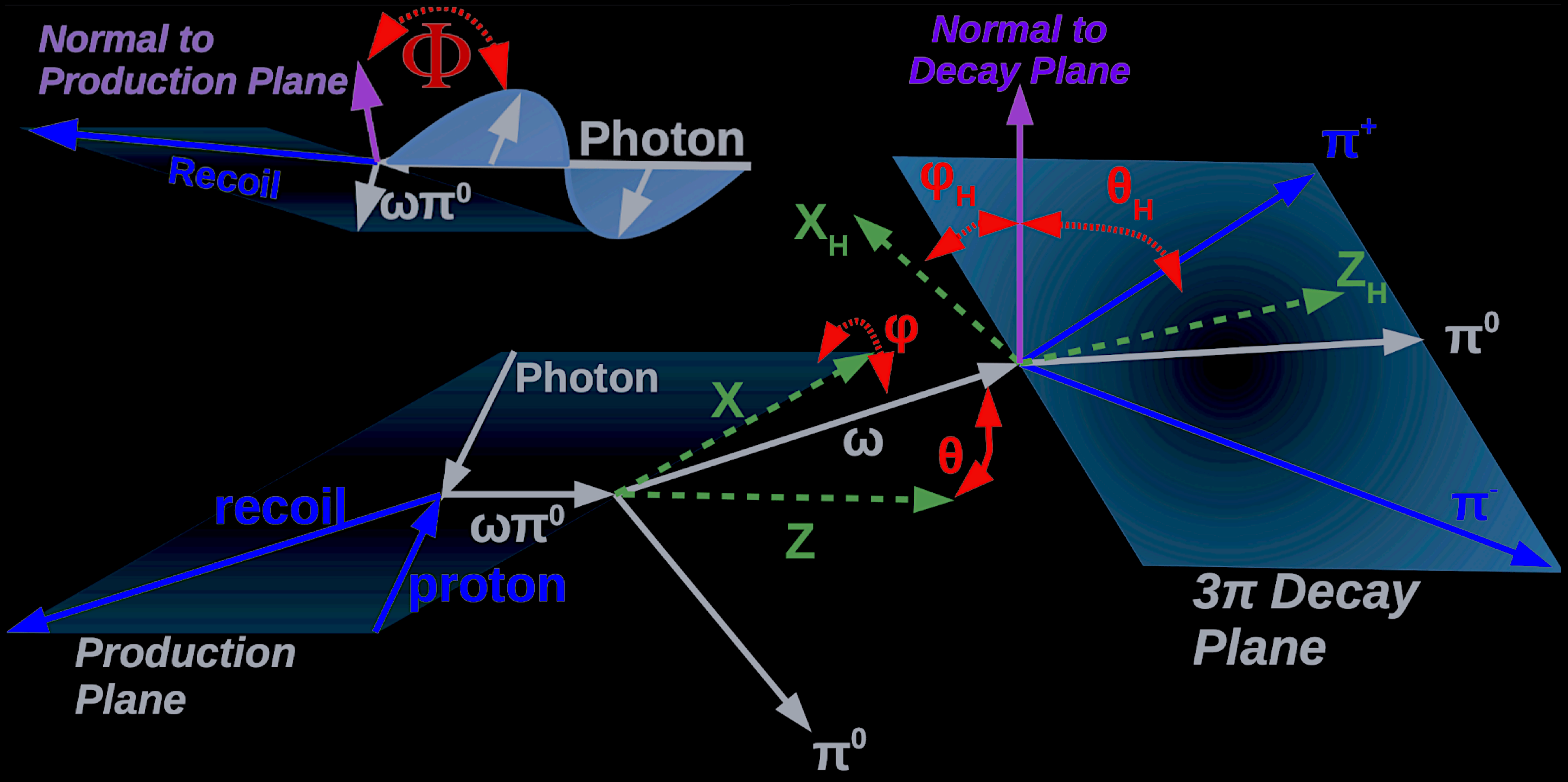
Kinematic factor Polarization factor

- How to extract contributions for J^{PC} from the spectrum?
- Using "only" mass spectrum incomplete
- Study and analyze intensity in more "dimensions"
- "Dimensions" - Decay angles of constituent particles. Develop model from scattering theory
- PWA - A tool extracting contribution of J^{PC} by studying intensity in multiple decay angles

Partial Wave Analysis

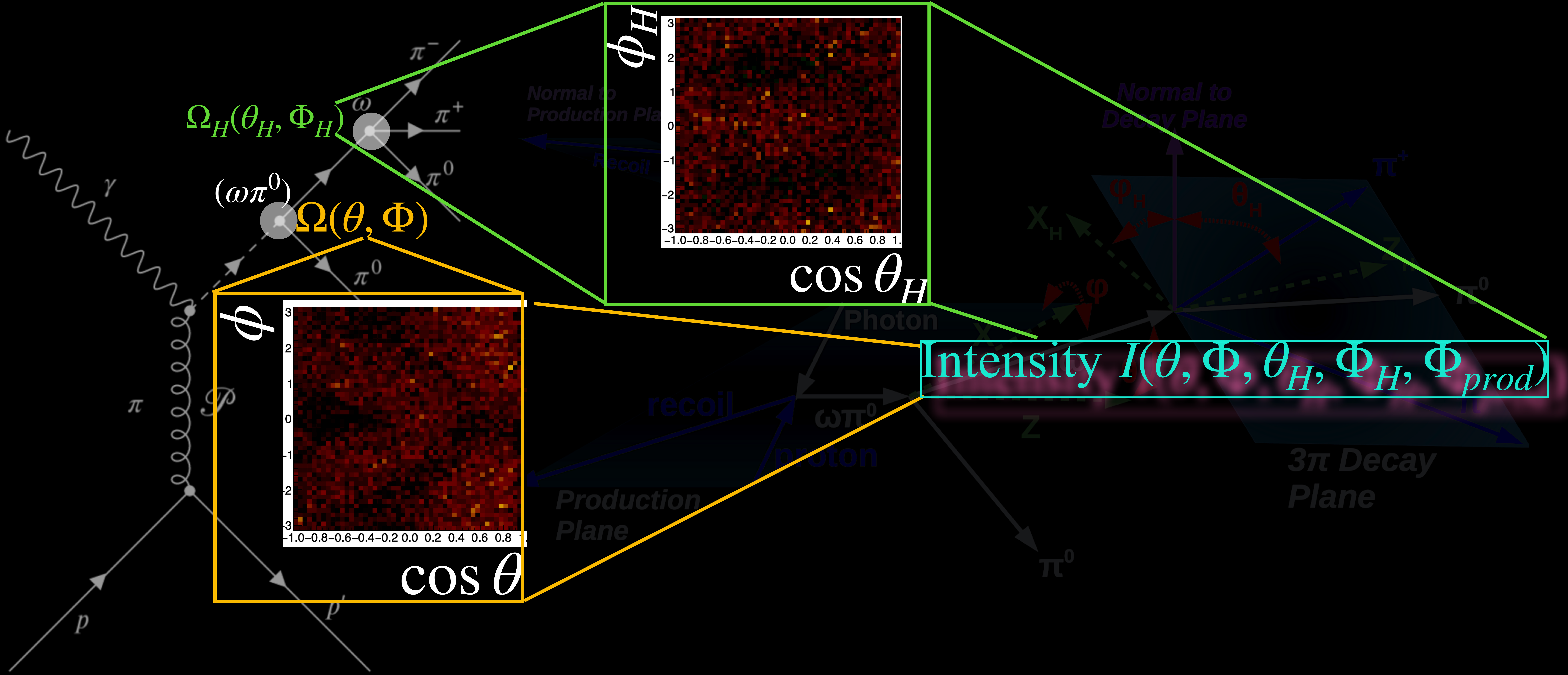
Intensity Model: Angular distribution in helicity frame





Partial Wave Analysis

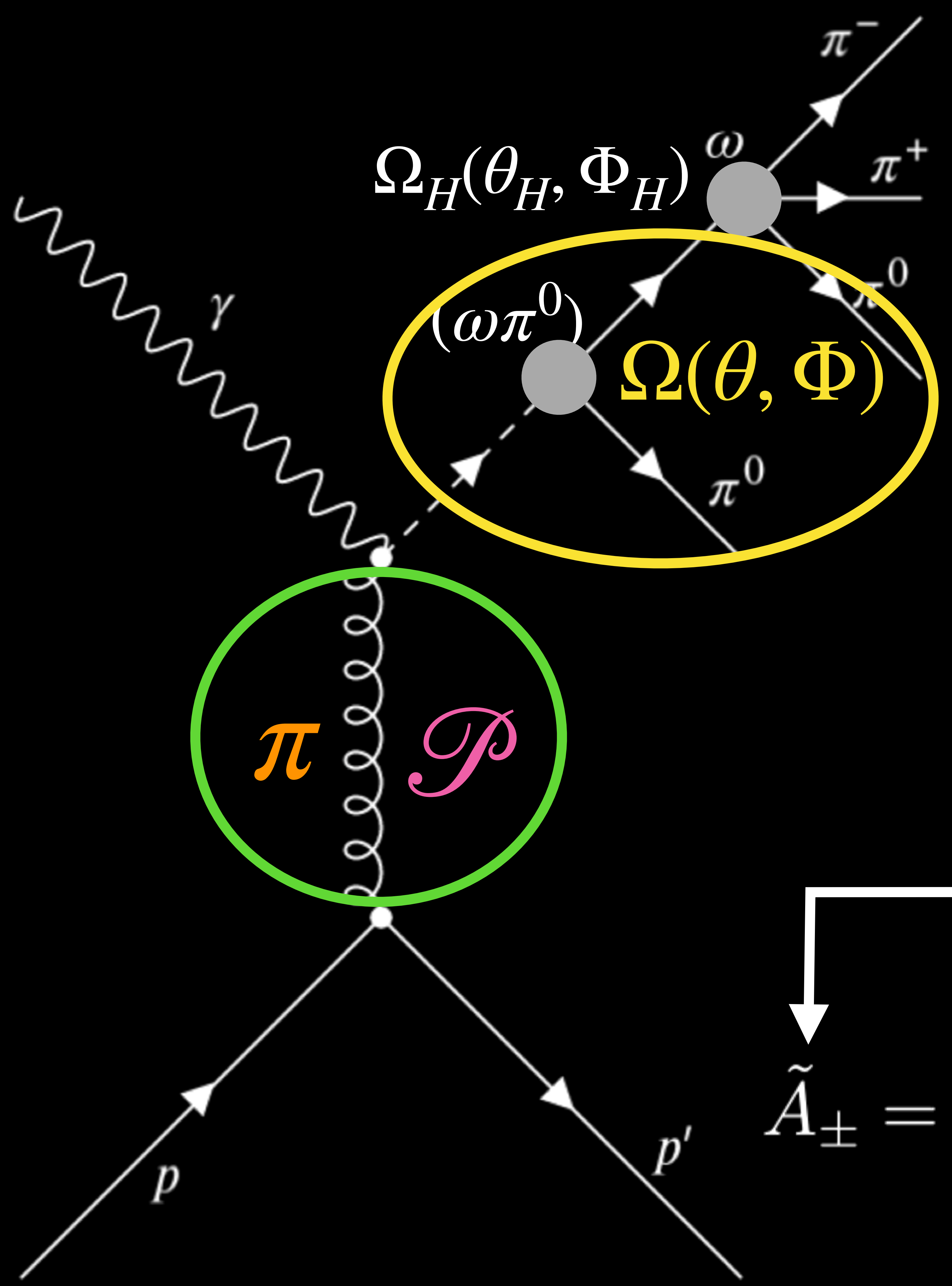
Intensity Model: Angular distribution in helicity frame



Intensity $I(\theta, \Phi, \theta_H, \Phi_H, \Phi_{prod})$

Partial Wave Analysis

Intensity Model: Measuring $b_1(1^{+\,-})$ in $\omega\pi^0$ spectrum



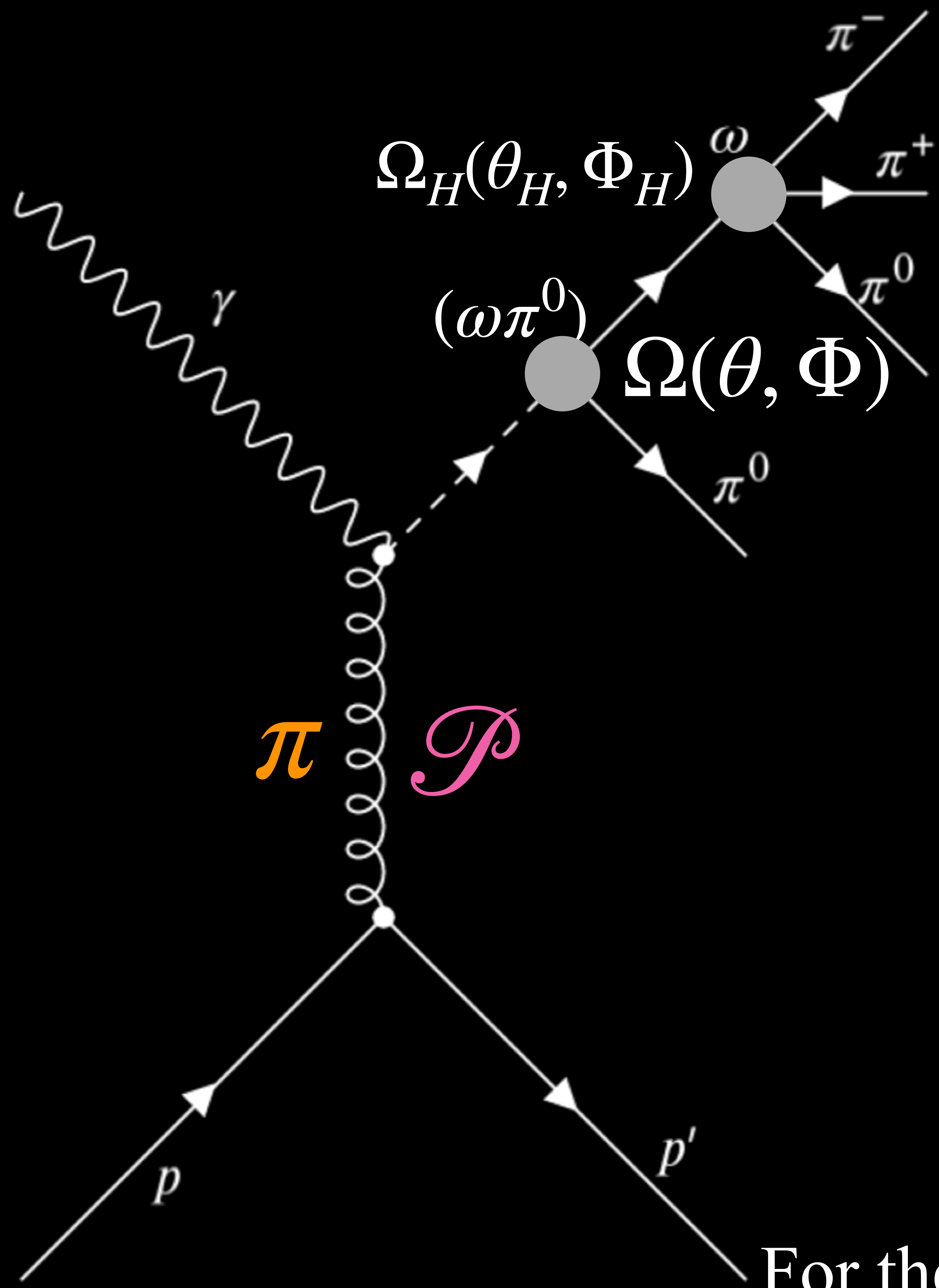
In "thin" $M(\omega\pi^0)$ and $|t|$ bin

$$I(\Omega, \Omega_H, \Phi) = \frac{\kappa}{4}(1 - P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) + \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2$$
$$+ \frac{\kappa}{4}(1 + P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) - \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2$$

$$\tilde{A}_\pm = \sum_{J_i=1,2,..} \sum_{m=-J_i,..,J_i} T^i_{\pm,m} \sum_{\lambda_\omega=-1,0,1} \overbrace{e^{\mp i\Phi} D^{J_i *}_{m,\lambda_\omega}(\Omega) F^i_{\lambda_\omega} D^{1*}_{m,0}(\Omega_H) G_{\text{Dalitz}} \mathfrak{F}(p_0)}^{Z^i_m(\Phi, \Omega, \Omega_H)}$$

Partial Wave Analysis

Intensity Model: Encoding of DS Ratio for 1^{+-} state



In “thin” $M(\omega\pi^0)$ and $|t|$ bin

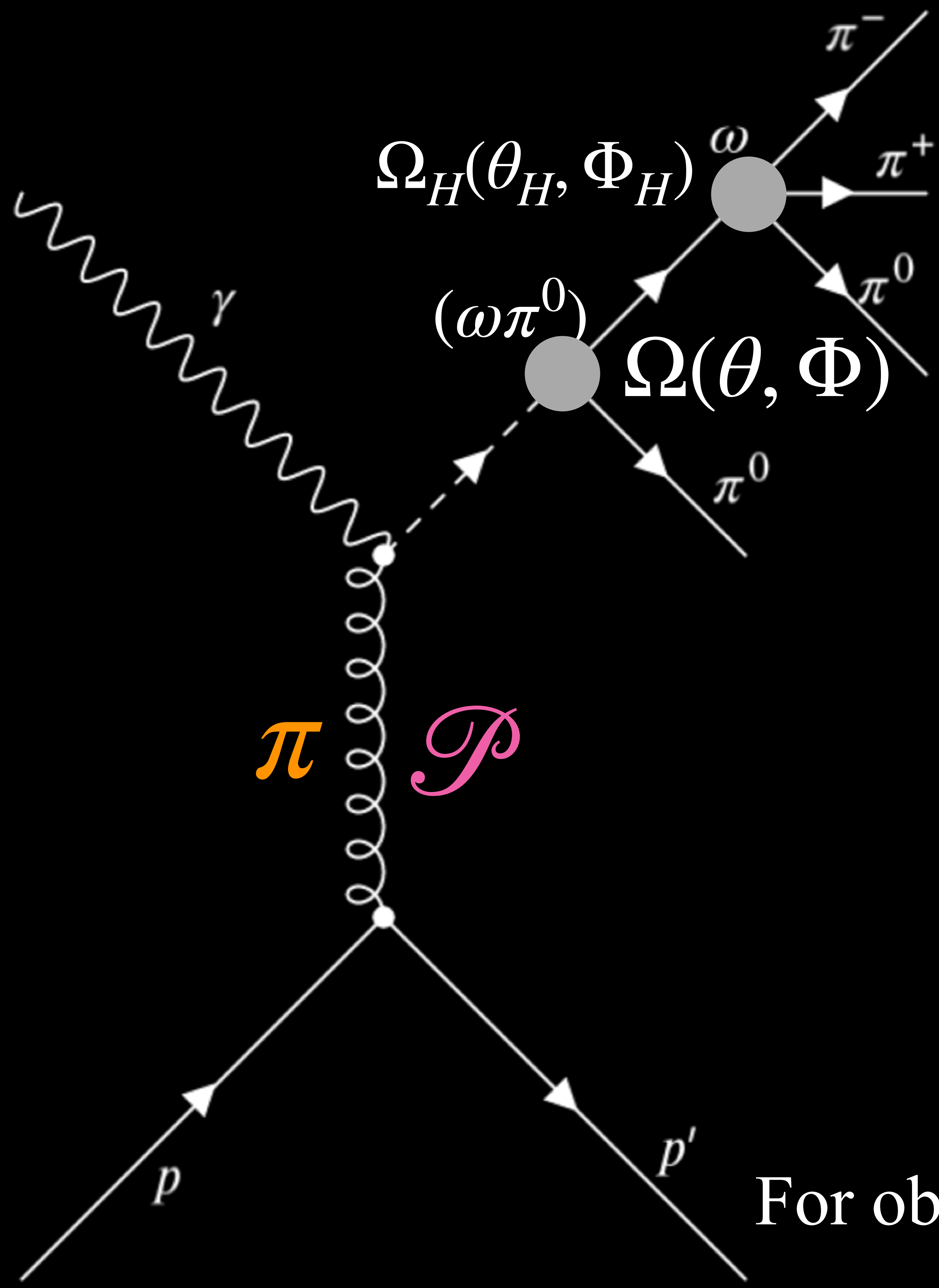
dsratio dphase

$$\mathcal{I}(\Phi,\Omega,\Omega_H) = 2\kappa\Bigg\{(1-P_\gamma)\Bigg[\Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(-)}_m\Big(\mathfrak{Im}(Z^{(S)}) + D/S\; e^{i\phi_{D-S}}\mathfrak{Im}(Z^{(D)})\Big)\Bigg|^2 + \Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(+)}_m\Big(\mathfrak{Re}(Z^{(S)}) + D/S\; e^{i\phi_{D-S}}\mathfrak{Re}(Z^{(D)})\Big)\Bigg|^2\Bigg] + (1+P_\gamma)\Bigg[\Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(+)}_m\Big(\mathfrak{Im}(Z^{(S)}) + D/S\; e^{i\phi_{D-S}}\mathfrak{Im}(Z^{(D)})\Big)\Bigg|^2 + \Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(-)}_m\Big(\mathfrak{Re}(Z^{(S)}) + D/S\; e^{i\phi_{D-S}}\mathfrak{Re}(Z^{(D)})\Big)\Bigg|^2\Bigg]\Bigg\}$$

For the state 1^{+-} which is b_1 extract ratio between D-S wave amplitude and phase

Partial Wave Analysis

Intensity Model: Measuring $b_1(1^{+-})$ in $\omega\pi^0$ spectrum



In "thin" $M(\omega\pi^0)$ and $|t|$ bin

$$I(\Phi, \Omega, \Omega_H) = 2\kappa \sum_k \Bigg\{ (1 - P_\gamma)\left[\left|\sum_{i,m}[J_i]^{(-)}_{m,k}\mathfrak{Im}(Z)\right|^2 + \left|\sum_{i,m}[J_i]^{(+)}_{m,k}\mathfrak{Re}(Z)\right|^2\right] + (1 + P_\gamma)\left[\left|\sum_{i,m}[J_i]^{(+)}_{m,k}\mathfrak{Im}(Z)\right|^2 + \left|\sum_{i,m}[J_i]^{(-)}_{m,k}\mathfrak{Re}(Z)\right|^2\right] \Bigg\}$$

For observed intensity, fit model with various J^{PC} states across various reflectivities

Partial Wave Analysis

Lets get to Fitting: AmpTools

AmpTools

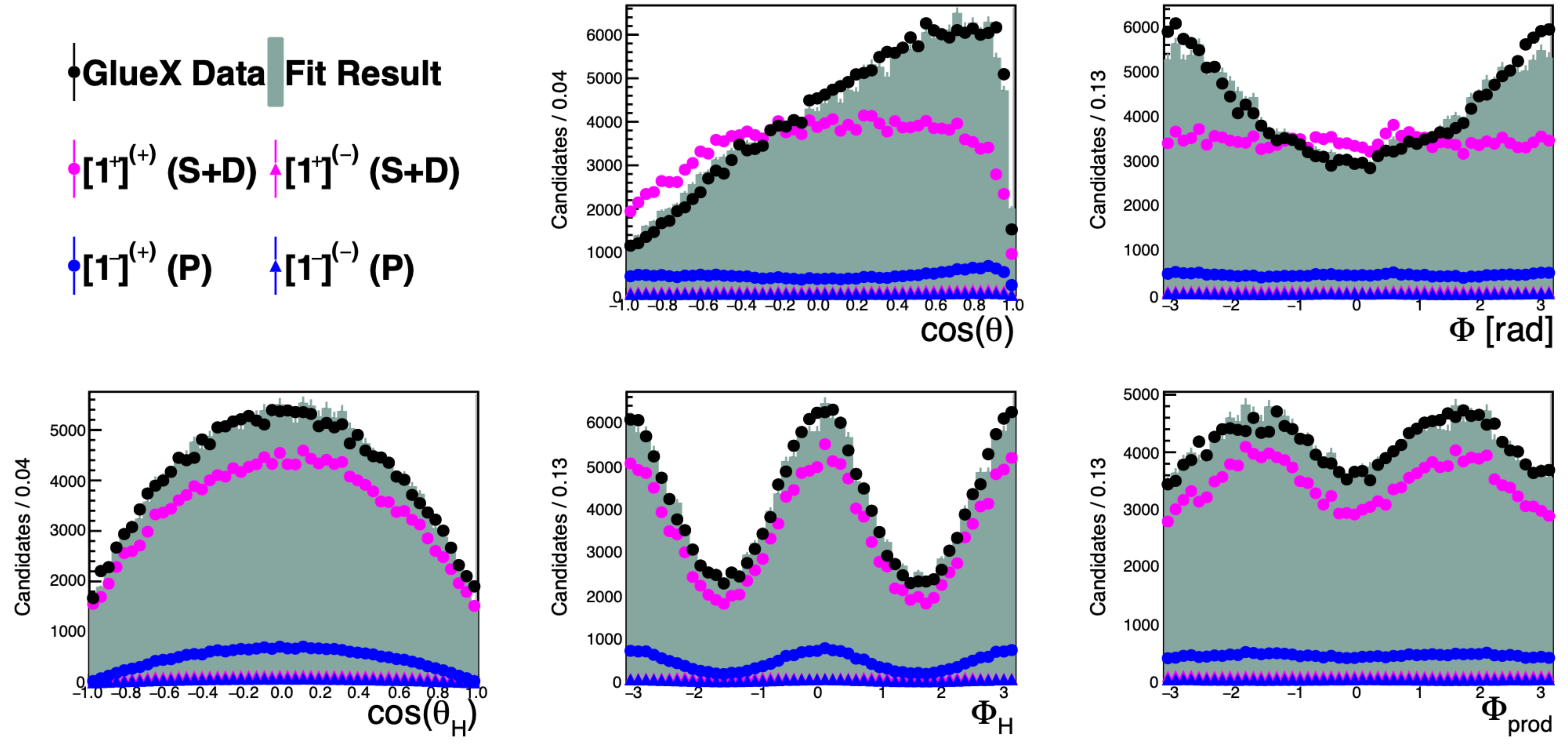
- Unbinned Maximum Likelihood fitting
- Input decay angles + model params, Eg. $[1^{+\,-}]^{(\pm)}, [1^{-\,-}]^{\pm}$

$$-2\ln\mathfrak{L}(\theta) = -2\left(\sum_{i=1}^{N}\ln I(x;\theta) - \mu\right) + c_1$$

  - θ — Model Parameters
  - x — 5D Decay angles

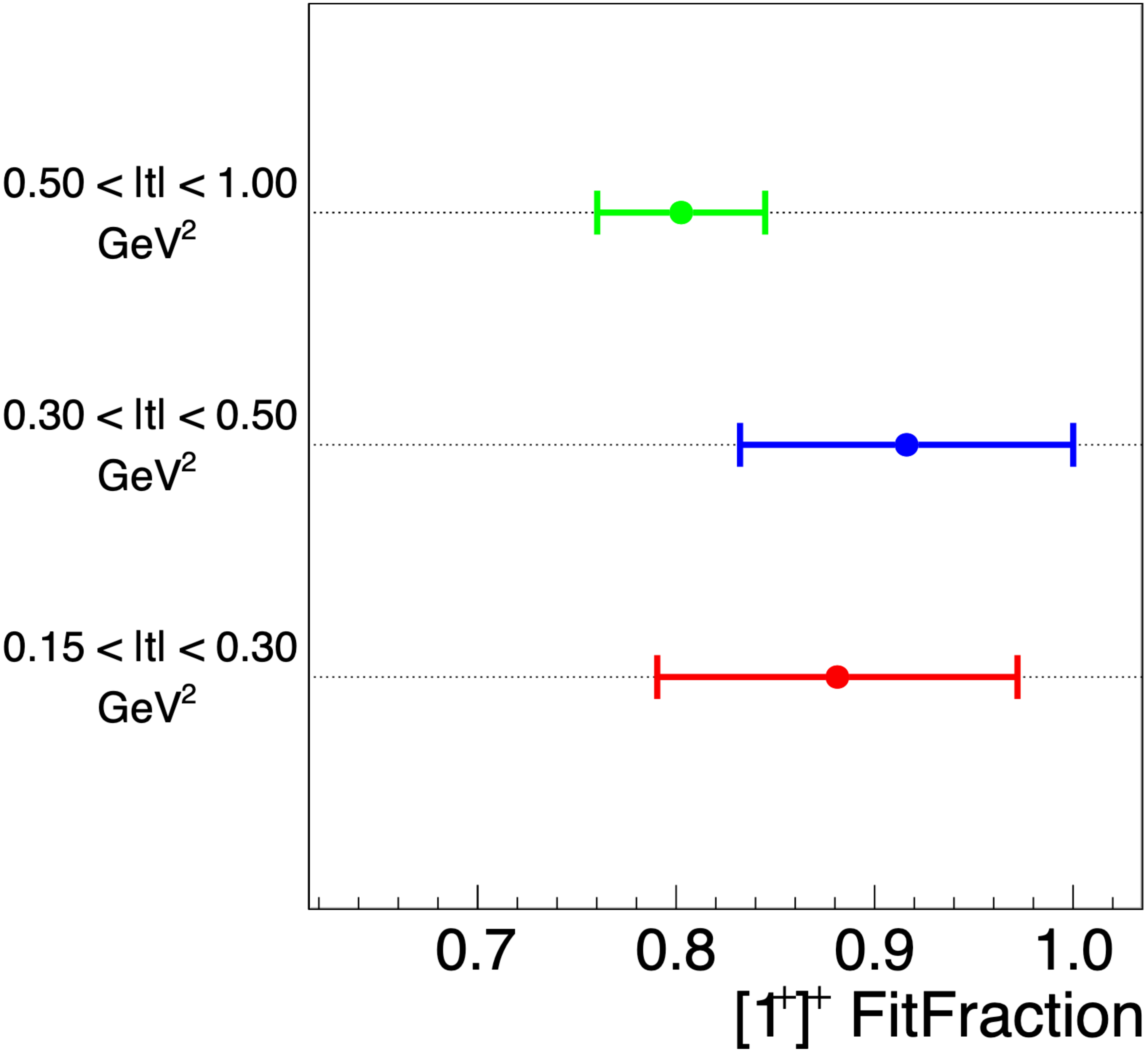
- Results presented as fit fractions for each J^{PC}
- Extract D/S Ratio as well

Parameters	Input	Type	Fit Results
D/S ratio	0.27	float	0.2697 ± 0.0062
$[1^{+}]^{(+)}$	0	Fit Fraction	0.0100 ± 0.0005
$[1^{+}]^{(-)}$	1	Fit Fraction	0.9871 ± 0.0065
$[1^{-}]^{(+)}$	0	Fit Fraction	0.0020 ± 0.001
$[1^{-}]^{(-)}$	0	Fit Fraction	0.0009 ± 0.0003



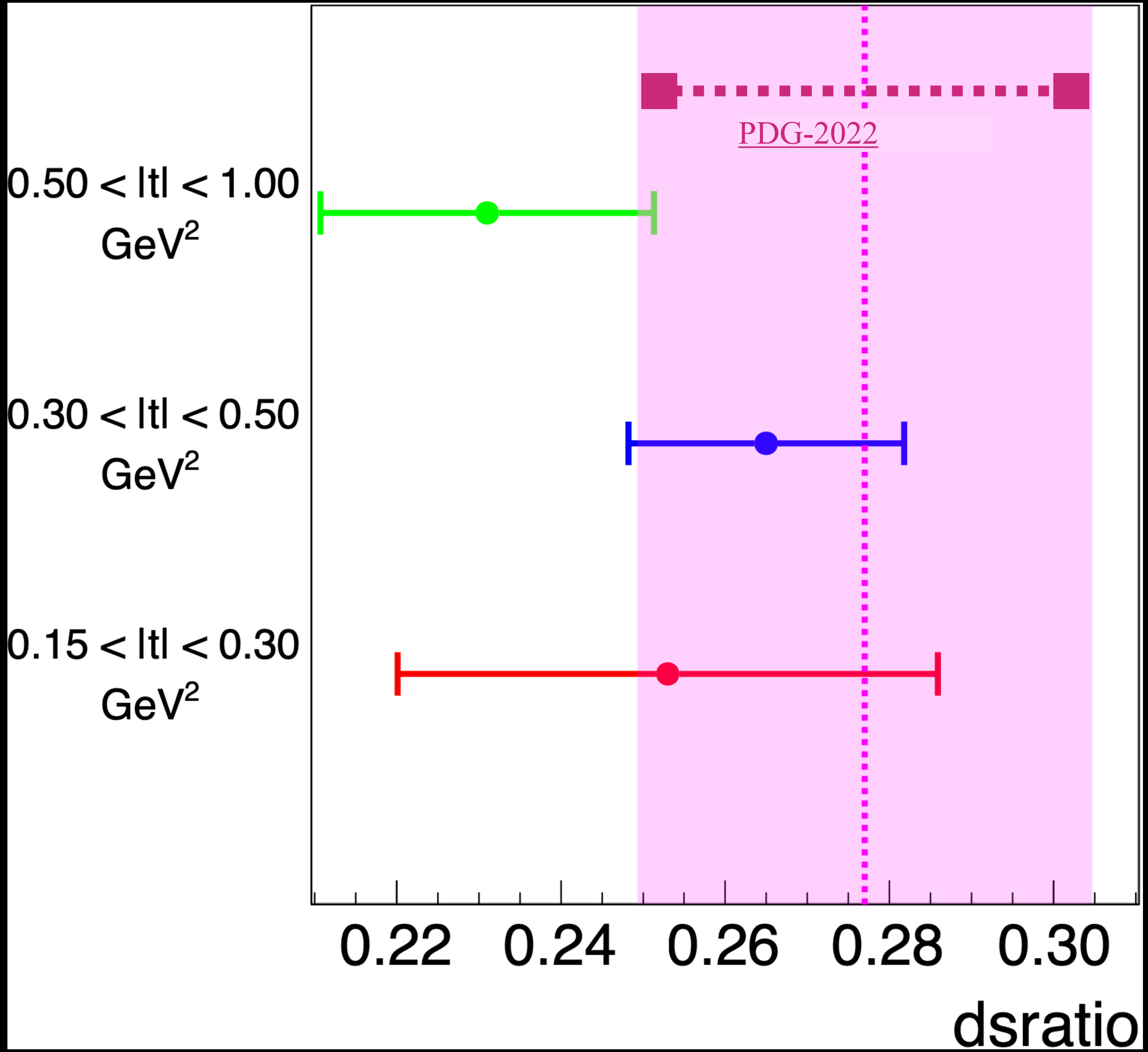
Partial Wave Analysis : Results

Extracted b_1 properties



$[1^{+}]^{(+)}$ dominant → b_1 decays

through **Natural** exchange

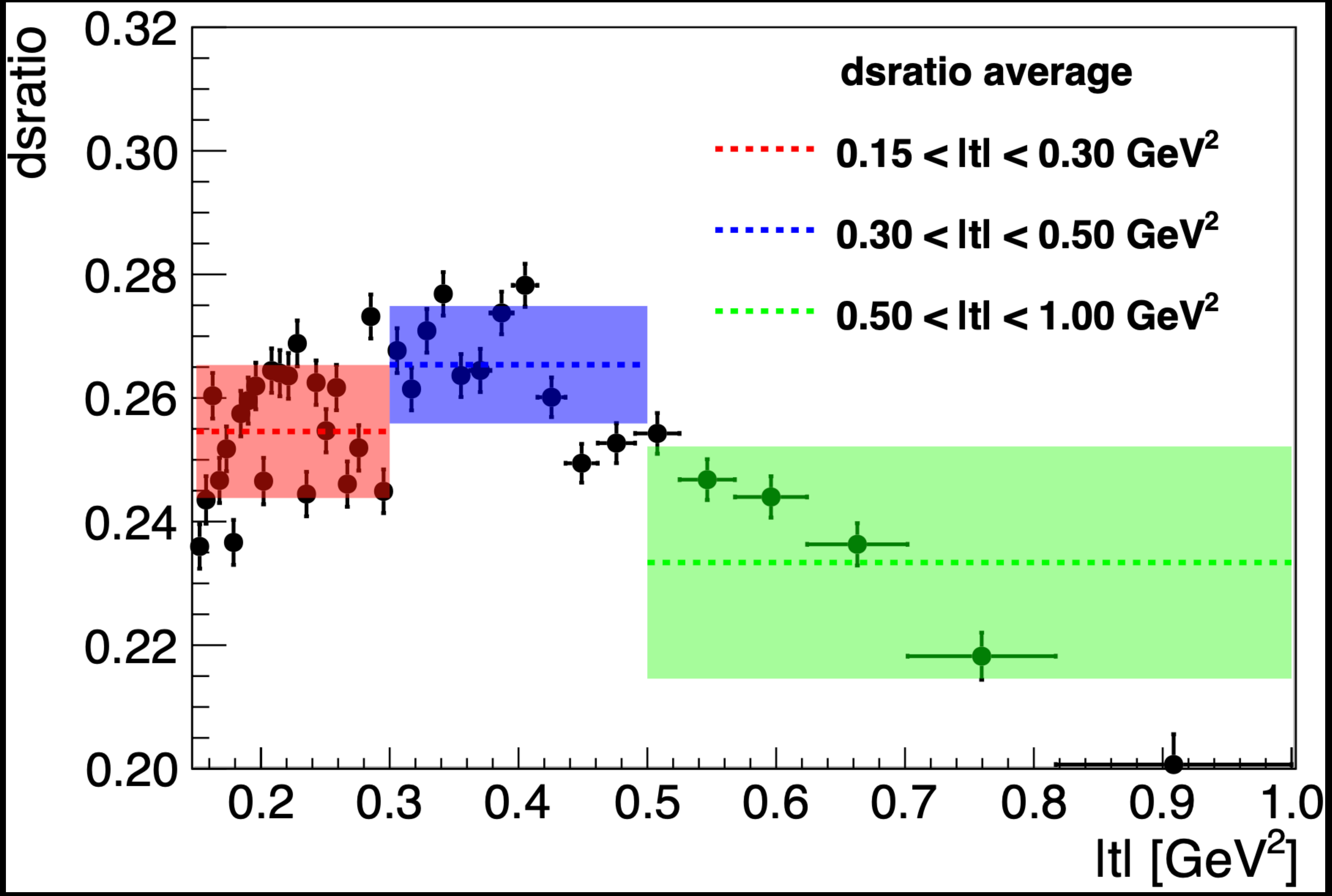


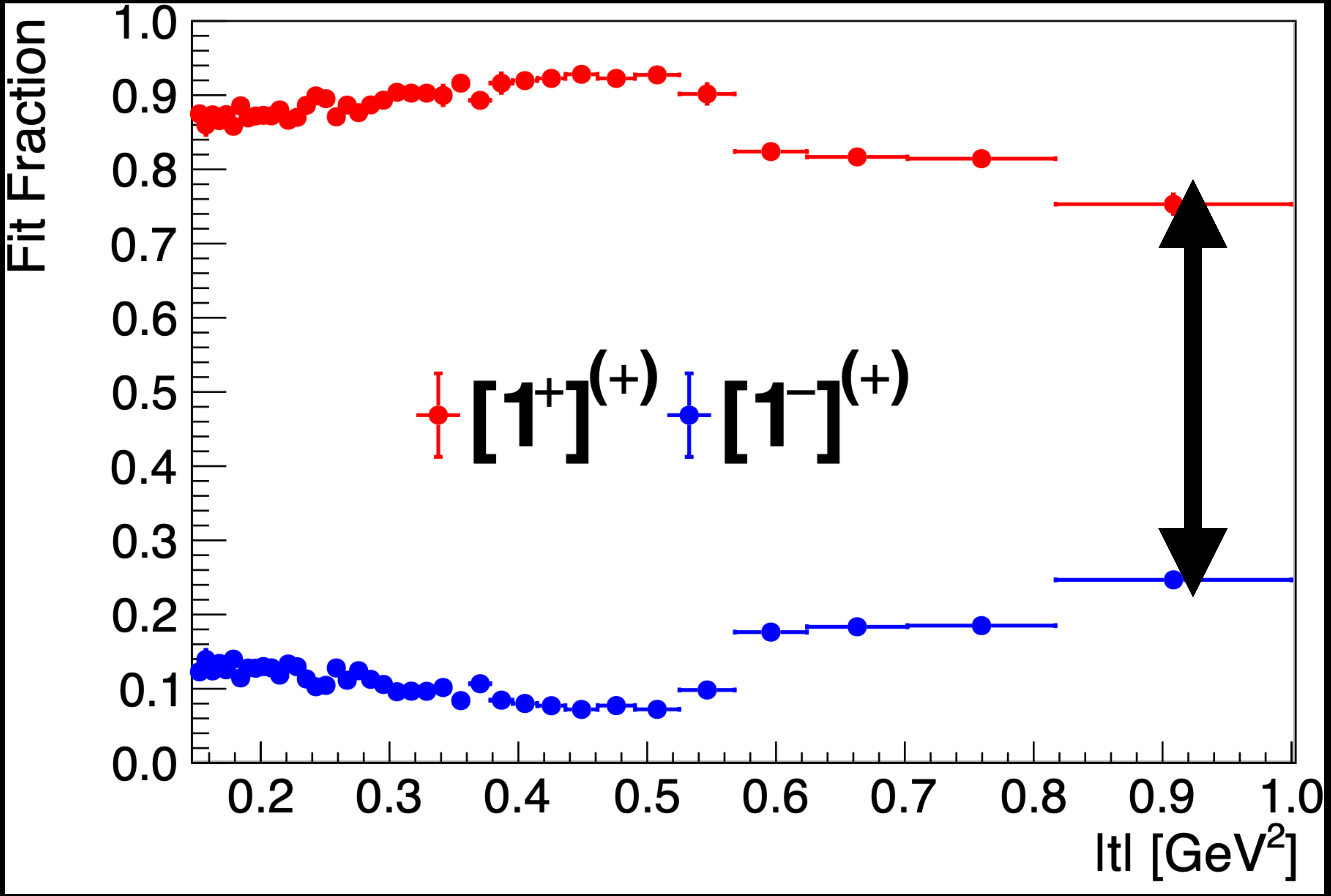
Cut Name	$\|t\|$ bins GeV^2		
	$0.15 < \|t\| < 0.30$	$0.30 < \|t\| < 0.50$	$0.50 < \|t\| < 1.00$
Fit Wave combos	0.0325	0.0165	0.0173
Mass bin	0.0048	0.0025	0.0104
Beam Energy	0.0012	0.0015	0.0019
Dalitz Parameter	0.0007	0.0007	0.0007
Benchmark DS Ratio	0.2530	0.2650	0.2310
Statistical Uncertainty Δ_{stat}	0.0011 0.0012	0.0008 0.0008	0.0013 0.0014
Systematic Uncertainty Δ_{sys}	**0.0329**	**0.0168**	**0.0203**

Partial Wave Analysis : Results

Extracted b_1 properties - A closer look in $|t|$

This overwhelming stats
allows us to look closer and finer !!!!



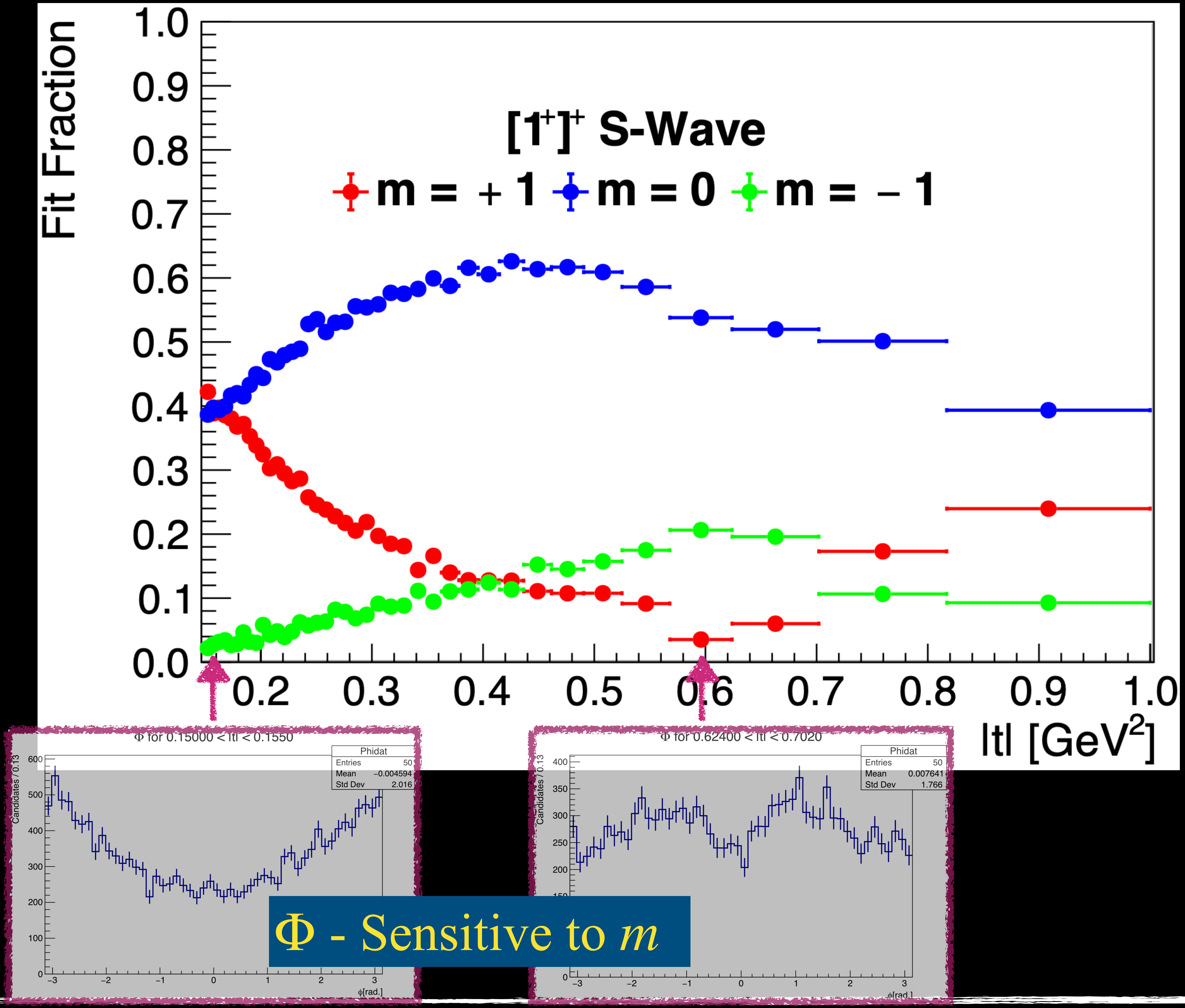


Strong monotonous
decrease at high $|t|$

Effect "Independent" of
possibly "other" effects?
— Baryonic effect $M(p\pi^0)$ — Work in progress

Partial Wave Analysis : Results

Extracted b_1 properties - A data driven observation



Φ - Sensitive to m

$$J = 1 \implies m = [-1,0,1]$$

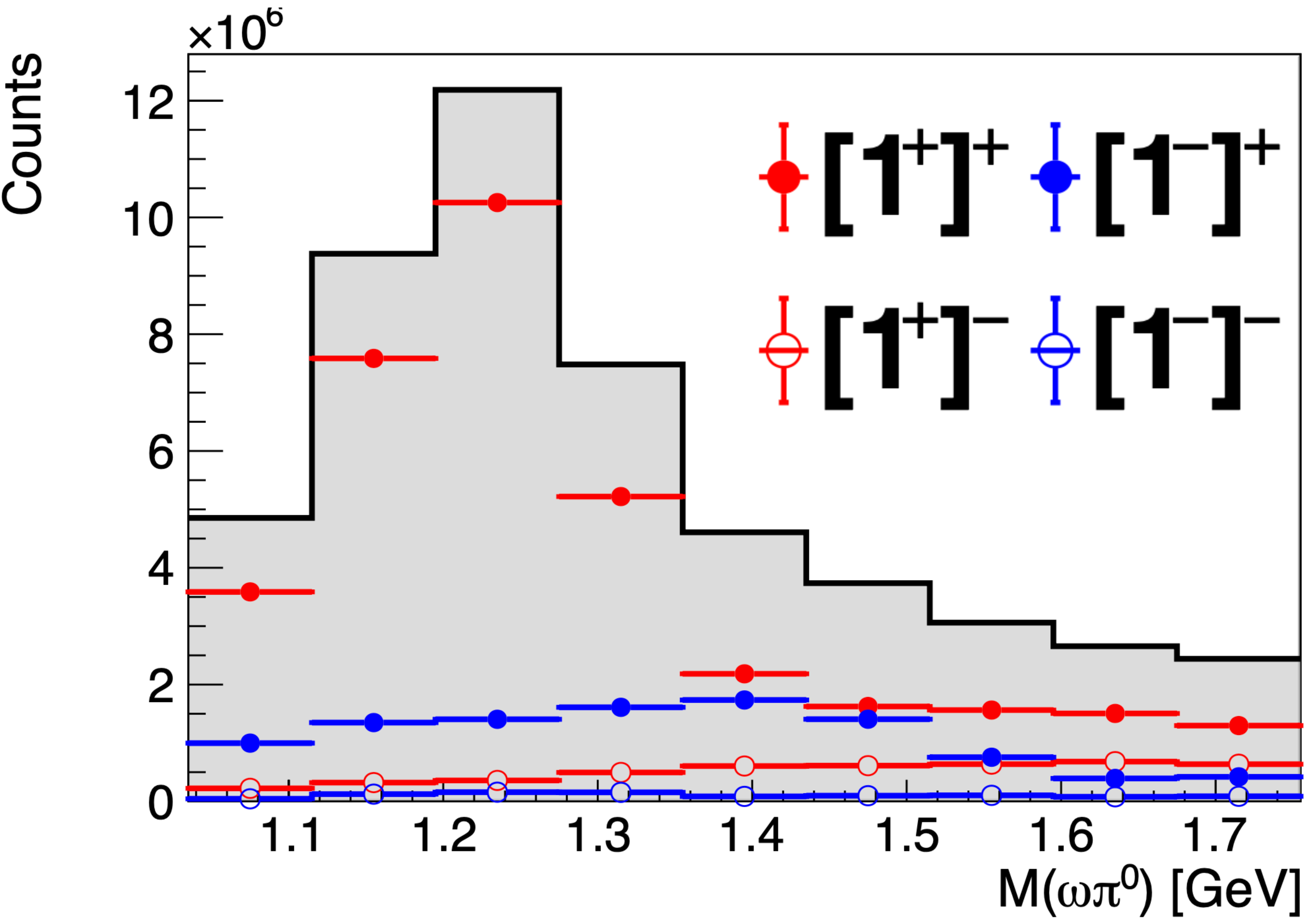
$$\sum_{\lambda_\omega=-1,0,1} D^{J_i *}_{m,\lambda_\omega}(\Omega) F^{i}_{\lambda_\omega} D^{1*}_{0,\lambda_\omega}(\Omega_H)$$

Data driven observations made on dependence of m on $|t|$

Note : No explicit dependence of $|t|$ encoded in the model

Partial Wave Analysis : Summary

- $\omega\pi^0$ spectrum ($1.135 < M(\omega\pi^0) < 1.155$ GeV) dominated by $1^{+\,-}$ state; over 80% Fit Fraction
  - **Natural** Exchange is preferred
  - DS Ratio consistent with PDG & theoretical prediction
  - Unprecedented statistical precision; systematics dominate
  - A strong correlation found in DS Ratio as a function of $|t|$
  - Extracted contribution of m states and their dependence on $|t|$
- Recipe for computing cross-section; over entire $\omega\pi^0$ mass range
  - Additional systematics to be done



Detector Design optimization

Multi Objective Design Optimization

Design space spanned by ‘x’

$$\min / \max \ \mathbf{f_m}(\mathbf{x}), m = 1, \dots, M$$

$$\text{s.t.} \ \mathbf{g_j}(\mathbf{x}) \leq 0,, j = 1, \dots, J$$

$$\mathbf{h_k}(\mathbf{x}) = 0,, k = 1, \dots, K$$

$$x_i^L \leq x_i \leq x_i^U,, i = 1, \dots, N$$

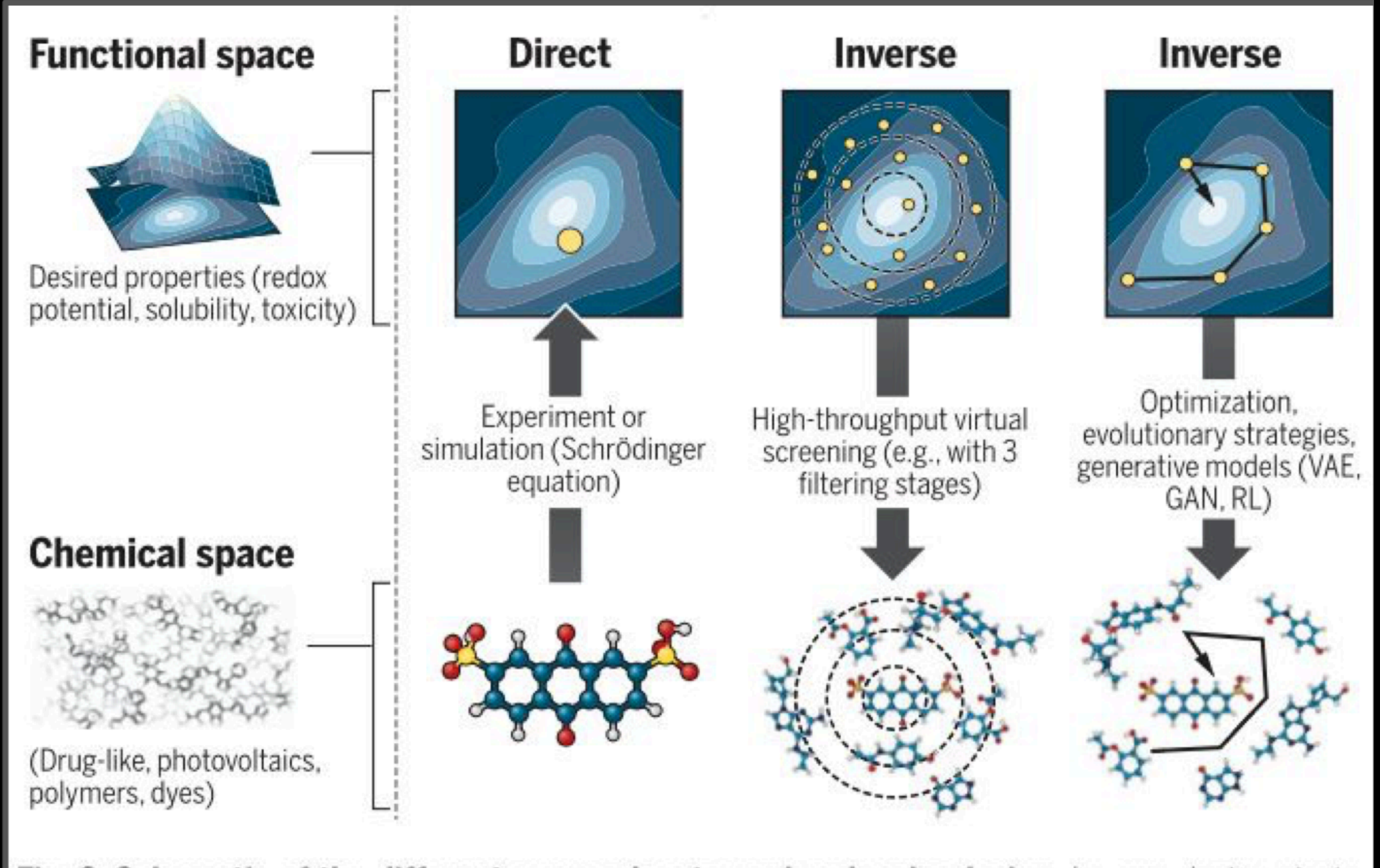


Fig. 2. Schematic of the different approaches toward molecular design. Inverse design starts from desired properties and ends in chemical space, unlike the direct approach that leads from chemical space to the properties.

B. Sanchez-Lengeling, A. Aspuru-Guzik. *Science* 361.6400 (2018): 360-365.

Multiobjective genetic algorithm approach to optimize beam matchin and beam transport in high-intensity hadron linacs

M. Yarmohammadi Satri,[1,2,*] A. M. Lombardi,[2] and F. Zimmermann[2]

[1]*School of Particles and Accelerators, Institute for Research in Fundamental Sciences (IPM),*
P.O. Box 19395-5531, Tehran, Iran
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BoTorch
BAYESIAN OPTIMIZATION IN PYTORCH

PyGMO

nextorch
NEXTorch
latest

Ax

Multi-objective Optimization in Python
pymoo

GPflow

jMetalPy

Guo, Kai, et al. *Materials Horizons* 8.4 (2021): 1153-1172.

Table 1 Popular ML methods in design of mechanical materials

ML method	Characteristics	Example applications in mechanical materials design
Linear regression; polynomial regression	Model the linear or polynomial relationship between input and output variables	Modulus[112] or strength[123] prediction
Support vector machine; SVR	Separate high-dimensional data space with one or a set of hyperplanes	Strength[123] or hardness[125] prediction; structural topology optimization[159]
Random forest	Construct multiple decision trees for classification or prediction	Modulus[112] or toughness[130] prediction
Feedforward neural network (FFNN); MLP	Connect nodes (neurons) with information flowing in one direction	Prediction of modulus,[97,112] strength,[93] toughness[130] or hardness;[97] prediction of hyperelastic or plastic behaviors;[143,145] identification of collision load conditions;[147] design of spinodoid metamaterials[163]
CNNs	Capture features at different hierarchical levels by calculating convolutions; operate on pixel-based or voxel-based data	Prediction of strain fields[104,105] or elastic properties[102,103] of high-contrast composites, modulus of unidirectional composites,[136] stress fields in cantilevered structures,[137] or yield strength of additive-manufactured metals;[121] prediction of fatigue crack propagation in polycrystalline alloys;[140] prediction of crystal plasticity;[120] design of tessellate composites;[107–109] design of stretchable graphene kirigami;[155] structural topology optimization[156–158]
Recurrent neural network (RNN); LSTM; GRU	Connect nodes (neurons) forming a directed graph with history information stored in hidden states; operate on sequential data	Prediction of fracture patterns in crystalline solids;[114] prediction of plastic behaviors in heterogeneous materials;[142,144] multi-scale modeling of porous media[173]
Generative adversarial networks (GANs)	Train two opponent neural networks to generate and discriminate separately until the two networks reach equilibrium; generate new data according to the distribution of training set	Prediction of modulus distribution by solving inverse elasticity problems;[138] prediction of strain or stress fields in composites;[139] composite design;[164] structural topology optimization;[165–167] architected materials design[115]
Gaussian process regression (GPR); Bayesian learning	Treat parameters as random variables and calculate the probability distribution of these variables; quantify the uncertainty of model predictions	Modulus[122] or strength[123,124] prediction; design of supercompressible and recoverable metamaterials[110]
Active learning	Interacts with a user on the fly for labeling new data; augment training data with post-hoc experiments or simulations	Strength prediction[124]
Genetic or evolutionary algorithms	Mimic evolutionary rules for optimizing objective function	Hardness prediction;[126] designs of active materials;[160,161] design of modular metamaterials[162]
Reinforcement learning	Maximize cumulative awards with agents reacting to the environments.	Deriving microstructure-based traction-separation laws[174]
Graph neural networks (GNNs)	Operate on non-Euclidean data structures; applicable tasks include link prediction, node classification and graph classification	Hardness prediction;[127] architected materials design[168]

Multi Objective Design Optimization

Design space spanned by ‘x’

$$\boxed{\min / \max \ \mathbf{f_m}(\mathbf{x}), m = 1, \ldots, M}$$

$$\text{s.t.} \ \mathbf{g_j}(\mathbf{x}) \leq 0,, j = 1, \ldots, J$$

$$\mathbf{h_k}(\mathbf{x}) = 0,, k = 1, \ldots, K$$

$$x_i^L \leq x_i \leq x_i^U,, i = 1, \ldots, N$$

Minimize/Maximize a set of objectives

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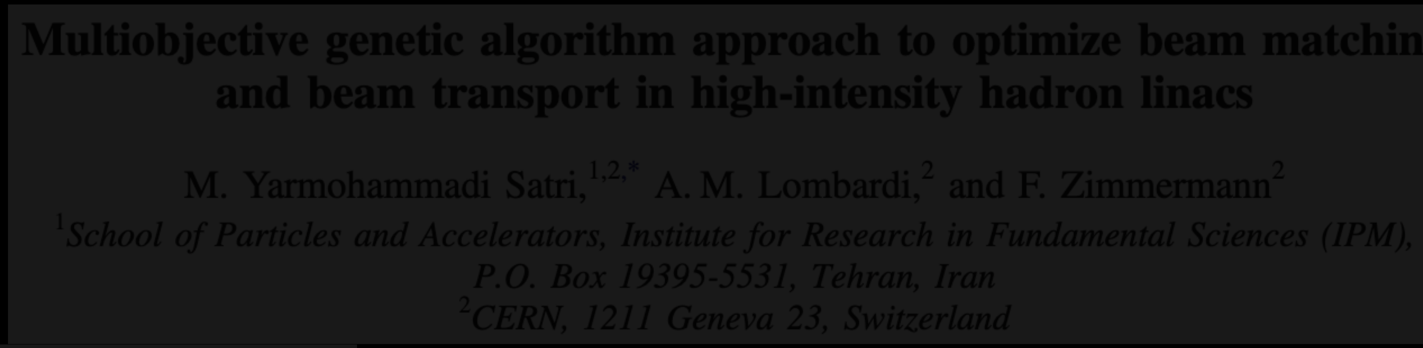

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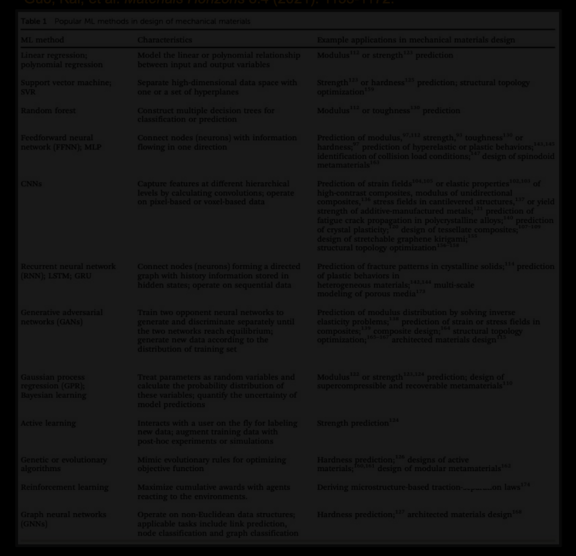

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$$x_i^L \leq x_i \leq x_i^U,, i = 1, \ldots, N$$

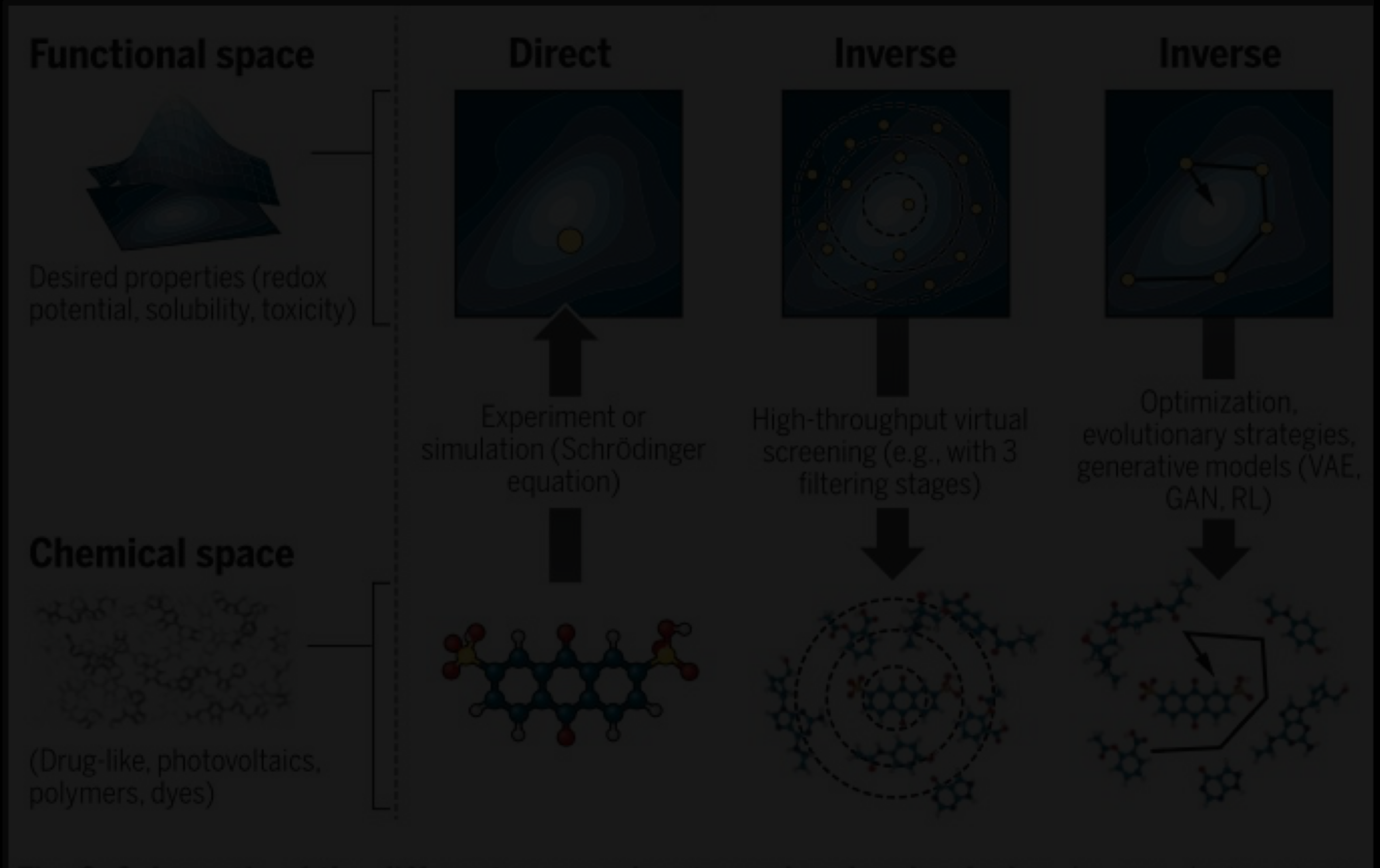

Fig. 2. Schematic of the different approaches toward molecular design. Inverse design starts from desired properties and ends in chemical space, unlike the direct approach that leads from chemical space to the properties.

Subject to a set of constraints….

B. Sanchez-Lengeling, A. Aspuru-Guzik. *Science* 361.6400 (2018): 360-365.

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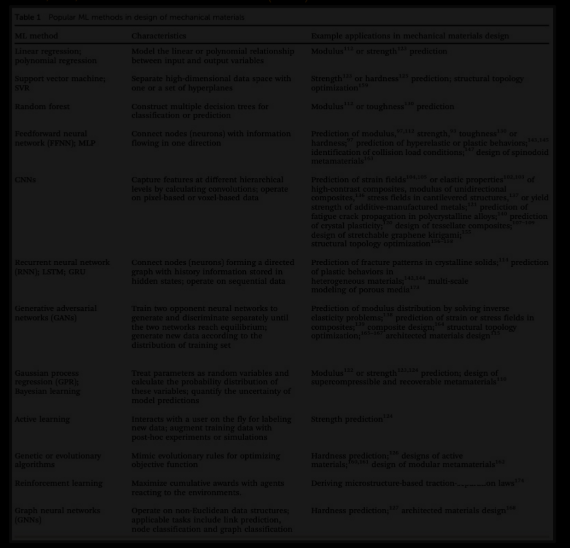


Multi Objective Design Optimization

Design space spanned by ‘x’

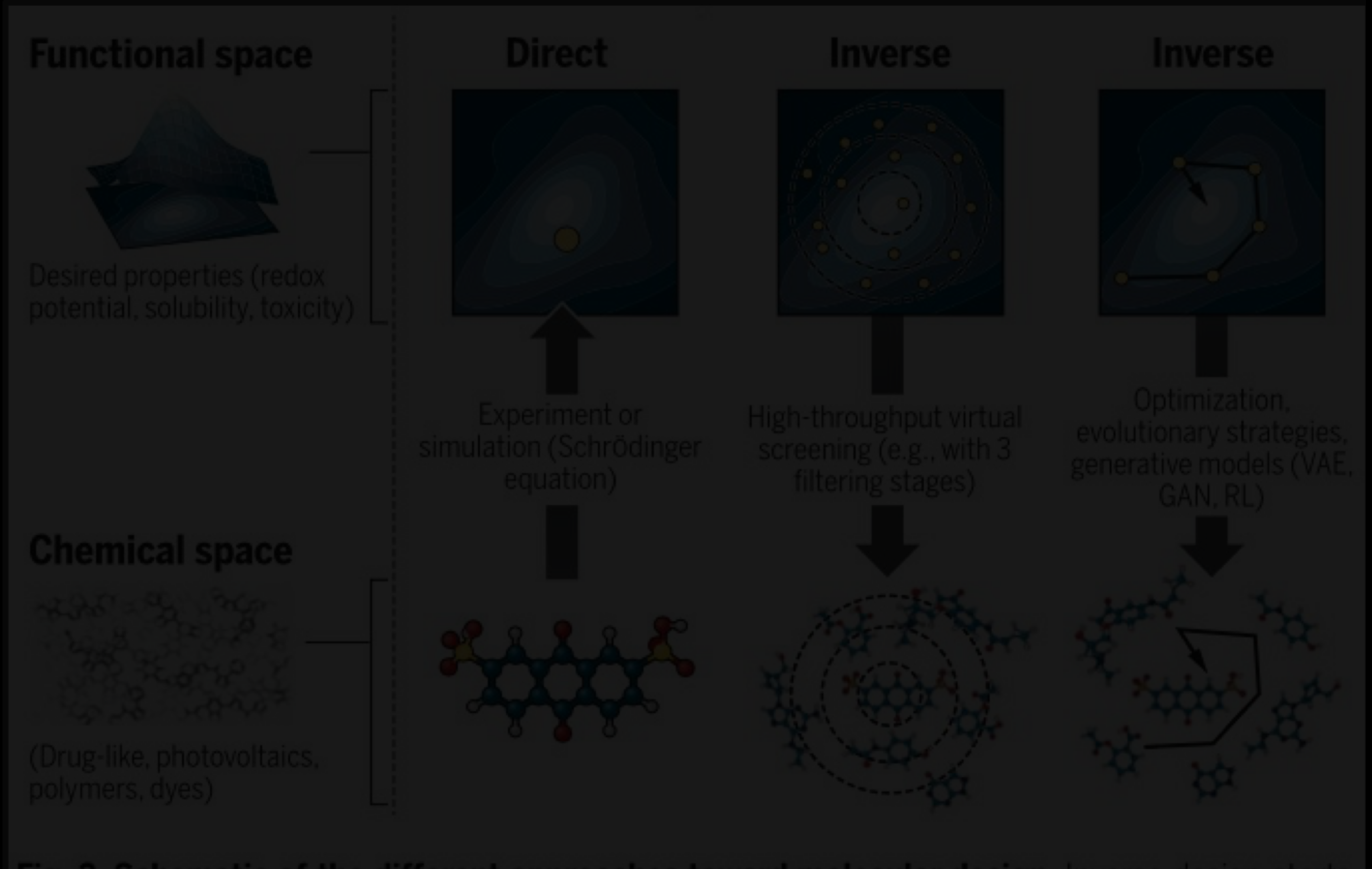
$$\min / \max \;\; \mathbf{f_m}(\mathbf{x}), m = 1, \ldots, M$$

$$\text{s.t.} \;\; \mathbf{g_j}(\mathbf{x}) \leq 0,, j = 1, \ldots, J$$

$$\mathbf{h_k}(\mathbf{x}) = 0,, k = 1, \ldots, K$$

$$\boxed{x_i^L \leq x_i \leq x_i^U,, i = 1, \ldots, N}$$

Bounded optimization



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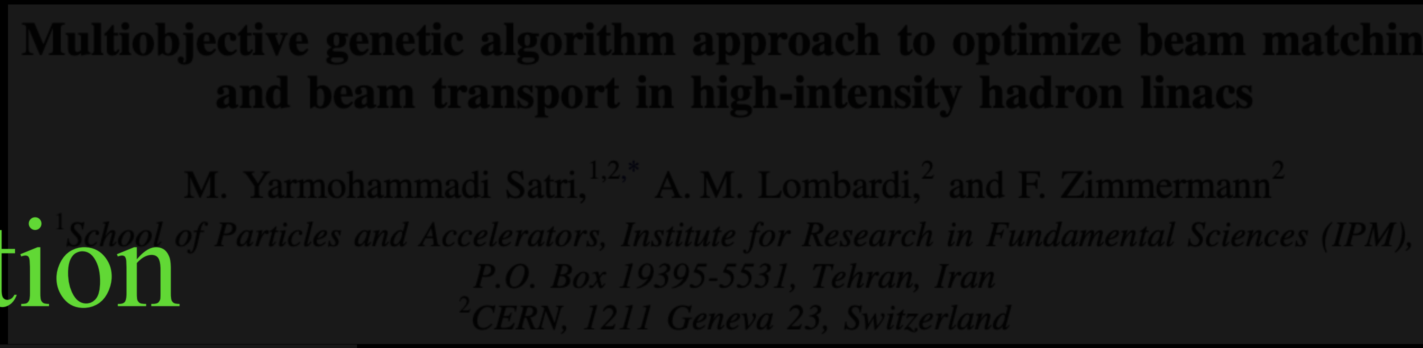

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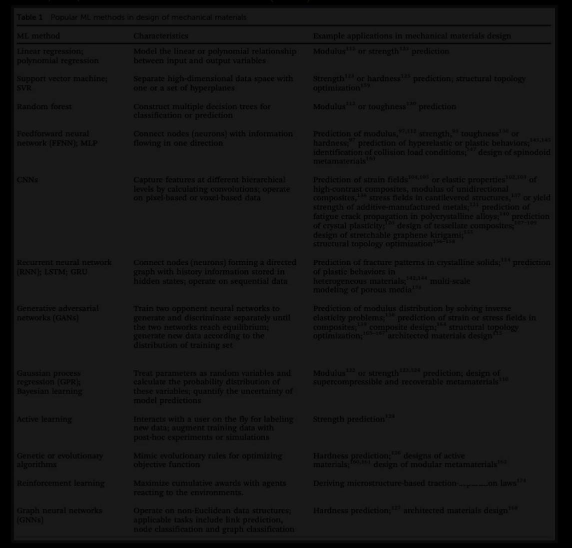
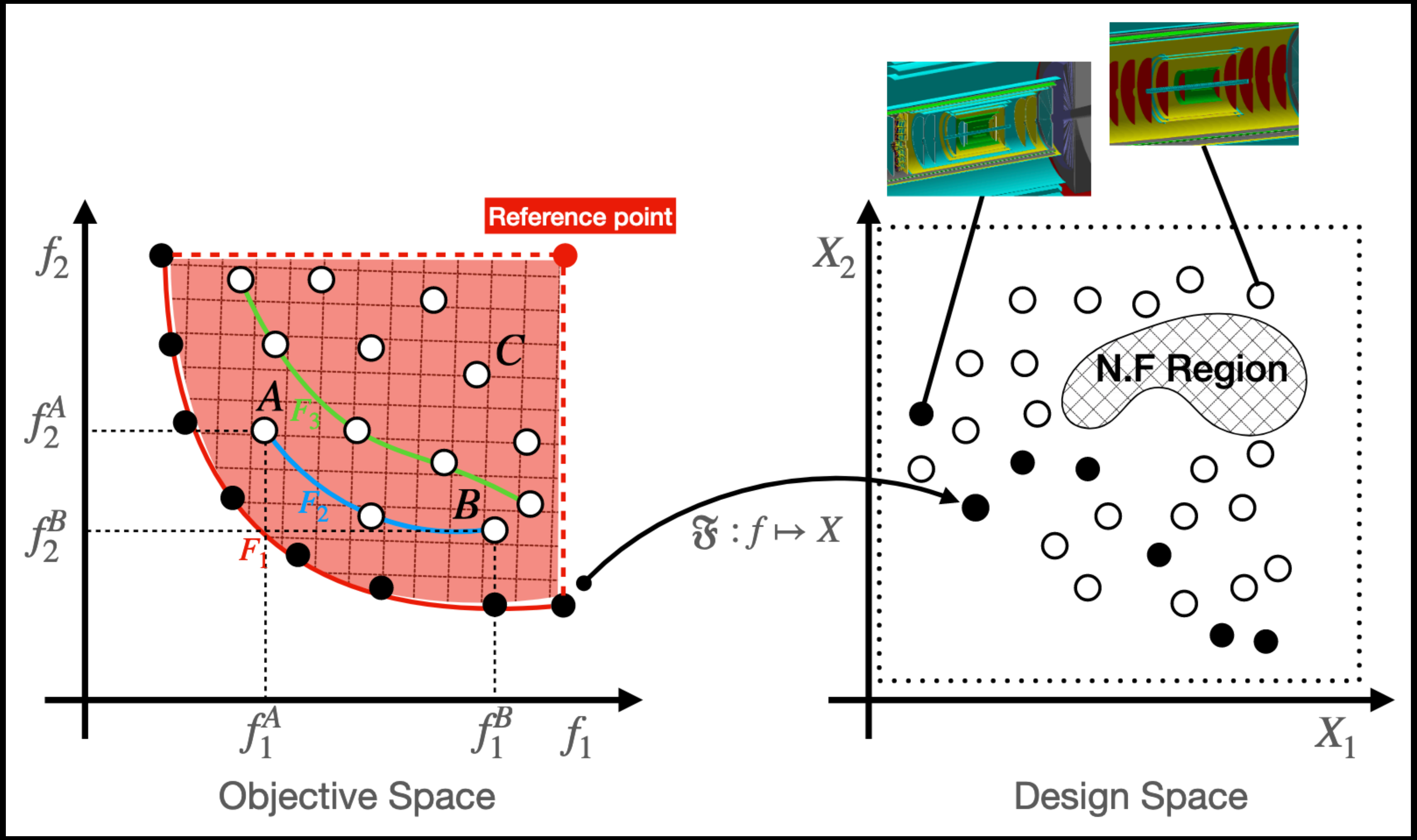


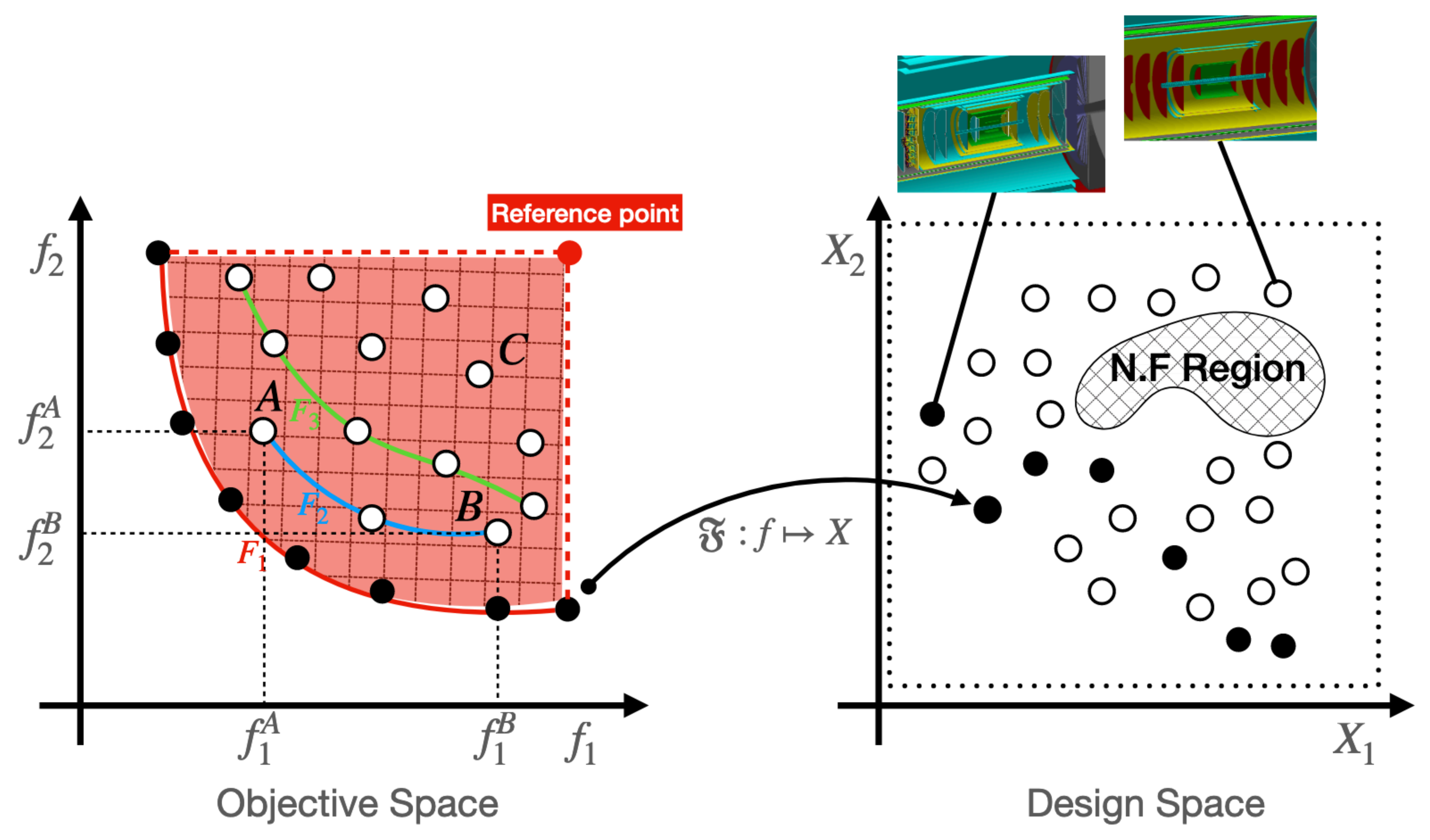
Multi Objective Optimization : Visual Intro

- Multiple “objectives”
  - Momentum resolution
  - ***θ*** resolution
  - KF efficiency
  - projected ***θ*** resolution @ PID
- Goal : “Optimize” these Objectives
- Map: “Design” ↔ “Objective”?
- Non-Feasbile region to be avoided



Multi Objective Optimization : Visual Intro

- What is “Optimal”?
- How to rank solutions?
- How to track convergence?
- Methods of MOO
    - Evolutionary
    - Bayesian inference
    - Preferential Learning, etc.

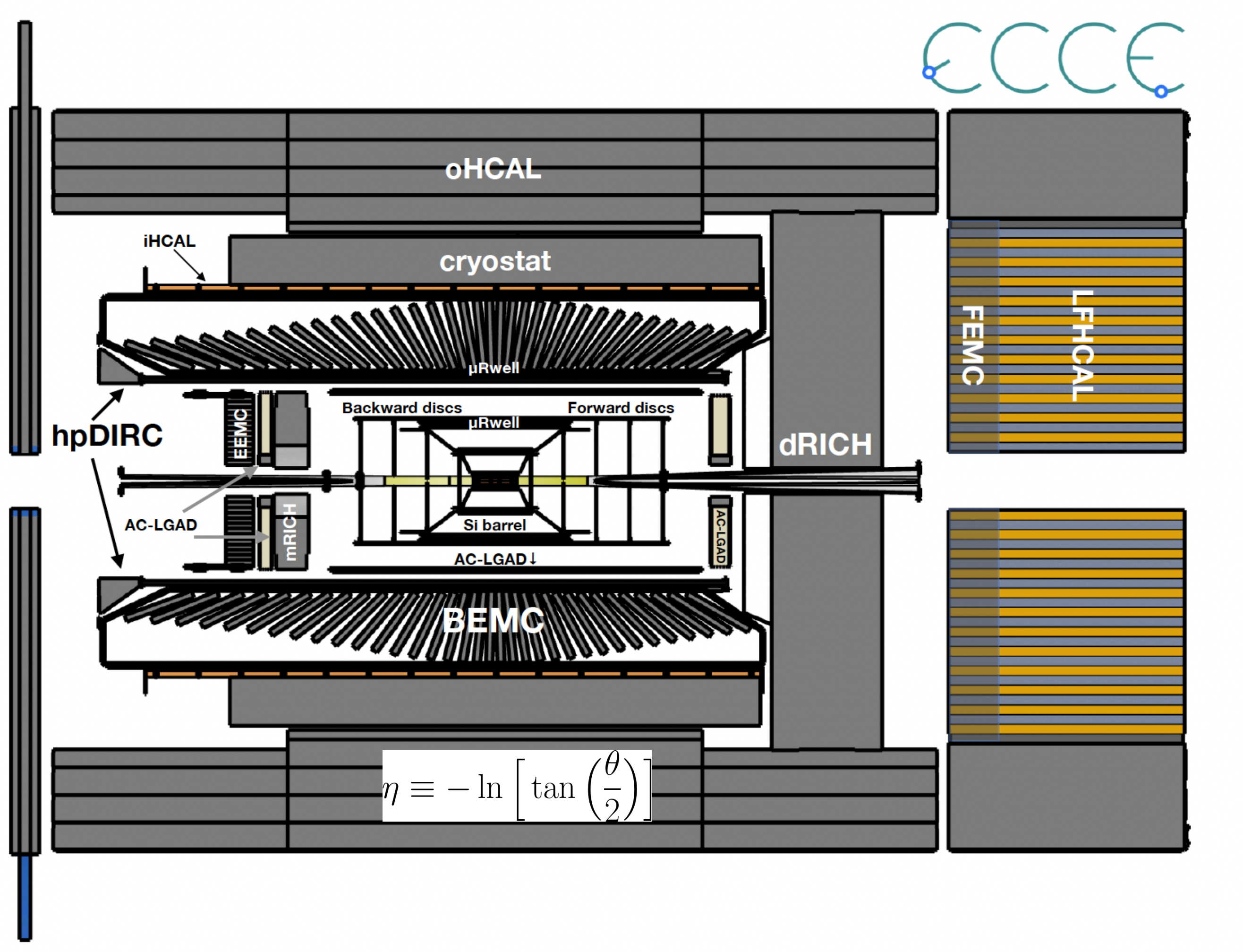


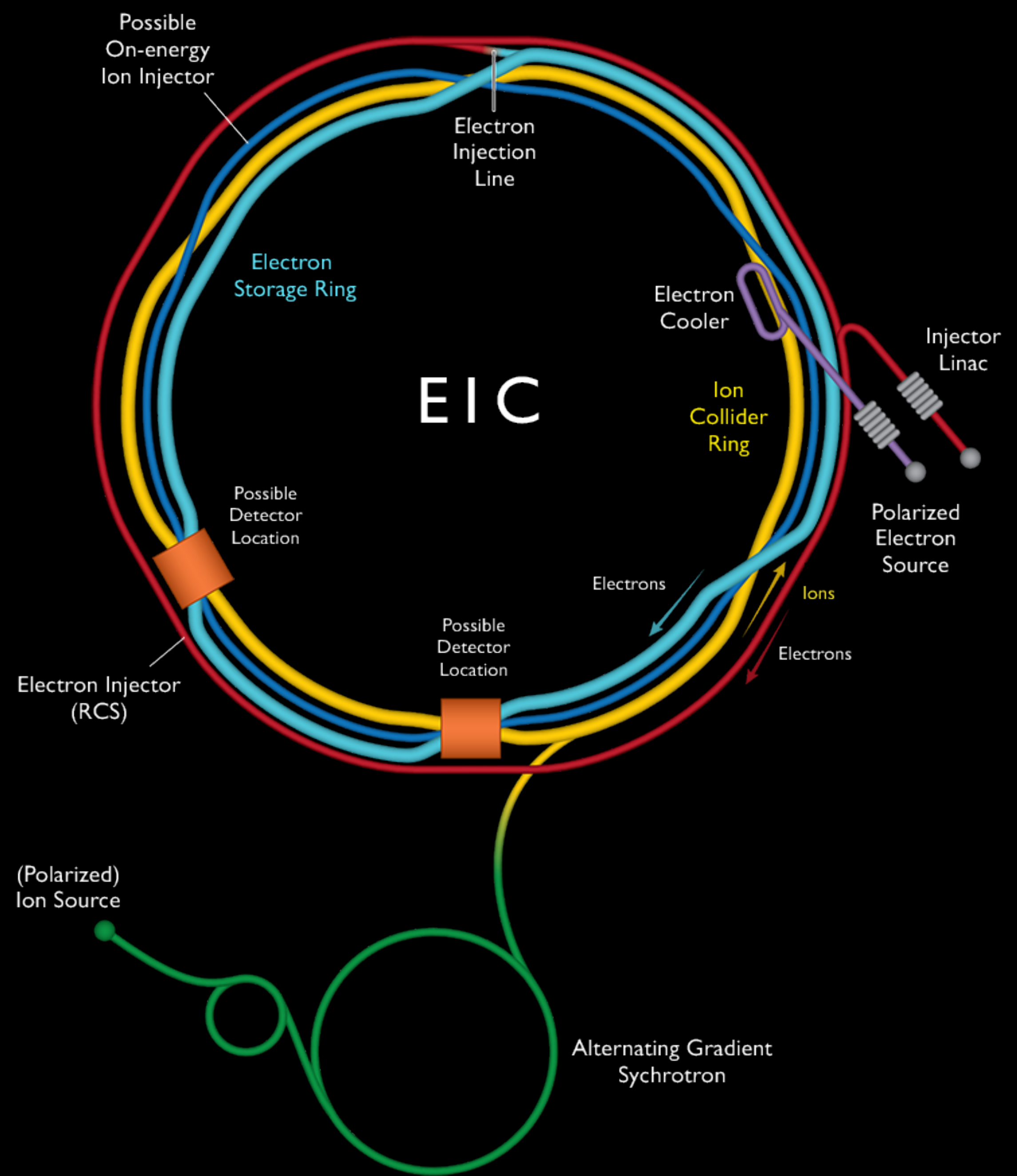
AI assisted Detector design

Electron Ion Collider

At Brookhaven National Laboratory

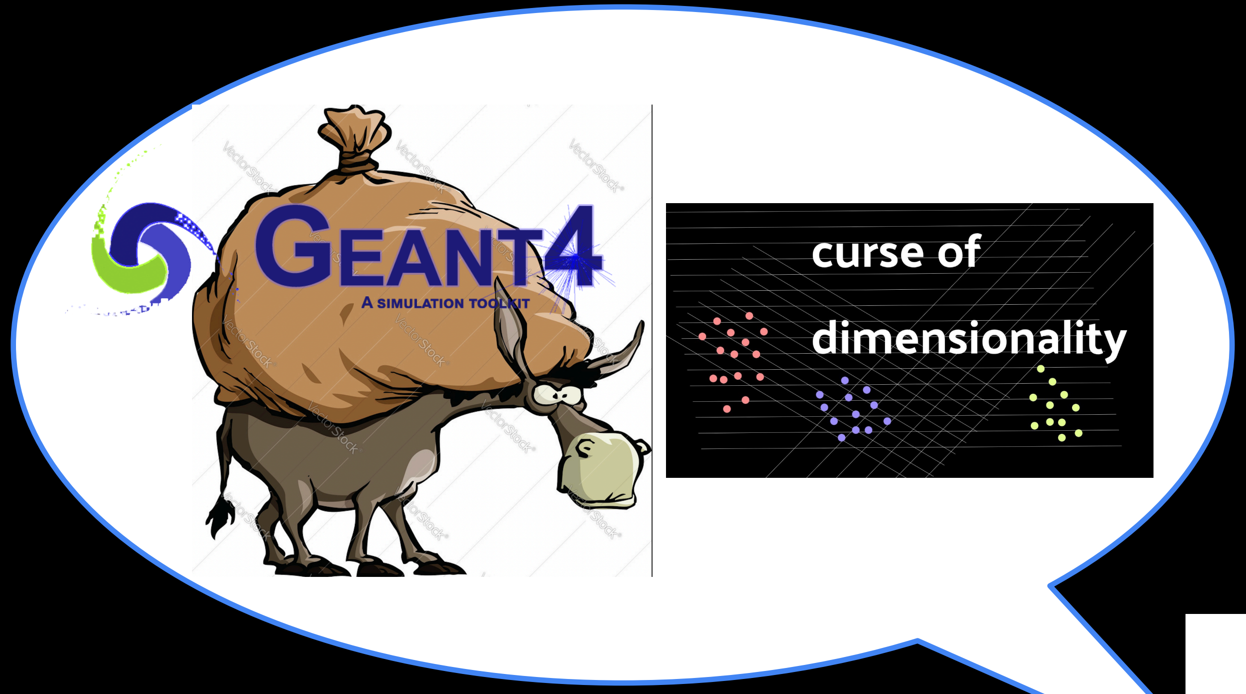
Physics Goal : Structure and dynamics of matter at high luminosity and energy using polarized beams [arXiv:1212.1701]

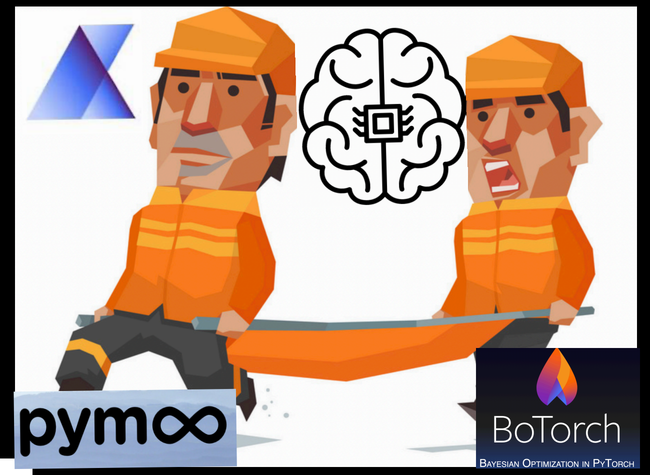




Detector design is inherently Multi Objective

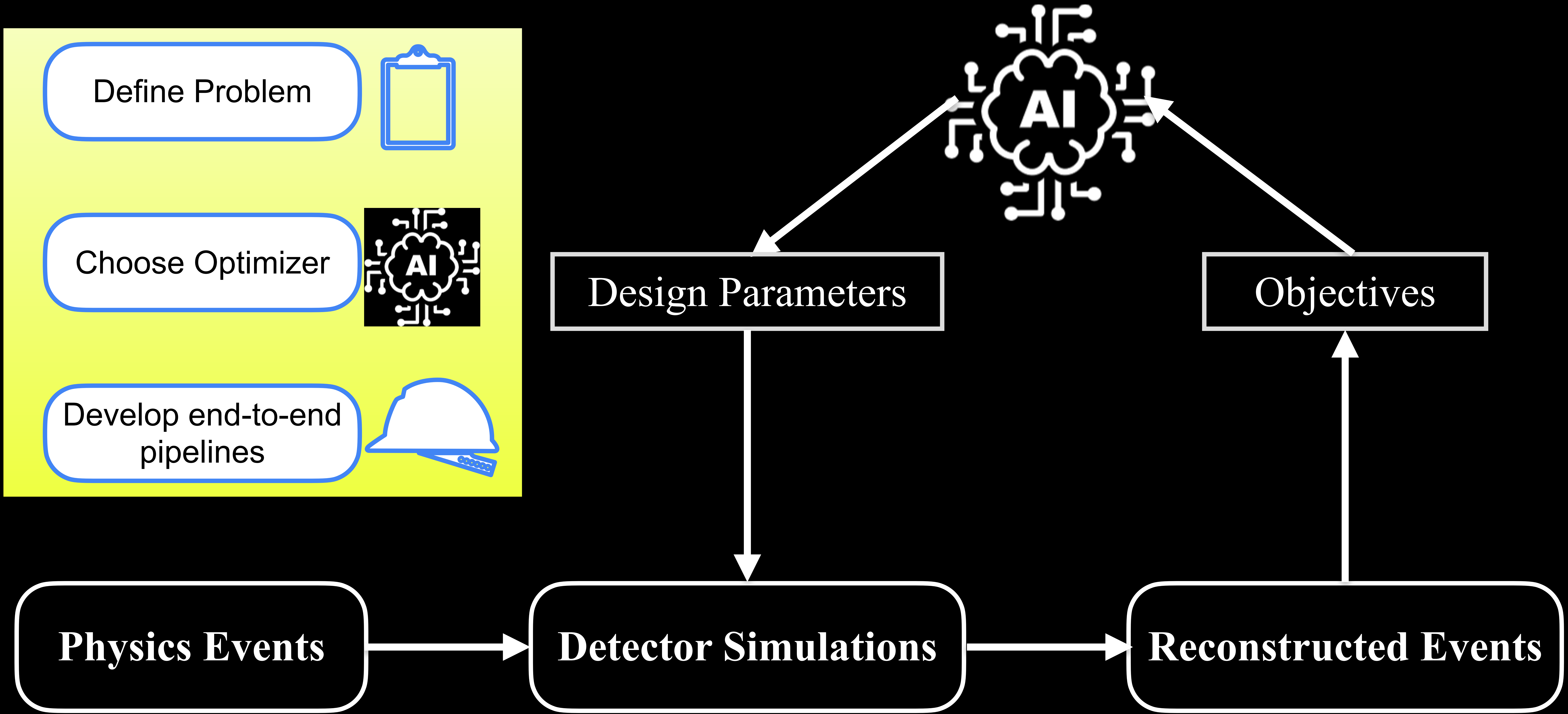
Simulations computationally expensive





AI advantage :
Handle a multi-dimensional parameter space in a multi-dimensional objective space

Workflow for AI assisted detector design



Define Problem

Choose Optimizer

Develop end-to-end pipelines

Design Parameters

Objectives

Physics Events

Detector Simulations

Reconstructed Events

Desired kinematic range

AI assisted EIC Detector optimization pipeline

AI Optimization block

AI Suggested
Design points

Evaluation of the Design points

Sort solutions
Approximate Pareto front
Suggest next set of design points

Parallelization

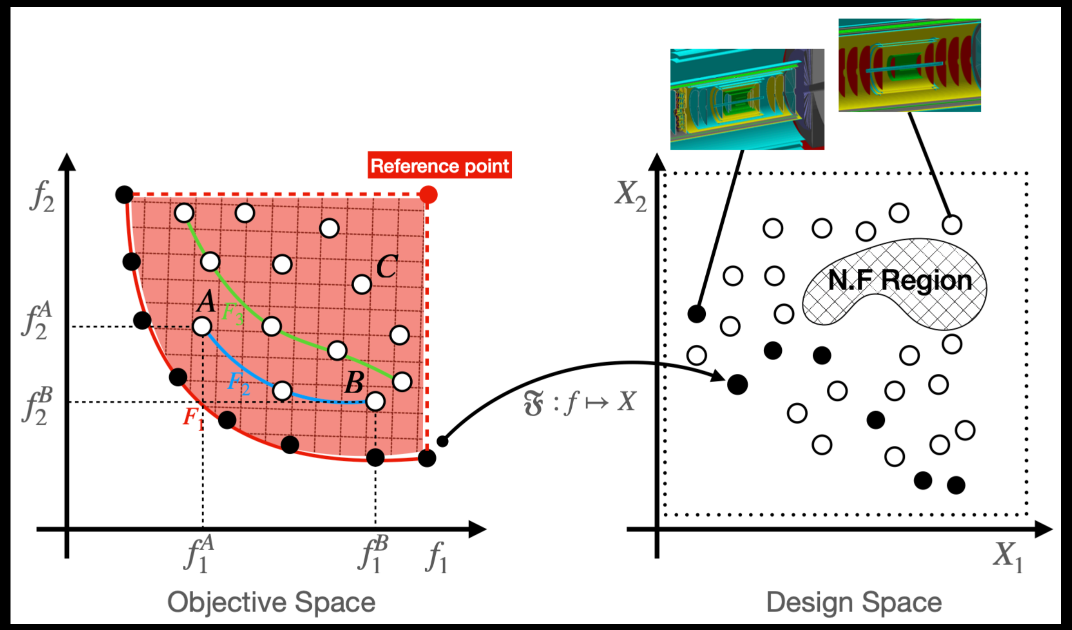
Detector/Physics Simulation

Fit objectives in η & p bins

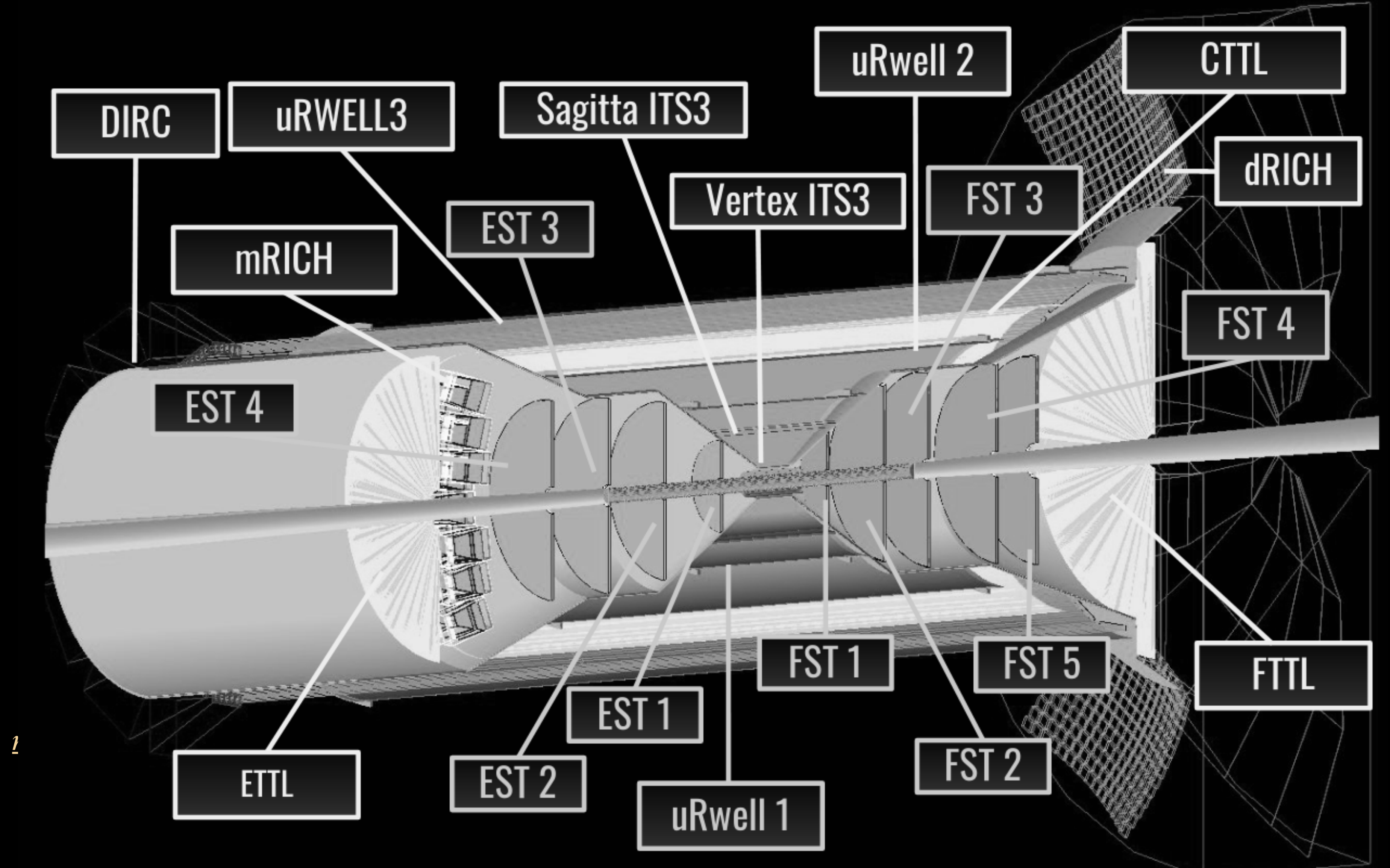
Compute Objectives and metrics

AI assisted Detector design

A Tracking system use case



- Multiple “objectives”
  - Across all η (angle)
  - Momentum resolution
  - Angular resolution
- O(10) design parameters
- Map : Objectives ↔ Design
- Embed constraints as well
- Multiple “Optimal Solutions”

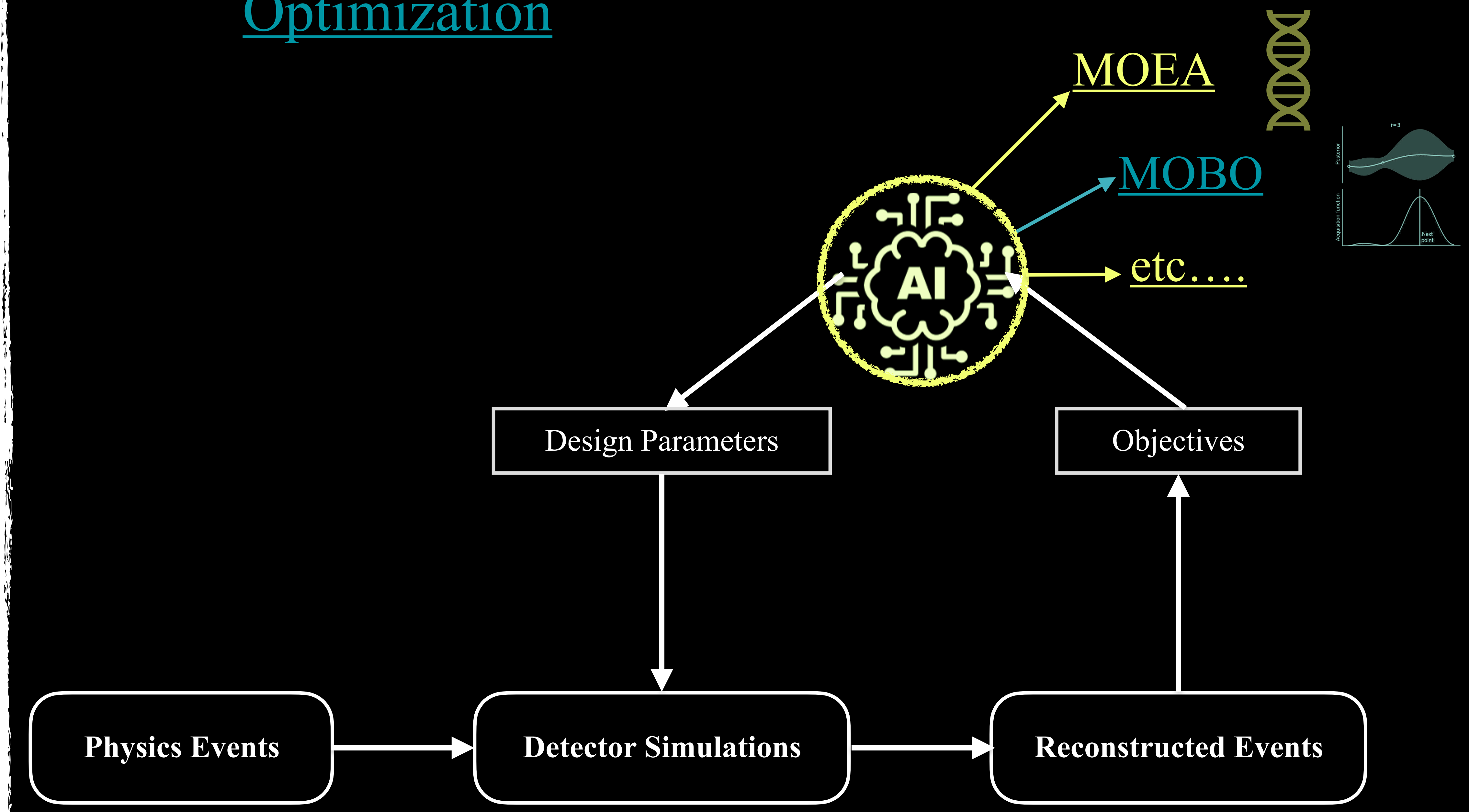


Optimization monitoring

arxiv:2205.09185, arxiv:2203.04530

Life cycle of design

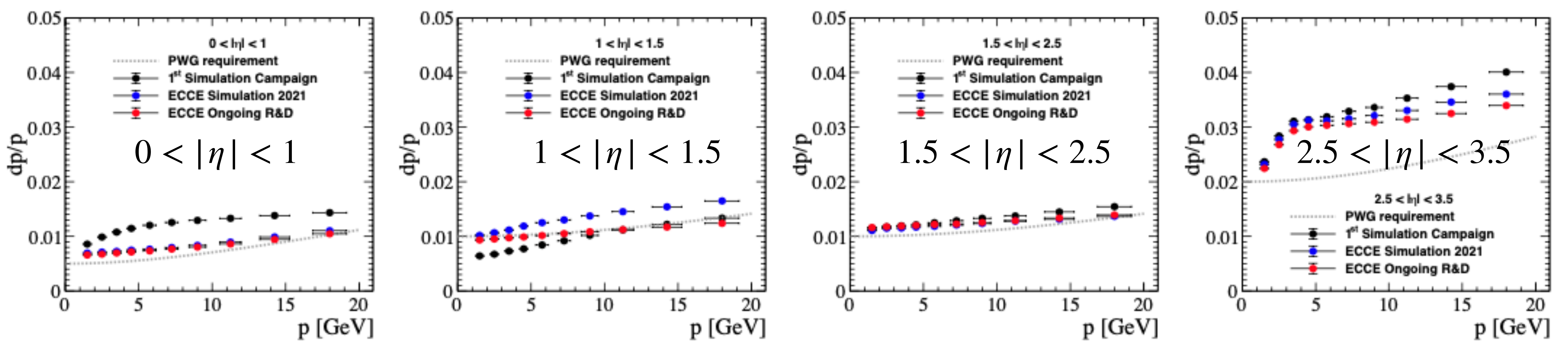
- MOEA - Multi Objective Evolutionary Algorithm
- MOBO - Multi Objective Bayesian Optimization



AI assisted Detector design : Result

Came up with design solution of the tracker that improved tracking performance by over 20%

j.nima.2022.167748 Interactive visualization of results



The AIDE Project

A scalable and distributed AI-assisted Detector Design for the EIC

A collaborative project (DE-FOA-0002875) by:

Brookhaven National Lab, CUA, Duke, Jefferson Lab, William & Mary

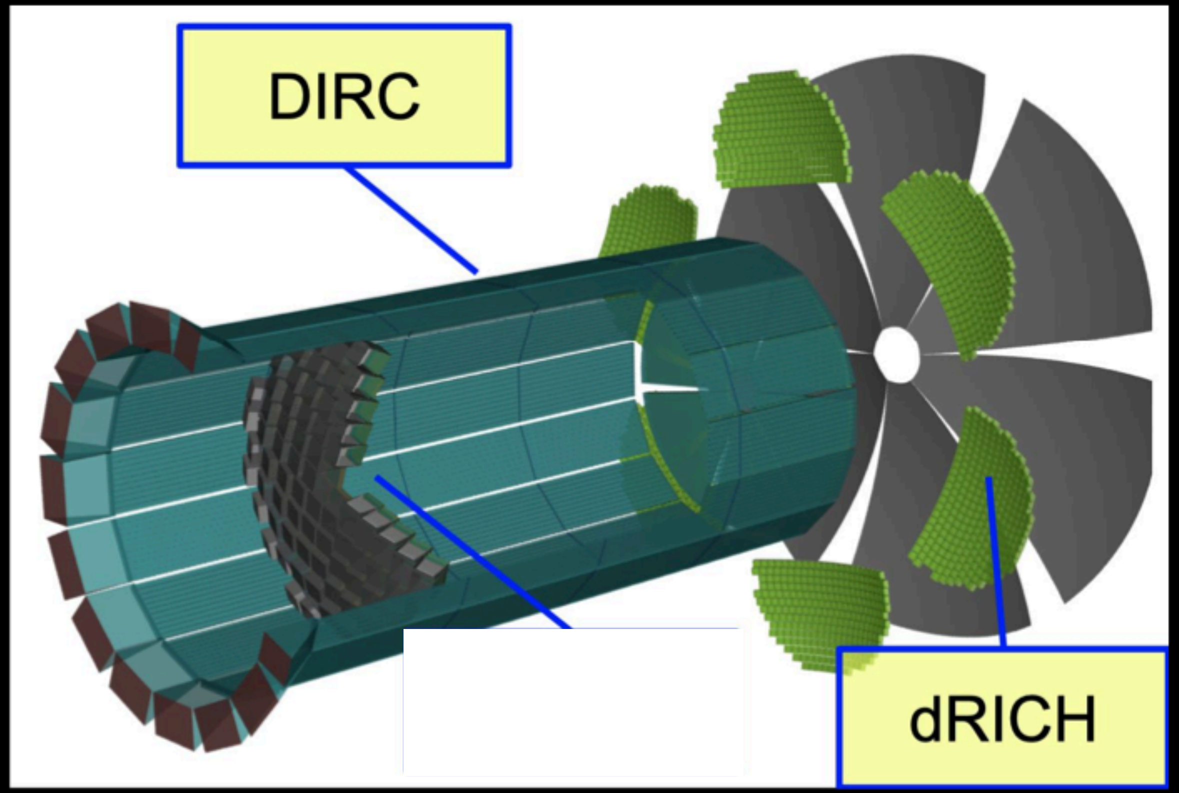
BNL: T. Wenaus, M. Lin
CUA: T. Horn
Duke: A. Vossen
JLab: M. Diefenthaler
W&M: C. Fanelli
Lead PI — C. Fanelli

Develop a software framework for distributed optimizat

Offic

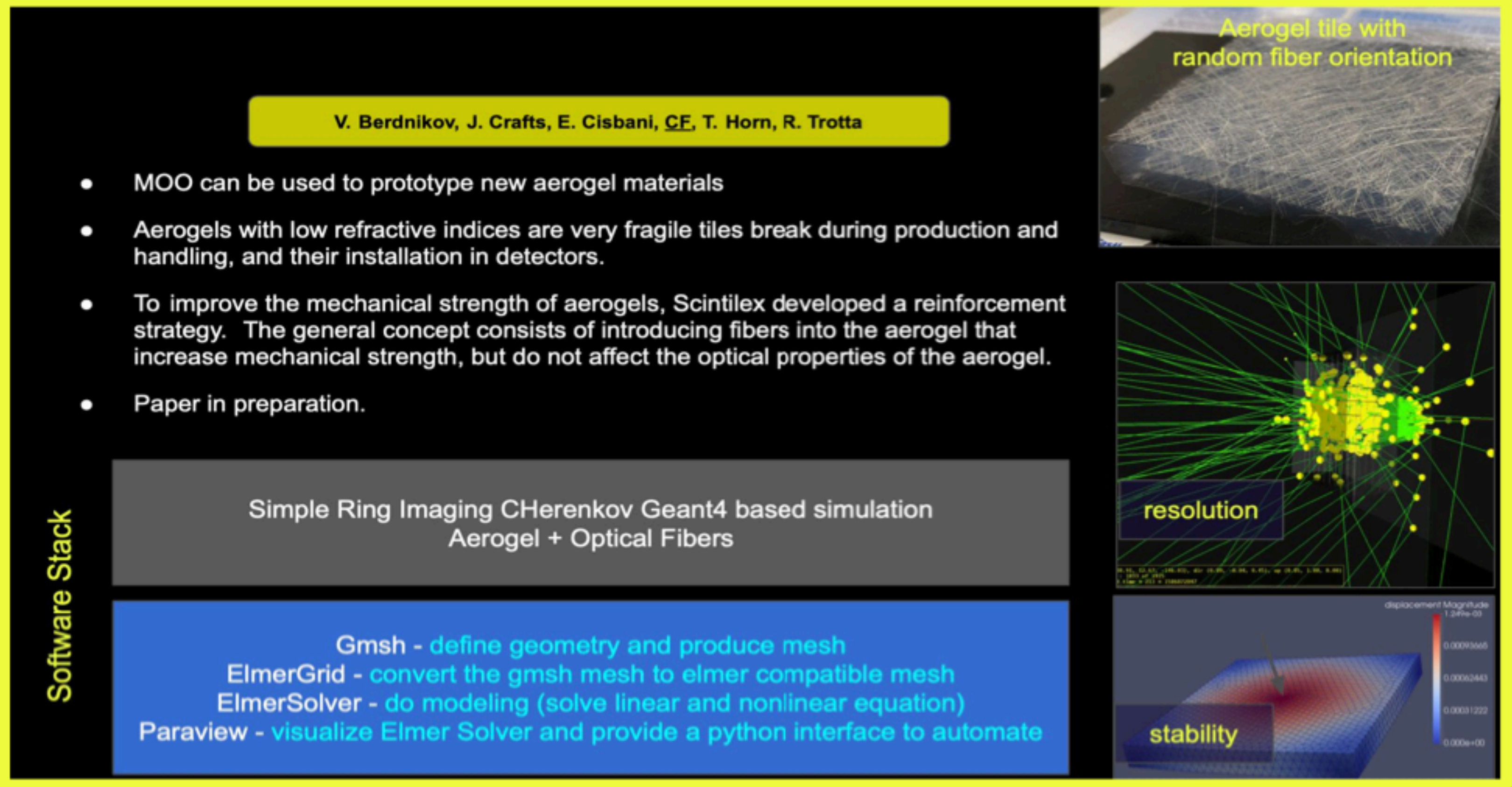
Glimpse of other detector design optimization at EIC

The AIDE Project



Imaging Cherenkov detectors constitute the backbone of PID for the EIC

MOO of Novel Aerogel Material



V. Berdnikov, J. Crafts, E. Cisbani, CF, T. Horn, R. Trotta

- MOO can be used to prototype new aerogel materials
- Aerogels with low refractive indices are very fragile tiles break during production and handling, and their installation in detectors.
- To improve the mechanical strength of aerogels, Scintilex developed a reinforcement strategy. The general concept consists of introducing fibers into the aerogel that increase mechanical strength, but do not affect the optical properties of the aerogel.
- Paper in preparation.

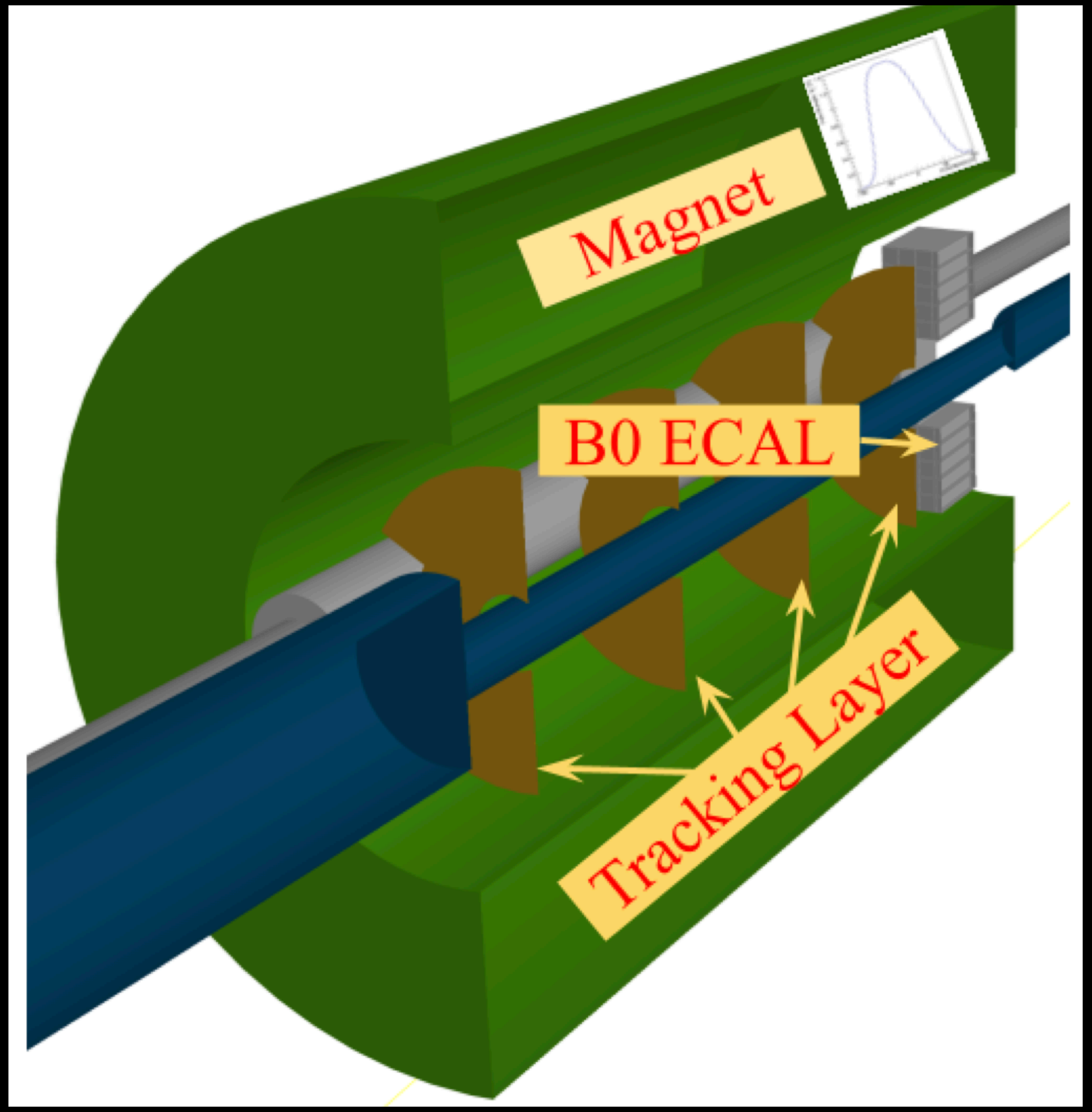
Software Stack

Simple Ring Imaging CHerenkov Geant4 based simulation
Aerogel + Optical Fibers

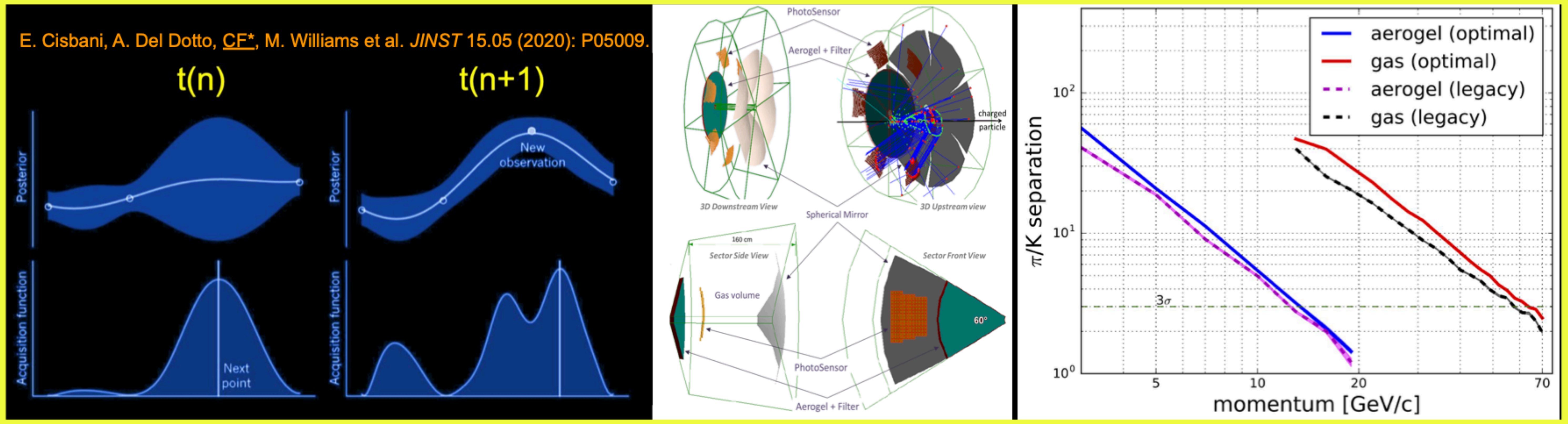
Gmsh - define geometry and produce mesh
ElmerGrid - convert the gmsh mesh to elmer compatible mesh
ElmerSolver - do modeling (solve linear and nonlinear equation)
Paraview - visualize Elmer Solver and provide a python interface to automate

[Production and Distributed Analysis (PanDA) System]

Far Forward B0 Detectors



Bayesian optimization of the dual-RICH



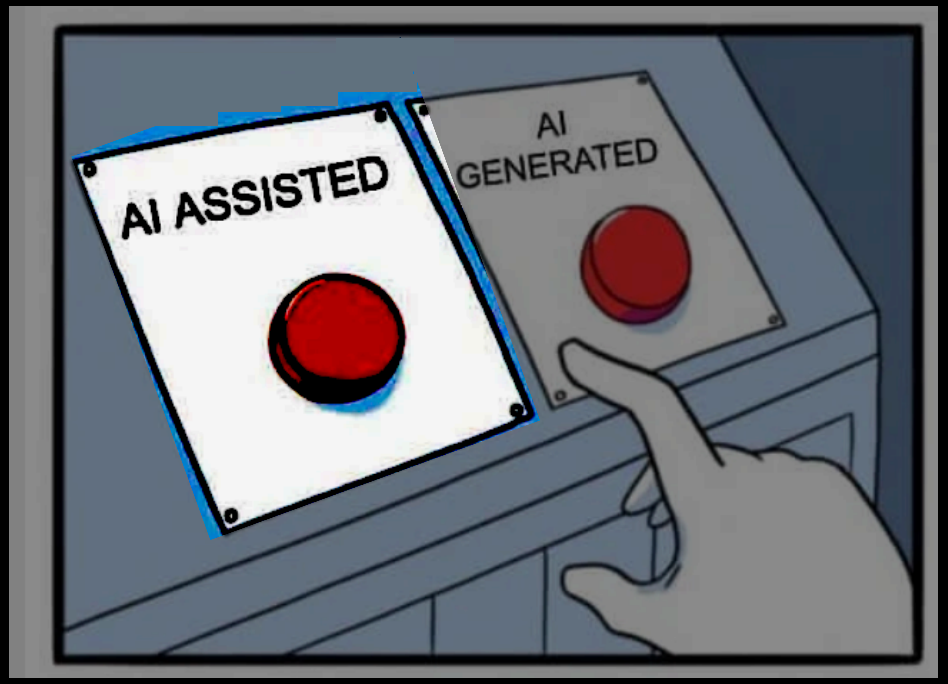
E. Cisbani, A. Del Dotto, CF*, M. Williams et al. *JINST* 15.05 (2020): P05009.

Cristiano Fanelli @ IAEA Technical Meeting

AI Assisted Detector Design: Summary

- AI can assist the design and R&D of complex experimental systems by providing more efficient design (considering multiple objectives) utilizing effectively the computing resources needed to achieve that.
- Optimization done in phases. Eg. include one detector system at a time arxiv:2205.09185
- May not have to reinvent the wheel, leverage on existing SOTA tools,
  - Co-develop tools to better adapt and serve our community (EIC Software: Statement of principles)

Acknowledgements



Thank You

NSERC CRSNG

Grant Contract No. DE-SC0024625

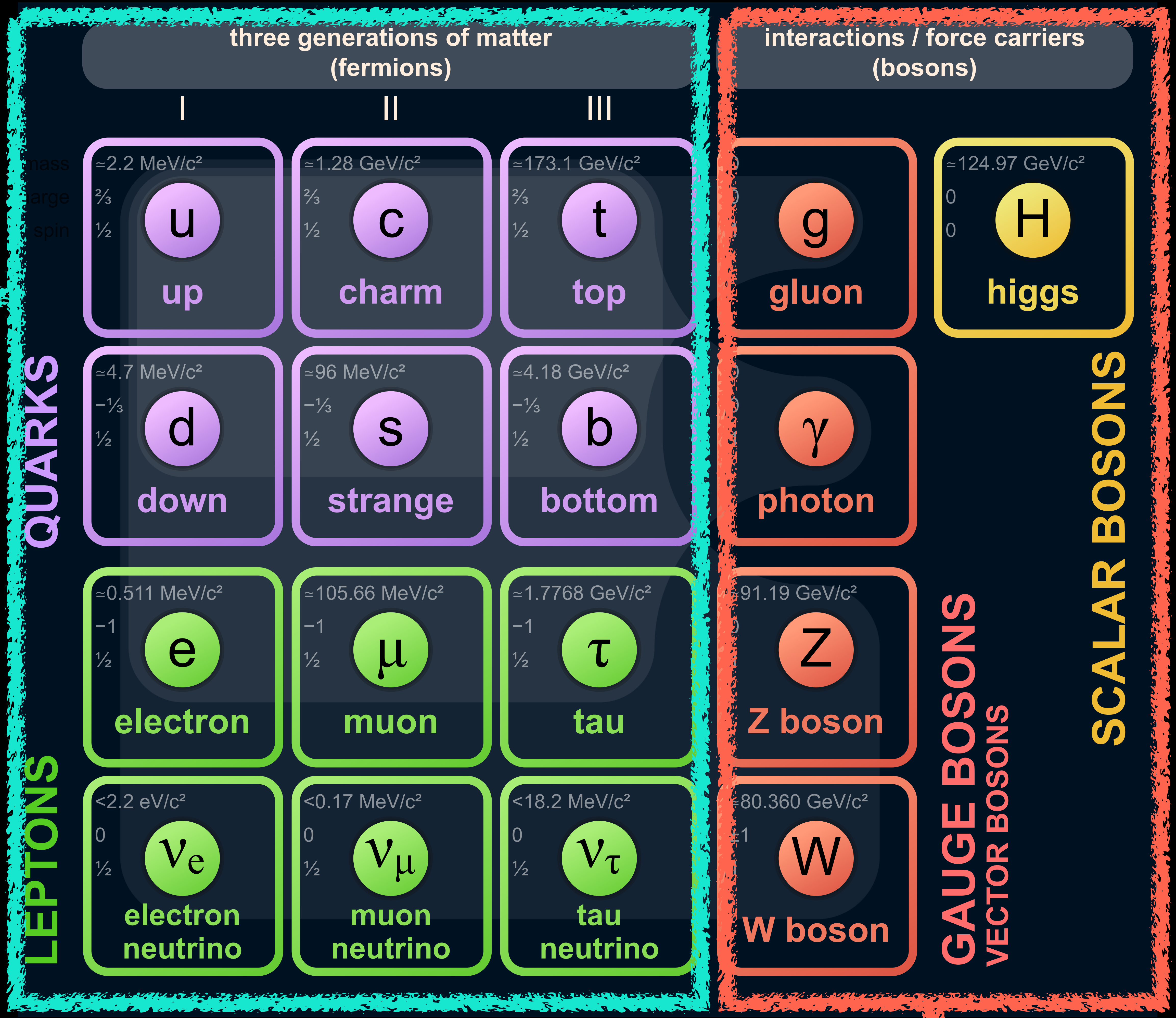
GlueX Thanks

Backups

The Standard Model of Physics

Fermions - half integer spin makes up everything…..

Bosons - integer spin force carriers



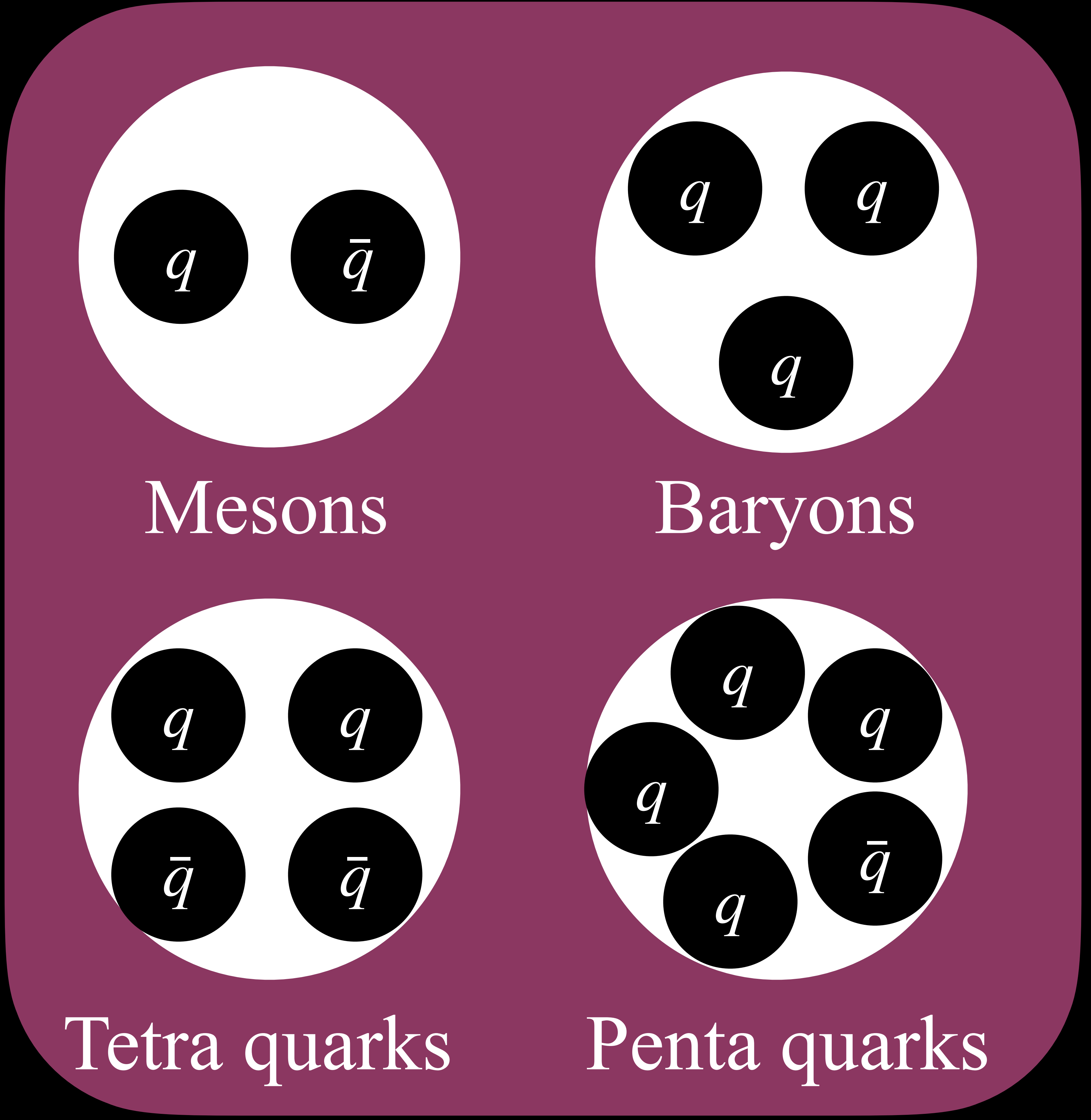
Hadrons : particles made of quarks

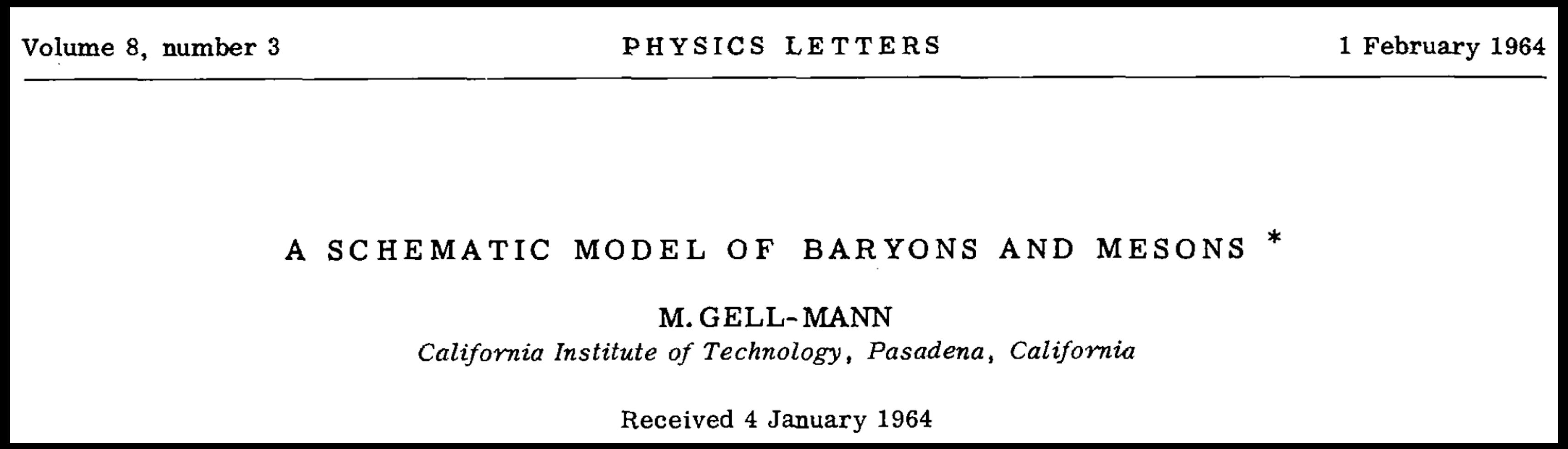
The "Molecule" held together by Strong Force

The Standard Model of Physics

Theory of Strong interactions : Quark Model

- Gell-Mann & Zweig for light flavors quarks in 1964[†]
- States are constructed using “quantum numbers” of the constituent quarks
  - Spin (S)
  - Electric Charge (Q)
  - Isospin (I)
  - …..
- Recipe to build periodic table of hadrons




Volume 8, number 3 PHYSICS LETTERS 1 February 1964

A SCHEMATIC MODEL OF BARYONS AND MESONS *

M. GELL-MANN
California Institute of Technology, Pasadena, California

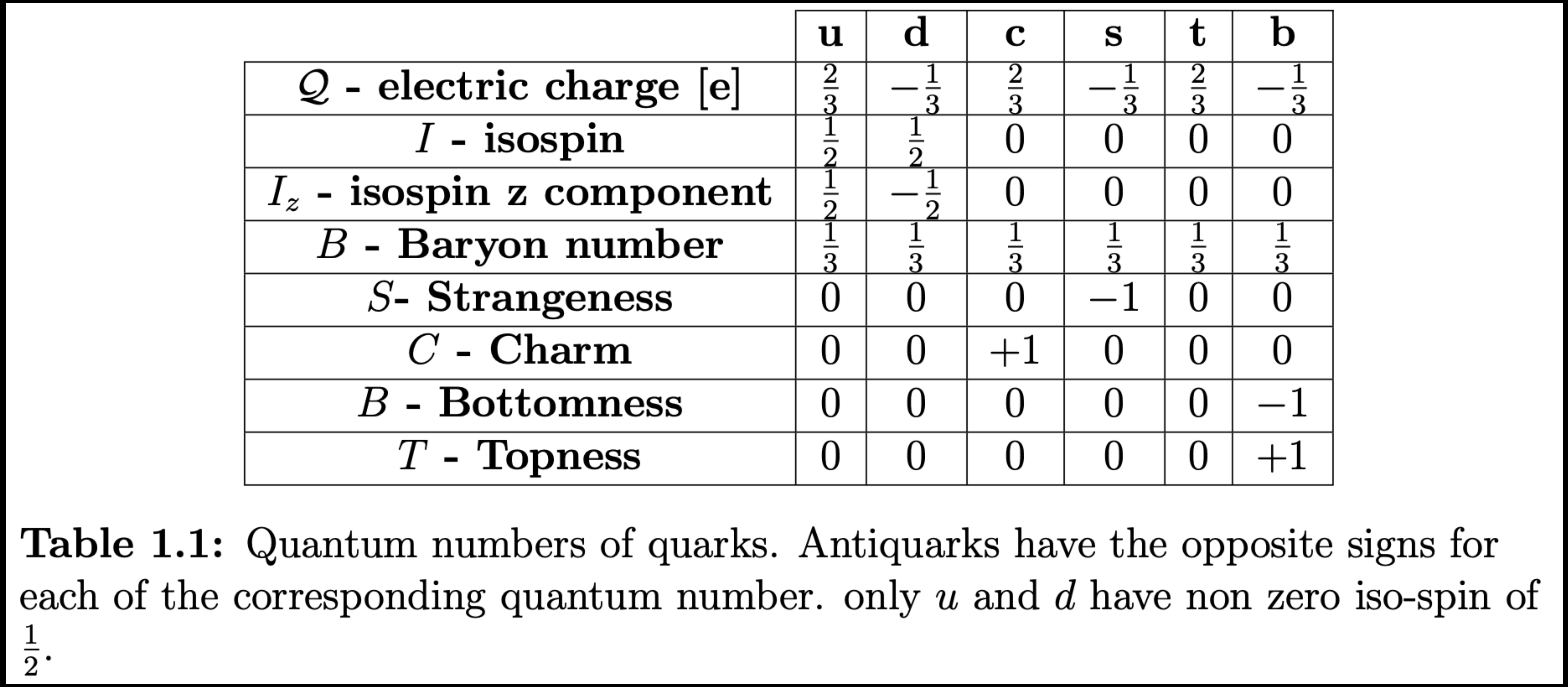
Received 4 January 1964

[†] A Schematic Model of Baryons and Mesons, Phys. Letter 8 (1964) 214-215

The Standard Model of Physics

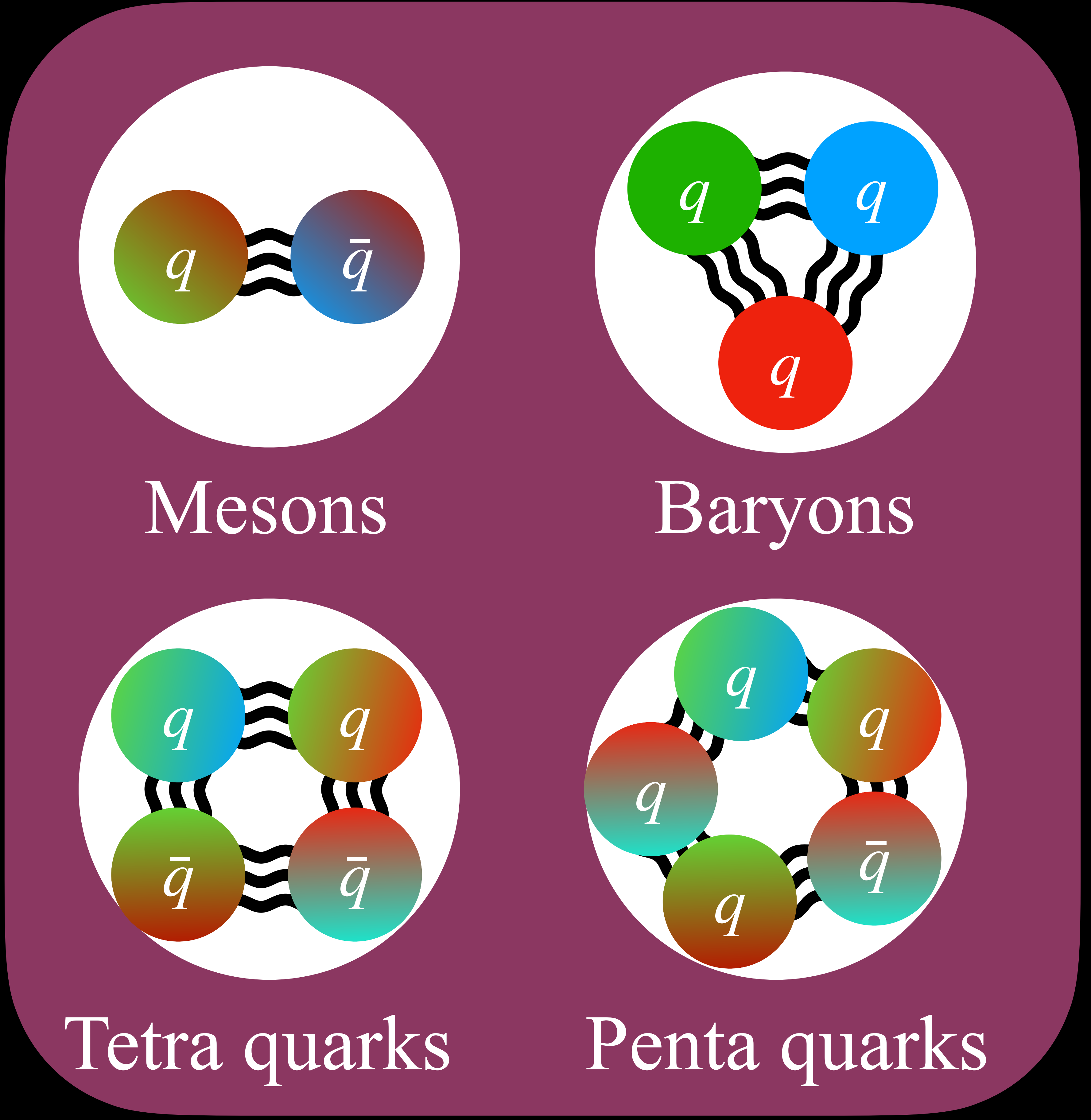
Theory of Strong interactions : Quark Model

Quark Quantum numbers



	u	d	c	s	t	b
Q - **electric charge [e]**	$\frac{2}{3}$	$-\frac{1}{3}$	$\frac{2}{3}$	$-\frac{1}{3}$	$\frac{2}{3}$	$-\frac{1}{3}$
I - **isospin**	$\frac{1}{2}$	$\frac{1}{2}$	0	0	0	0
I_z - **isospin z component**	$\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0
B - **Baryon number**	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
S- **Strangeness**	0	0	0	-1	0	0
C - **Charm**	0	0	$+1$	0	0	0
B - **Bottomness**	0	0	0	0	0	-1
T - **Topness**	0	0	0	0	0	$+1$

Table 1.1: Quantum numbers of quarks. Antiquarks have the opposite signs for each of the corresponding quantum number. only u and d have non zero iso-spin of $\frac{1}{2}$.

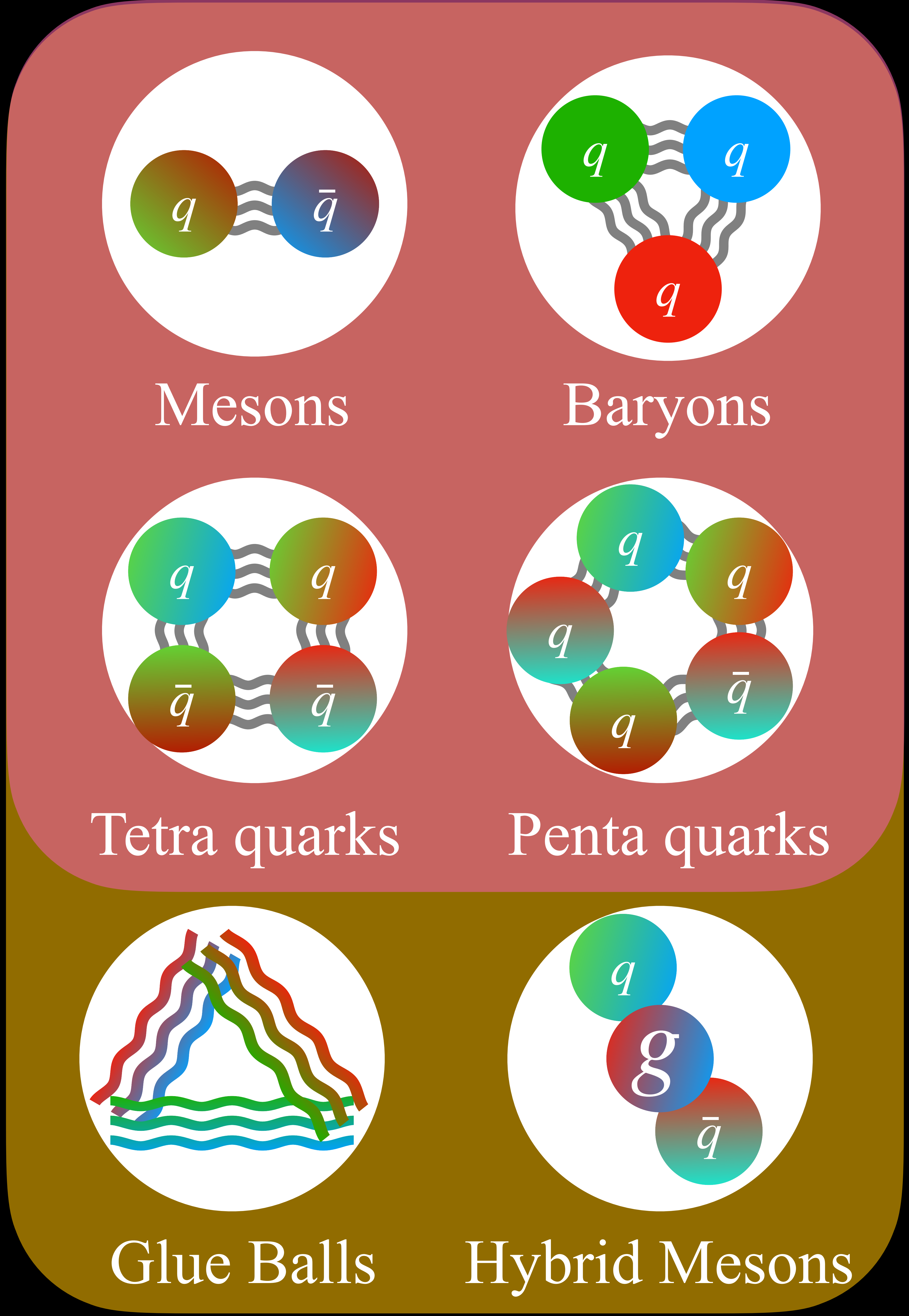


$q\bar{q}$	Isospin	$^1(L_{\text{even}})_J$	$^1(L_{\text{odd}})_J$	$^3(L_{\text{even}})_J$	$^3(L_{\text{odd}})_J$
$u\bar{d}$,$u\bar{u}-d\bar{d}$,$d\bar{u}$	$I=1$	π_J	b_J	ρ_J	a_J
$s\bar{s}$,$u\bar{u}+d\bar{d}$	$I=0$	η_J,η'_J	h_J,h'_J	ω_J,ϕ_J	f_J,f'_J
$u\bar{s}$,$d\bar{s}$	$I=\frac{1}{2}$	$J^P=0^-,1^+,2^-,\cdots$	K_J	$J^P=0^+,1^-,2^+,\cdots$	K^*_J

The Standard Model of Physics

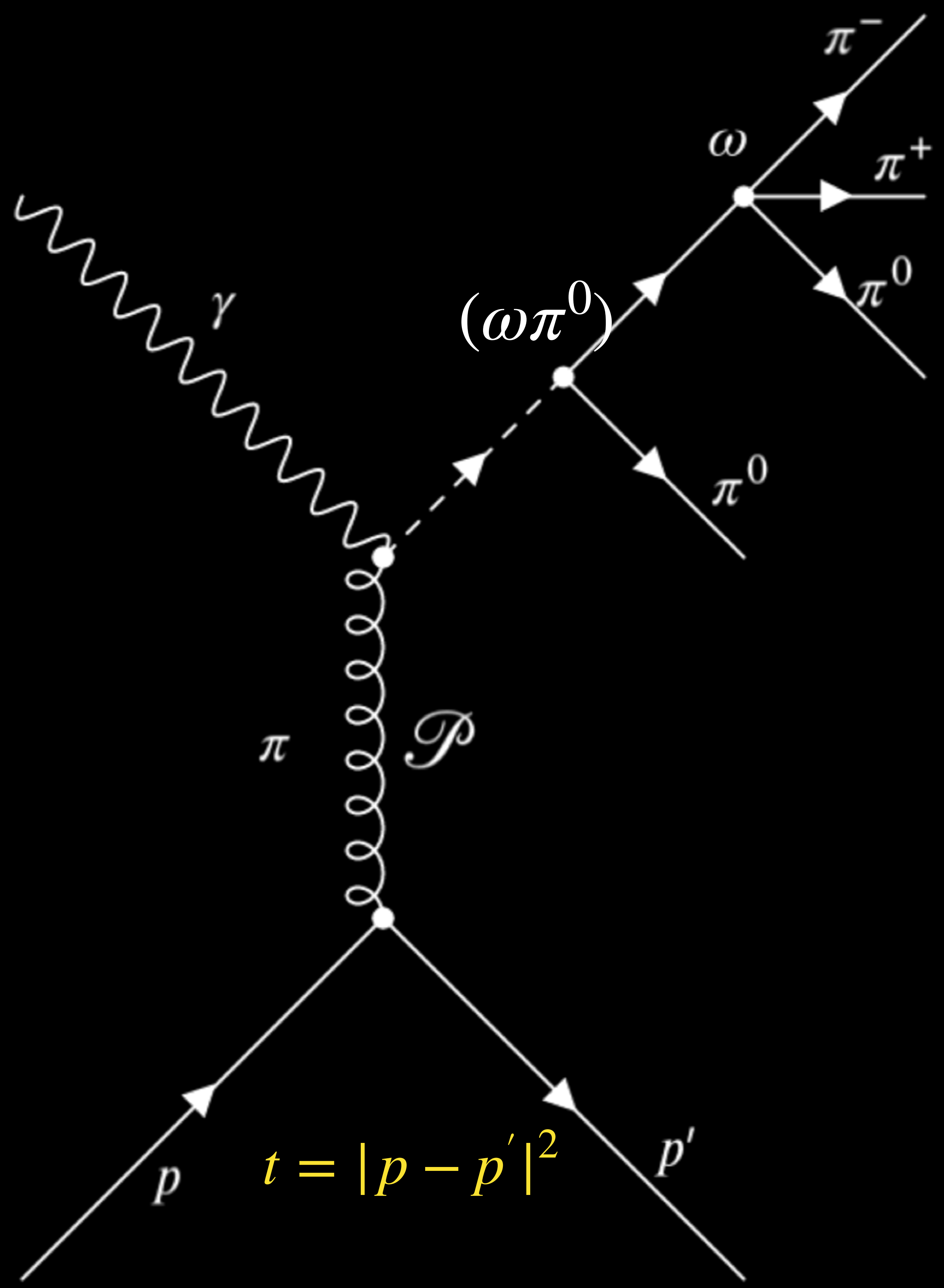
Quantum ChromoDynamics

- Formalized a decade later than Quark Model
- Introduces - “color charge” to quarks and gluons
- Includes “gluonic” interactions to build up states
- Predicts
  - “Hybrid ” mesons
  - “Exotic” States **NOT** allowed in Quark Model $J^{PC} = [0^{+\,-}, 1^{-\,+}, 2^{+\,-}, 3^{-\,+}]$
- Important outcomes
  - Color confinement — “Free” quarks cannot be observed
  - Non negligible α_s at low energy scale — “Lattice QCD”



Photoproduction of $\omega\pi^0$ at GlueX

$$\gamma p \to \omega\pi^0 p \to (\pi^+\pi^-\pi^0)\pi^0 p$$



Selection Cuts

"Hard" Cut Selection

Particle Hypothesis

KinFit CL $> 10^{-2}$; $\chi^2/NDF < 2.25$

Detector response cuts

PID-Timing, Calorimetry

Phasespace cuts

$0.15 < |t| < 1.0$ GeV^2

$8.2 <$ E_Beam < 8.8 GeV

MM$^2 \leq 0.05$ GeV^2

Weighted events

Statistical Accounting of beam γ

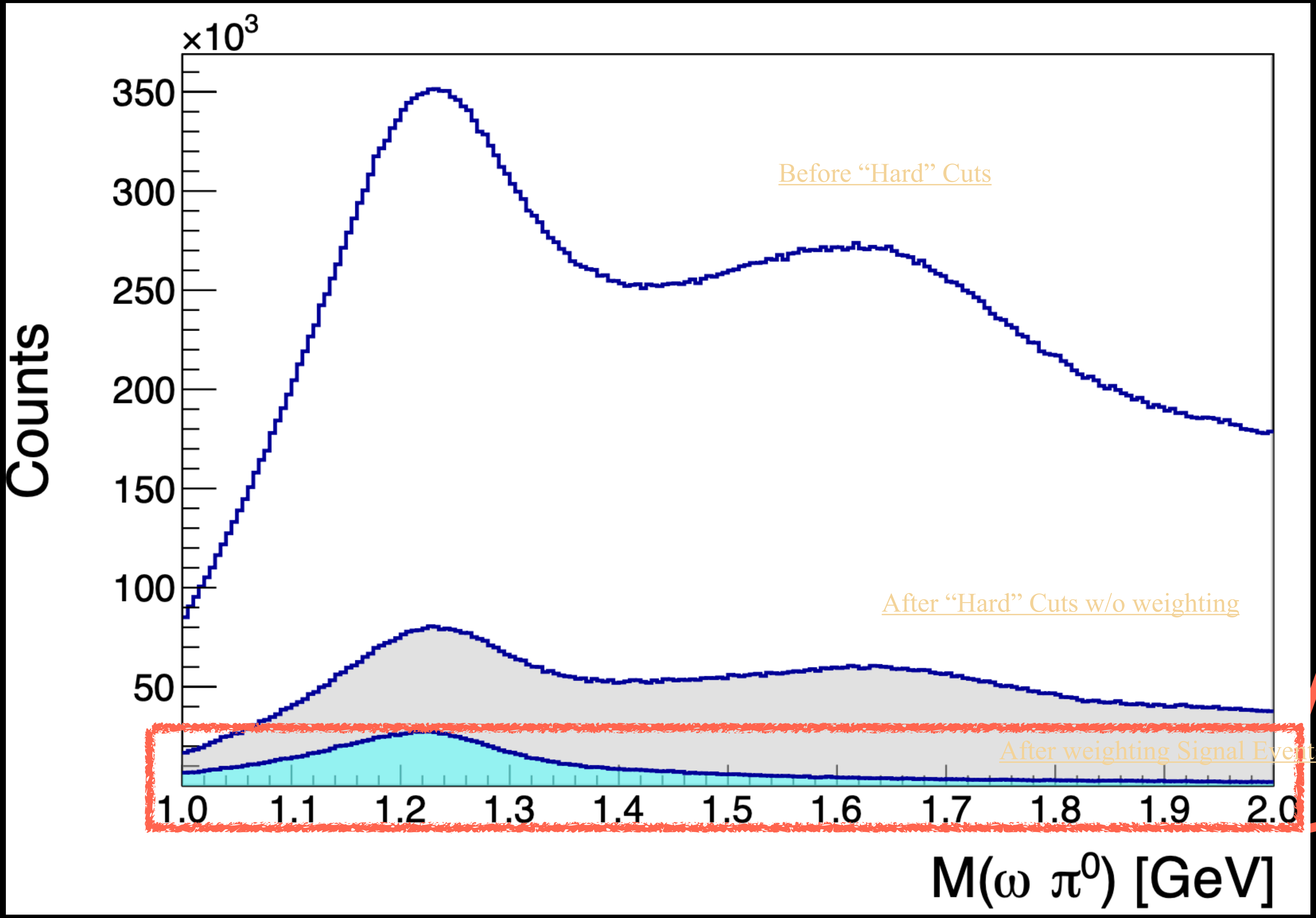
Accidental Side band subtraction

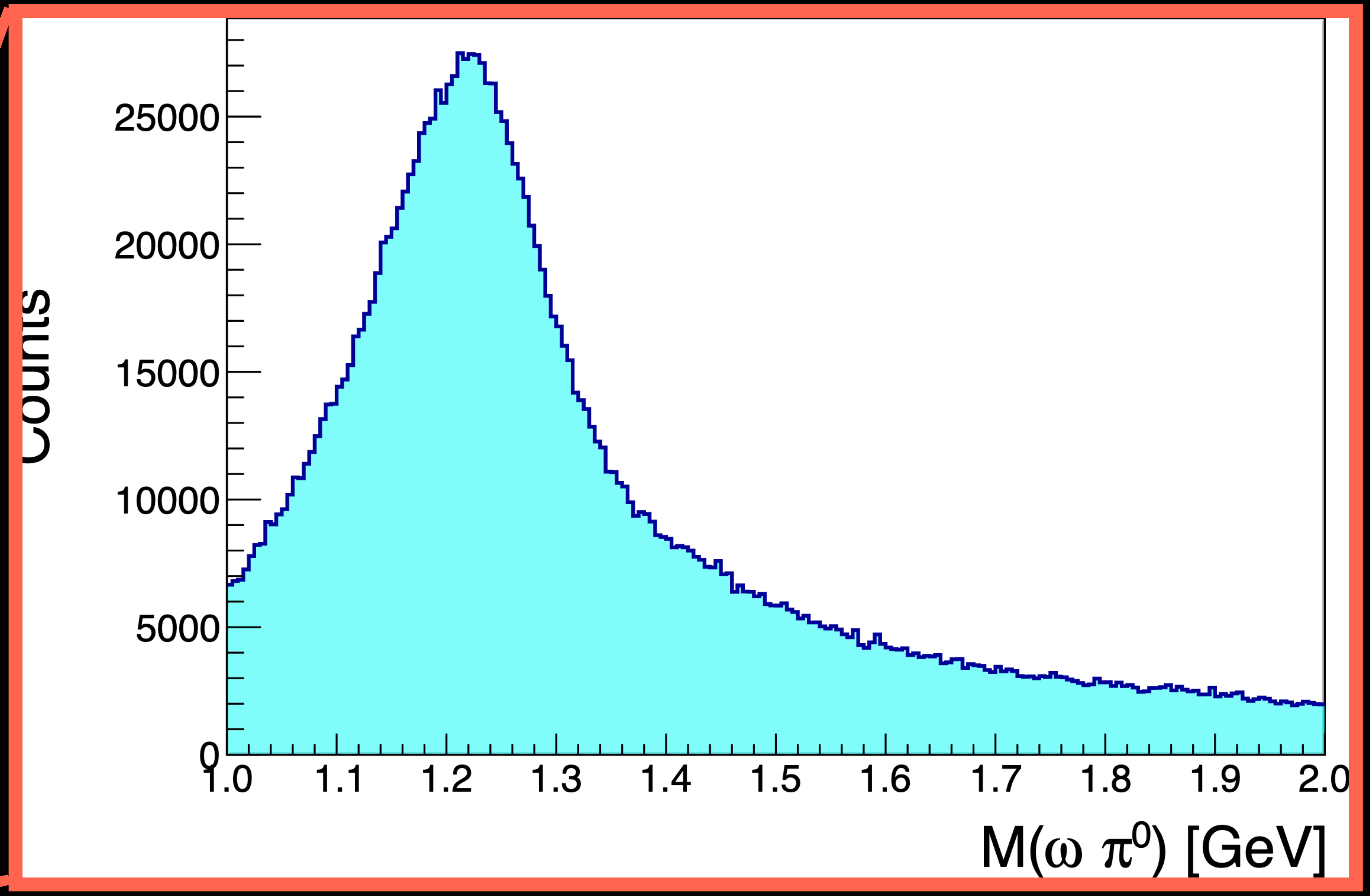
Accounting for "non-ω" events

2D-ω side band subtraction

Photoproduction of $\omega\pi^0$ at GlueX

$\omega\pi^0$ mass* after background subtraction



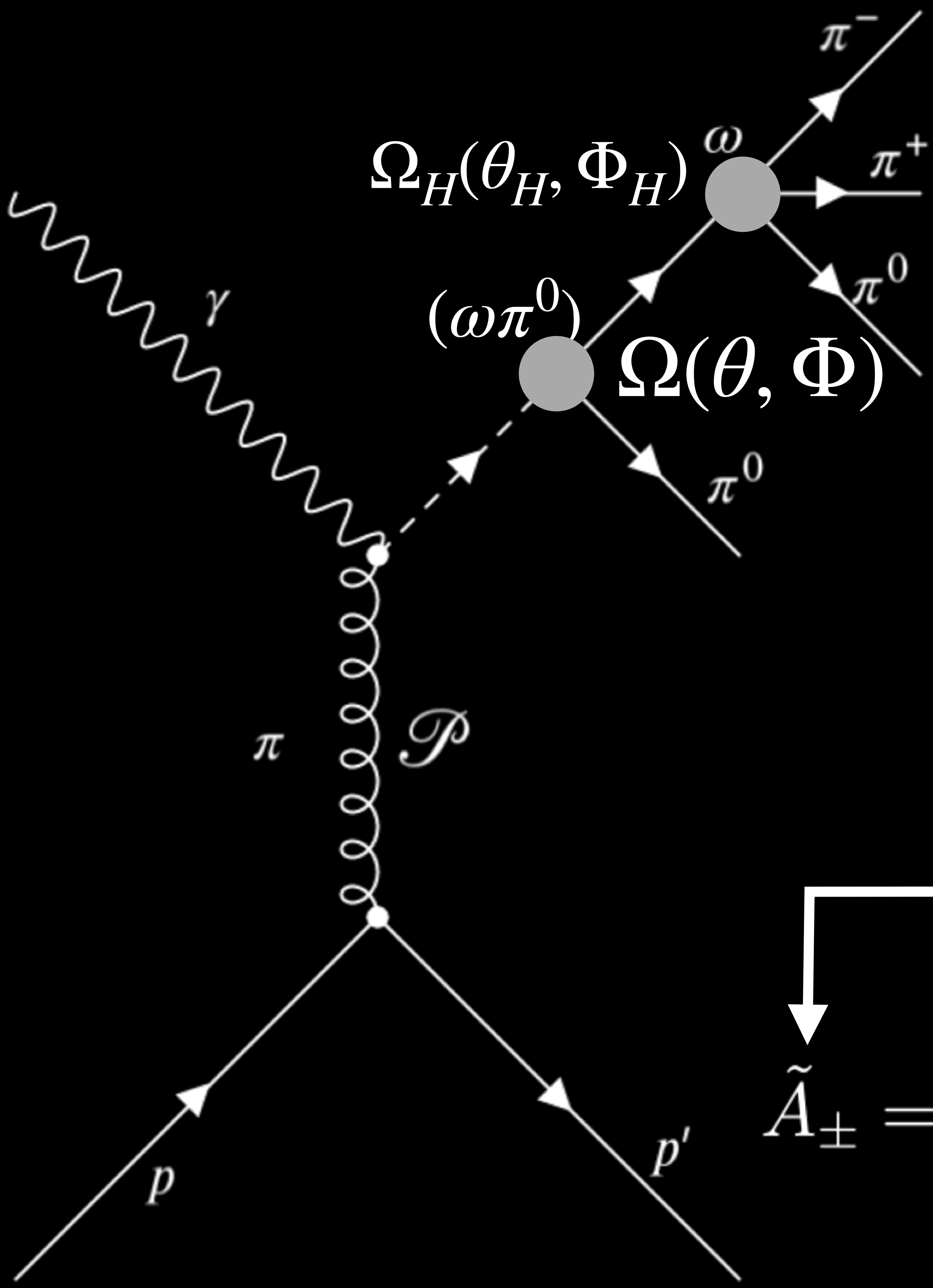


High purity events of $\omega\pi^0$ selected.

*Only Fall2018 PARA0

Partial Wave Analysis

Intensity Model: Measuring $b_1(1^{+\,-})$ in $\omega\pi^0$ spectrum



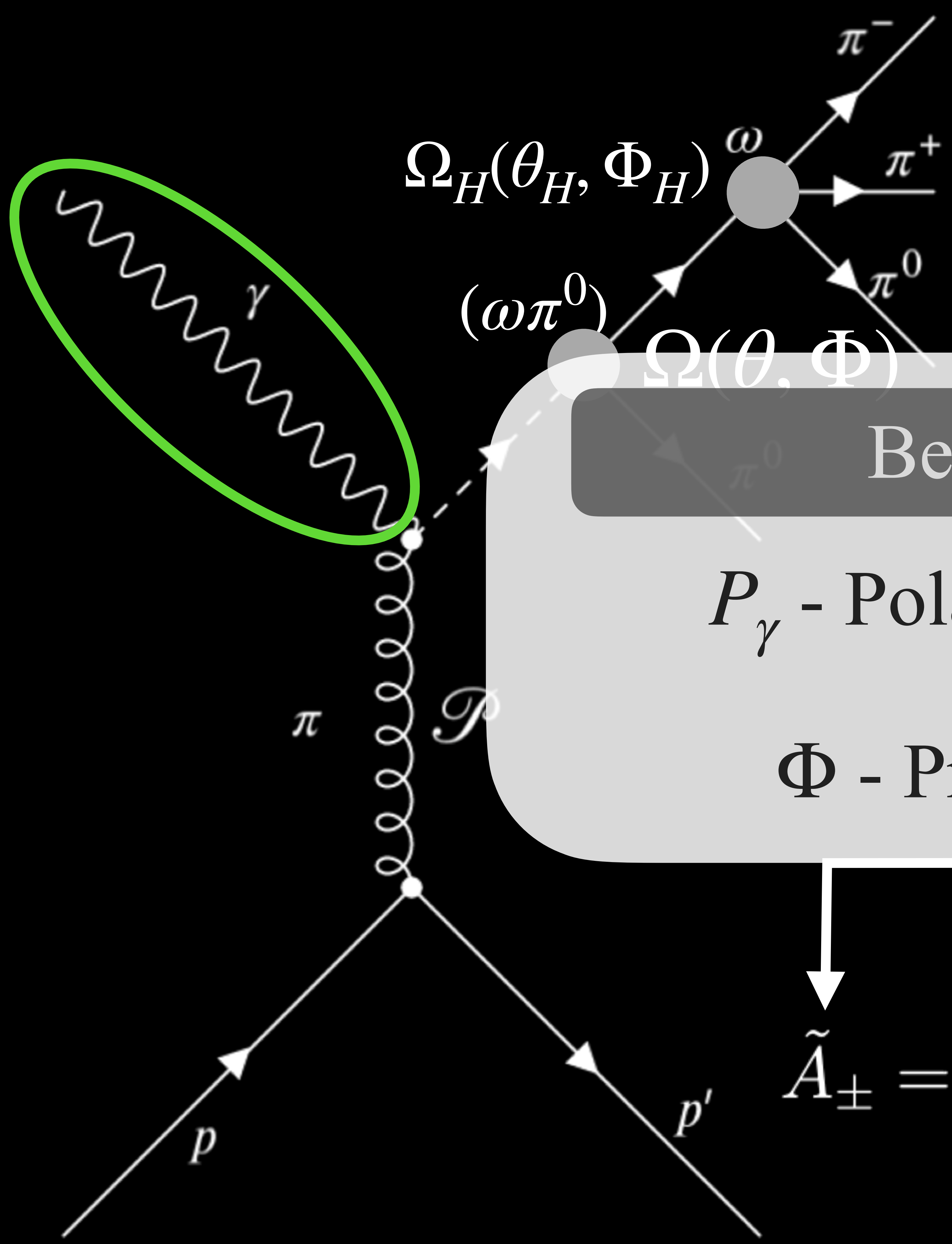
In "thin" $M(\omega\pi^0)$ and $|t|$ bin

$$I(\Omega, \Omega_H, \Phi) = \frac{\kappa}{4}(1 - P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) + \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2 + \frac{\kappa}{4}(1 + P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) - \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2$$

$$\tilde{A}_\pm = \sum_{J_i=1,2,..} \sum_{m=-J_i,..,J_i} T^i_{\pm,m} \sum_{\lambda_\omega=-1,0,1} \overbrace{e^{\mp i\Phi} D^{J_i*}_{m,\lambda_\omega}(\Omega) F^i_{\lambda_\omega} D^{1*}_{m,0}(\Omega_H) G_{\text{Dalitz}} \mathfrak{F}(p_0)}^{Z^i_m(\Phi, \Omega, \Omega_H)}$$

Partial Wave Analysis

Intensity Model: Measuring $b_1(1^{+-})$ in $\omega\pi^0$ spectrum



In "thin" $M(\omega\pi^0)$ and $|t|$ bin

Beam Photon γ

P_γ - Polarization Fraction

Φ - Production angle

$$I(\Omega, \Omega_H, \Phi) = \frac{\kappa}{4}(1 - P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) + \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2 + \frac{\kappa}{4}(1 + P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) - \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2$$

$$\tilde{A}_\pm = \sum_{J_i=1,2,..}\sum_{m=-J_i,..,J_i} T^i_{\pm,m} \sum_{\lambda_\omega=-1,0,1} \overbrace{e^{\mp i\Phi} D^{J_i*}_{m,\lambda_\omega}(\Omega) F^i_{\lambda_\omega} D^{1*}_{m,0}(\Omega_H) G_{\text{Dalitz}} \mathfrak{F}(p_0)}^{Z^i_m(\Phi, \Omega, \Omega_H)}$$

Partial Wave Analysis

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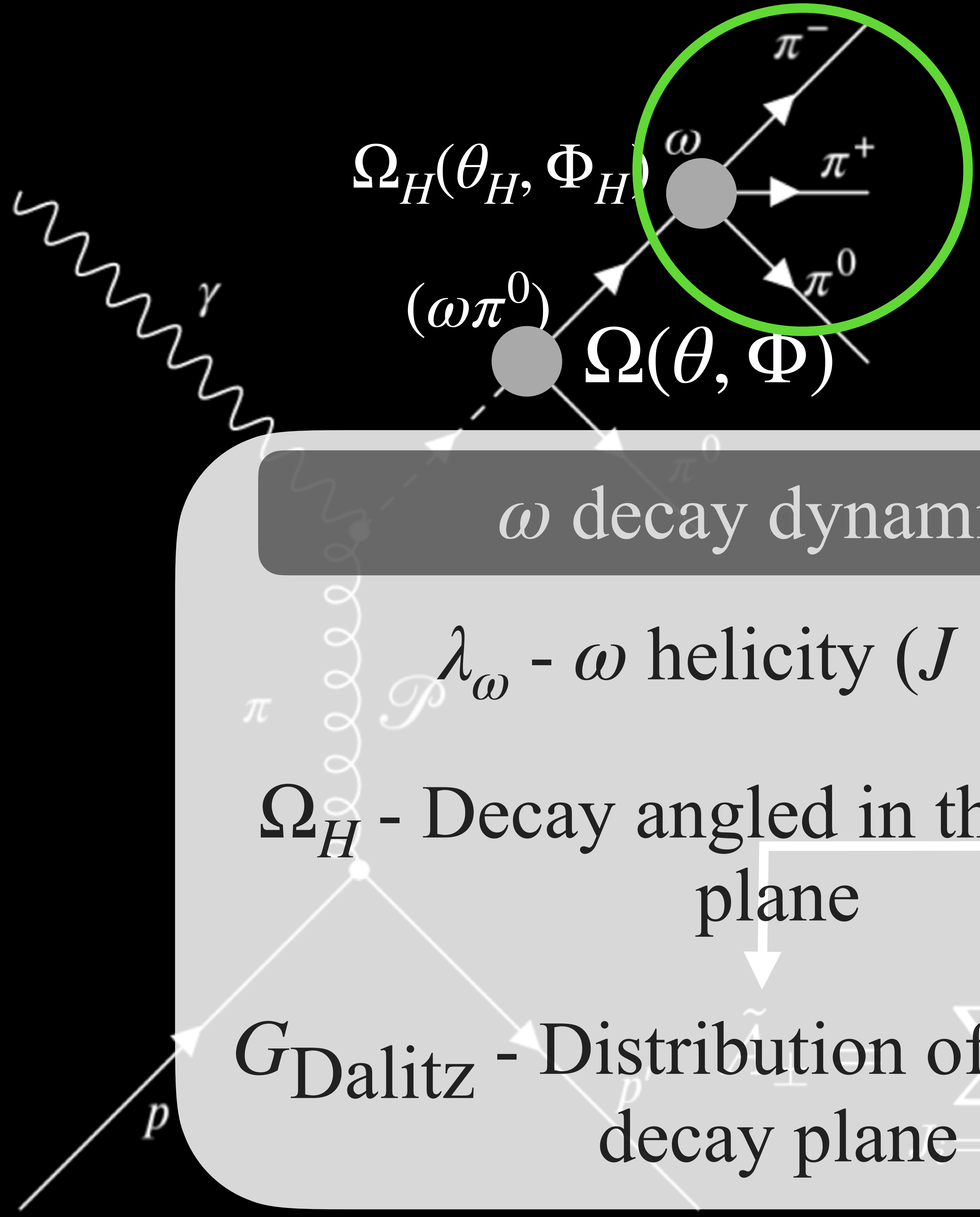

ω decay dynamics

λ_ω - ω helicity ($J = 1$)

Ω_H - Decay angled in the ω decay plane

G_{Dalitz} - Distribution of pions in ω decay plane

In “thin” $M(\omega\pi^0)$ and $|t|$ bin

$$I(\Omega, \Omega_H, \Phi) = \frac{\kappa}{4}(1 - P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) + \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2 + \frac{\kappa}{4}(1 + P_\gamma)|\tilde{A}_+(\Omega, \Omega_H, \Phi) - \tilde{A}_-(\Omega, \Omega_H, \Phi)|^2$$

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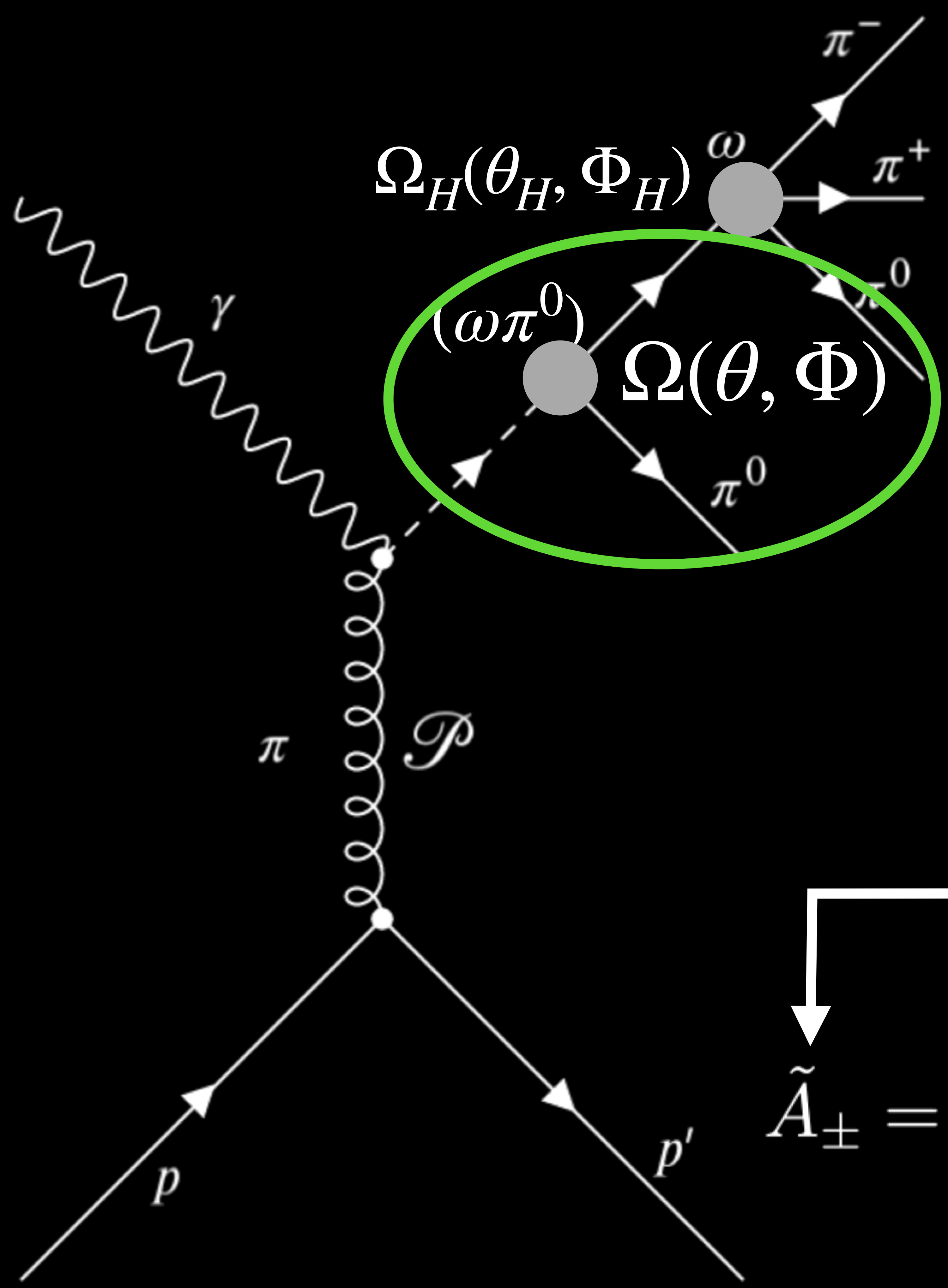
Partial Wave Analysis

Intensity Model: Measuring $b_1(1^{+\,-})$ in $\omega\pi^0$ spectrum



In “thin” $M(\omega\pi^0)$ and $|t|$ bin

$$I(\Omega,\Omega_H,\Phi) = \frac{\kappa}{4}(1-P_\gamma)|\tilde{A}_+(\Omega,\Omega_H,\Phi)+\tilde{A}_-(\Omega,\Omega_H,\Phi)|^2 + \frac{\kappa}{4}(1+P_\gamma)|\tilde{A}_+(\Omega,\Omega_H,\Phi)-\tilde{A}_-(\Omega,\Omega_H,\Phi)|^2$$

$\omega\pi^0$ decay dynamics

- $T^i_{\pm,m}$ - decay amplitude. Depends $\omega\pi^0$ relative spin, naturality of exchange
- Ω - Decay angled in the $\omega\pi^0$ decay plane
- $F^i_{\lambda_\omega}$ - ω helicity amplitude

$$\text{For } b_1;\ F^i_{\lambda_\omega} = \left\langle 1\lambda_\omega | 00, 1\lambda_\omega \right\rangle C_0 + \left\langle 1\lambda_\omega | 20, 1\lambda_\omega \right\rangle C_2$$

$$\text{Defined DS Ratio} = \frac{C_2}{C_0}$$

- $\mathfrak{F}(p_0)$ - Biatt-Weisskopf angular momentum barrier factor. Suppress high l waves in low $\omega\pi^0$ mass

$$\tilde{A}_\pm = \sum_{J_i=1,2,..}\ \sum_{m=-J_i,..,J_i} T^i_{\pm,m} \sum_{\lambda_\omega=-1,0,1} \overbrace{e^{\mp i\Phi} D^{J_i *}_{m,\lambda_\omega}(\Omega) F^i_{\lambda_\omega} D^{1*}_{m,0}(\Omega_H) G_{\text{Dalitz}} \mathfrak{F}(p_0)}^{Z^i_m(\Phi,\Omega,\Omega_H)}$$

Partial Wave Analysis

Lets get to Fitting: AmpTools

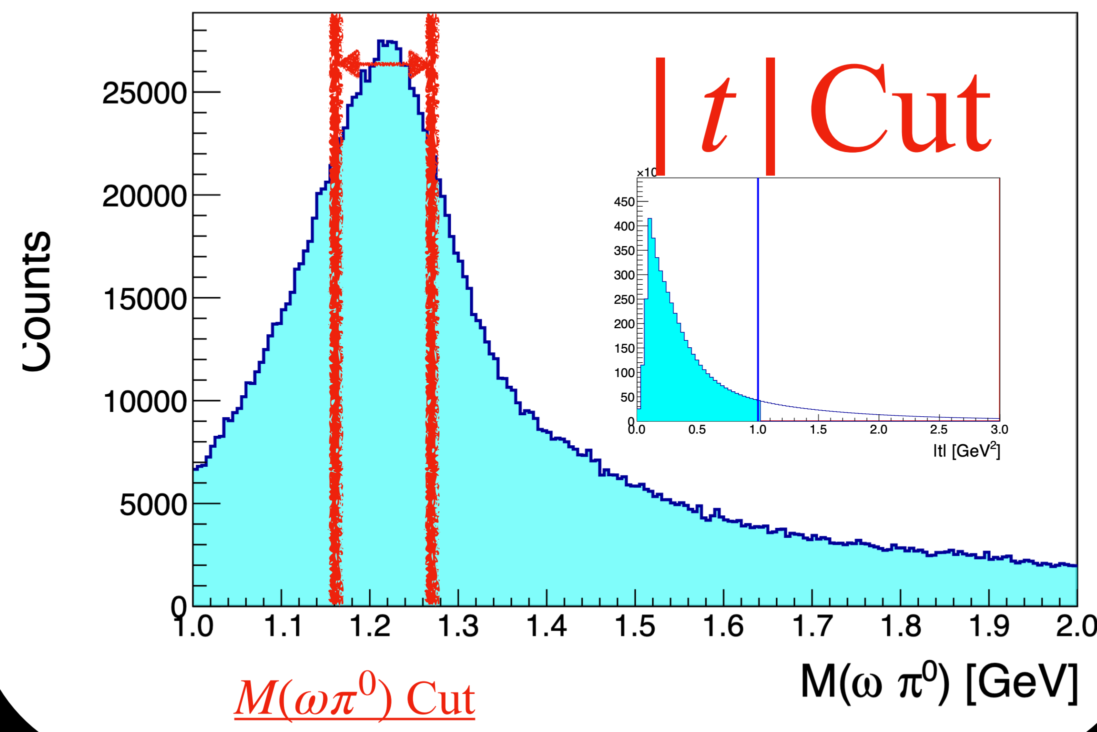
Data Selection cuts

Beam E cut

$|t|$ Cut

$M(\omega\pi^0)$ Cut

Make $p_4(\omega\pi^0)$ system



AmpTools

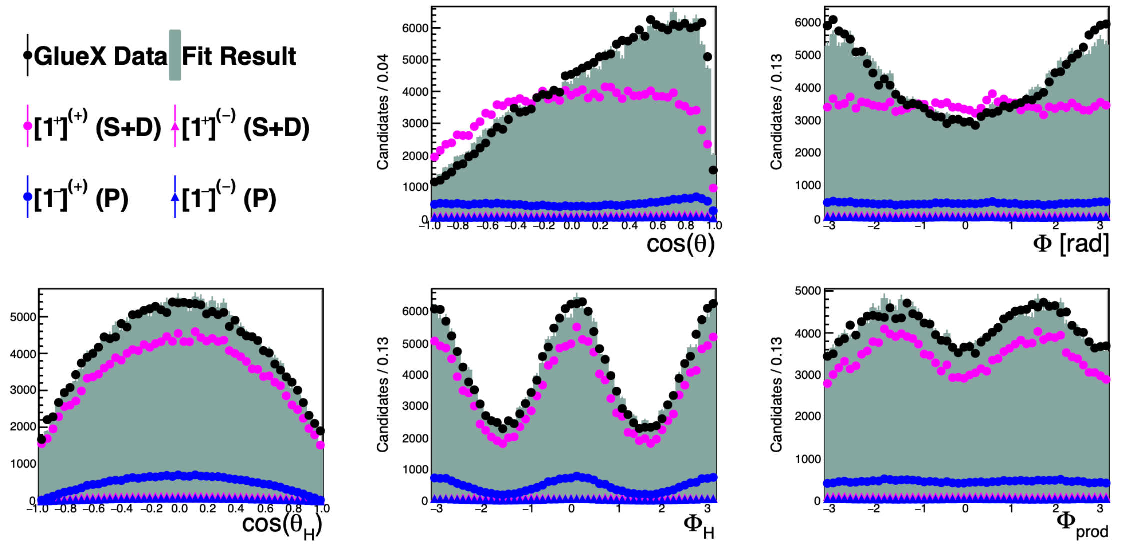
- Unbinned Maximum Likelihood fitting

$$-2\ln\mathfrak{L}(\theta) = -2\left(\sum_{i=1}^{N}\ln I(x;\theta) - \mu\right) + c_1$$

- Uses GPU computation with CUDA backend.
- Input Vectors + model params
- Eg. $[1^{+-}]^{(\pm)}, [1^{--}]^{\pm}$

- Results extracted for each parameter in the intensity model
- Contribution of J^{PC} state extracted by computing fit fractions from complex amplitudes

Parameters	Input	Type	Fit Results
D/S ratio	0.27	float	0.2697 ± 0.0062
$[1^+]^{(+)}$	0	Fit Fraction	0.0100 ± 0.0005
$[1^+]^{(-)}$	1	Fit Fraction	0.9871 ± 0.0065
$[1^-]^{(+)}$	0	Fit Fraction	0.0020 ± 0.001
$[1^-]^{(-)}$	0	Fit Fraction	0.0009 ± 0.0003

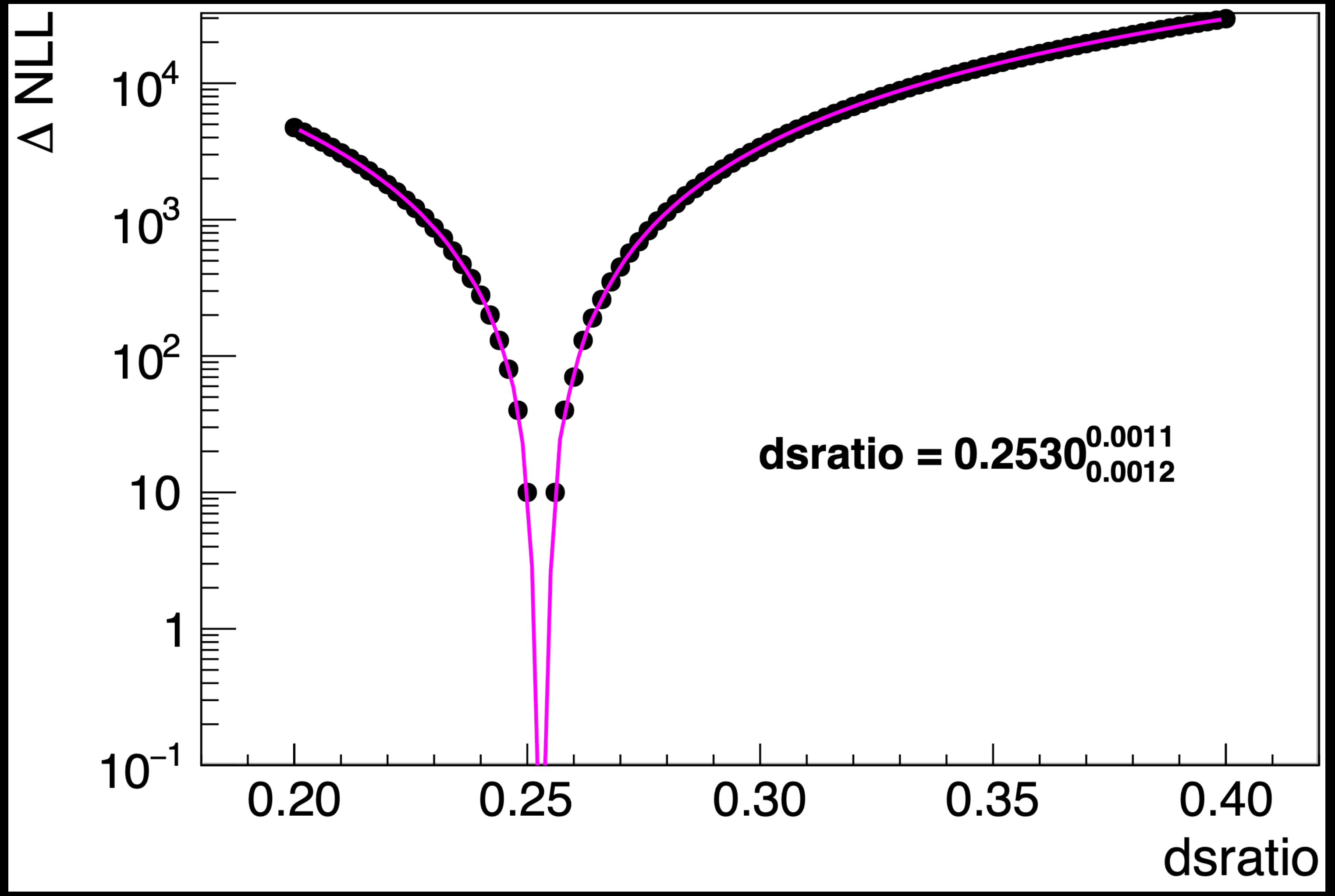


Partial Wave Analysis

Extracting DSRatio uncertainties

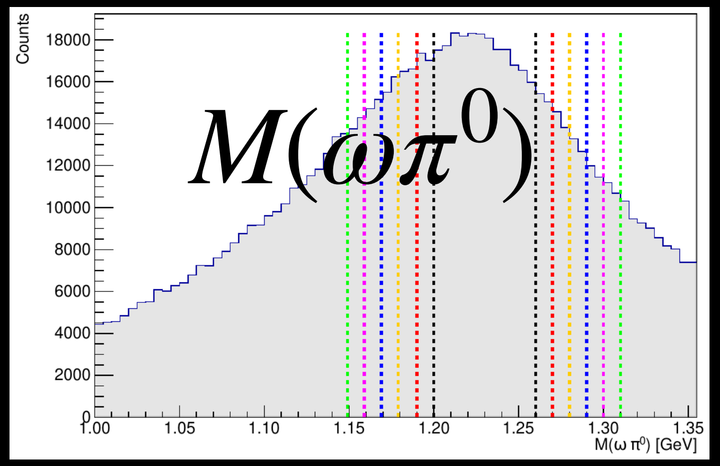
Parameter Name	**Value**	**Remarks**
N Randomized Fits	25	Ensures diversity in solution space
$M(\omega\pi^0)$ [GeV]	1.155 - 1.315 GeV	Systematics done
$\lvert t\rvert$ [GeV^2]	[(0.15 - 0.30), (0.30, 0.50), (0.50, 1.00)] GeV^2	DS Ratio Strong correlation
Fit Waves	Combinations of $J^P = 0^-, 1^+, 1^-, 2^-$	The most dominant systematic
Beam Energy [GeV]	8.2 – 8.8 GeV	Maximum Polarization Fraction
Dalitz Parameters (α, β, γ)	$\alpha = 0.1212$; $\beta = 0.0257$; $\gamma = 0.0$	From JPAC 10052-020-08576-6
Polarization Fraction (P_γ)	$\sim 35\%$	Systematics done
Event Selection	Discussed previous slides	Expected minimal systematics
`dphase`	Fixed to 0.0	Studied floating `dphase`

Statistical Precision



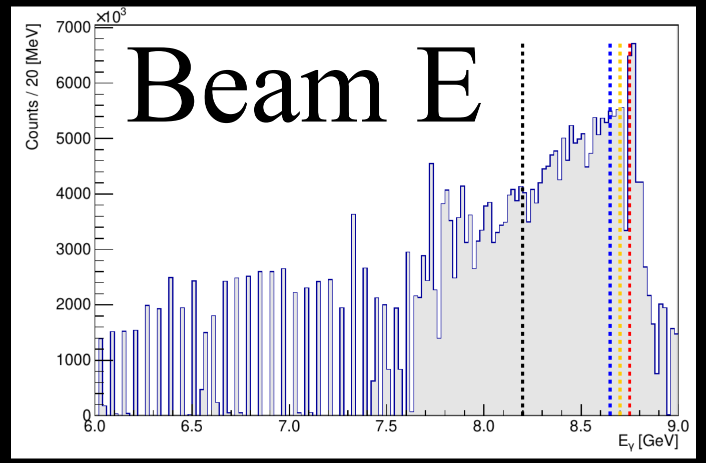
$$\Delta_{\text{stat}} = (\text{dsratio})\big|_{\Delta - 2\ln\mathfrak{L} = 1}$$

Systematic Variations



Benchmark Waveset = $J^P = ([1^+]^{(+)}, [1^-]^{(+)})$

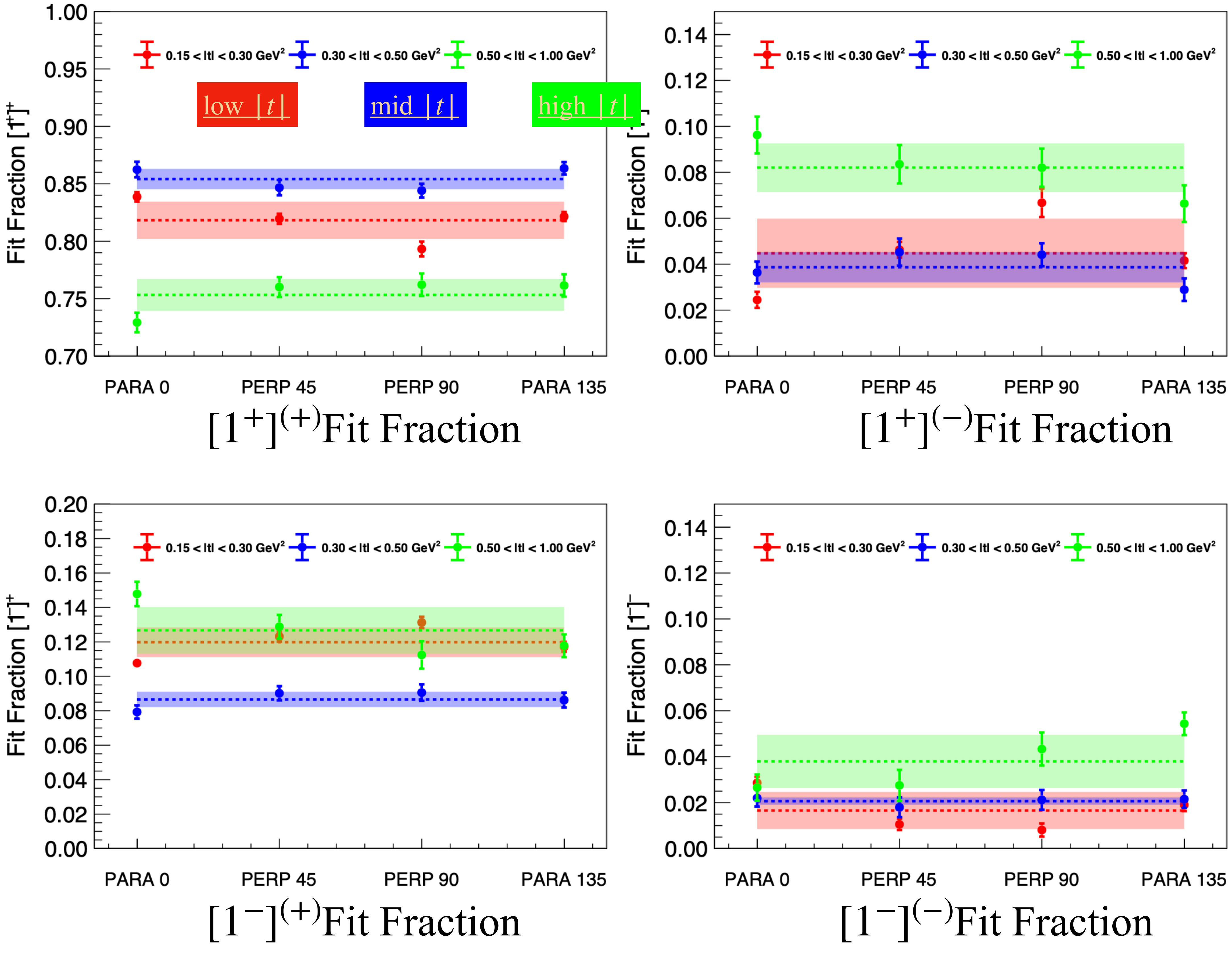
$$\Delta_{\text{sys}} = \sqrt{\frac{\sum_i^N (\text{dsratio}_i - \text{dsratio}_{ref})^2}{N-1}}$$

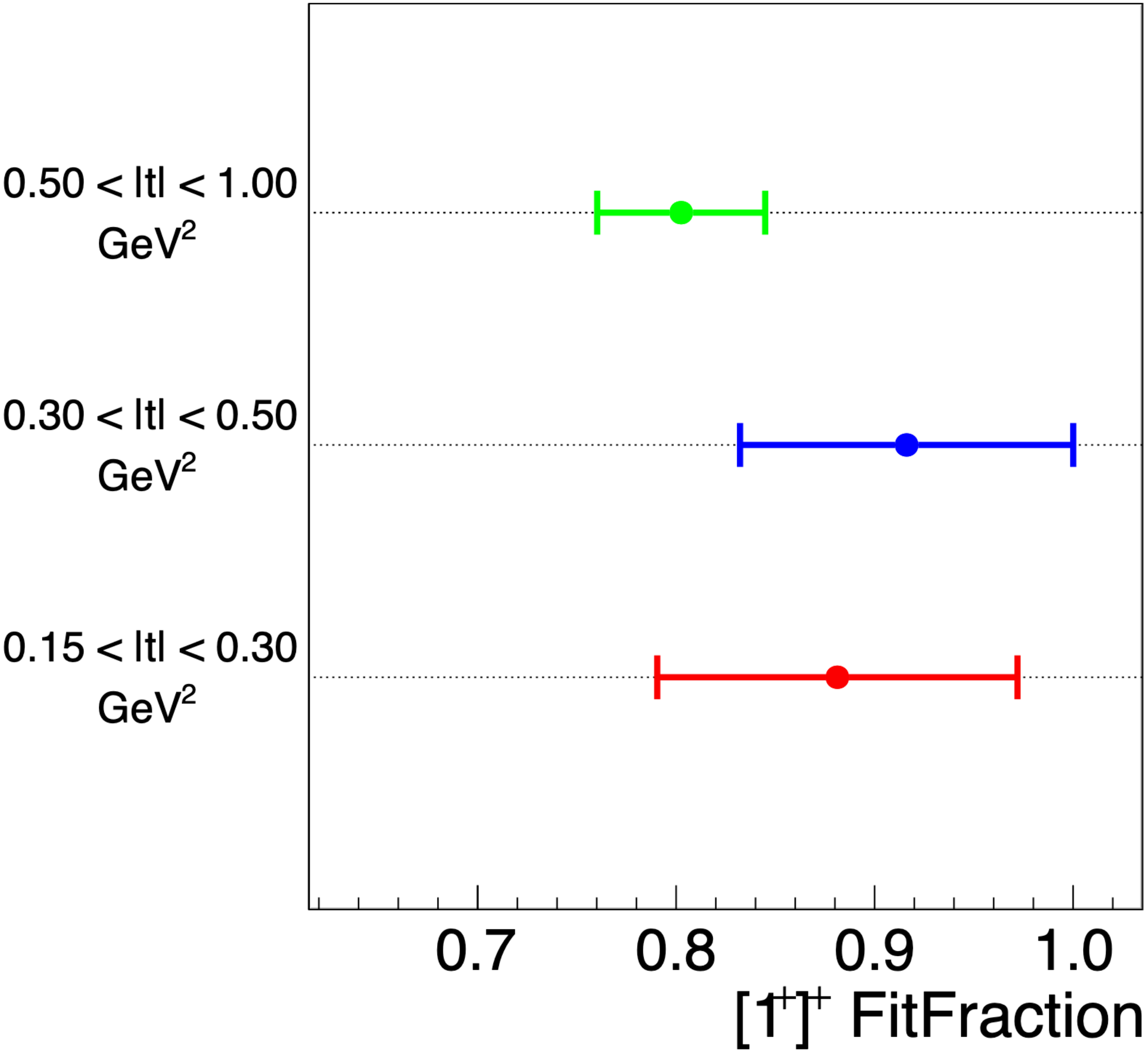


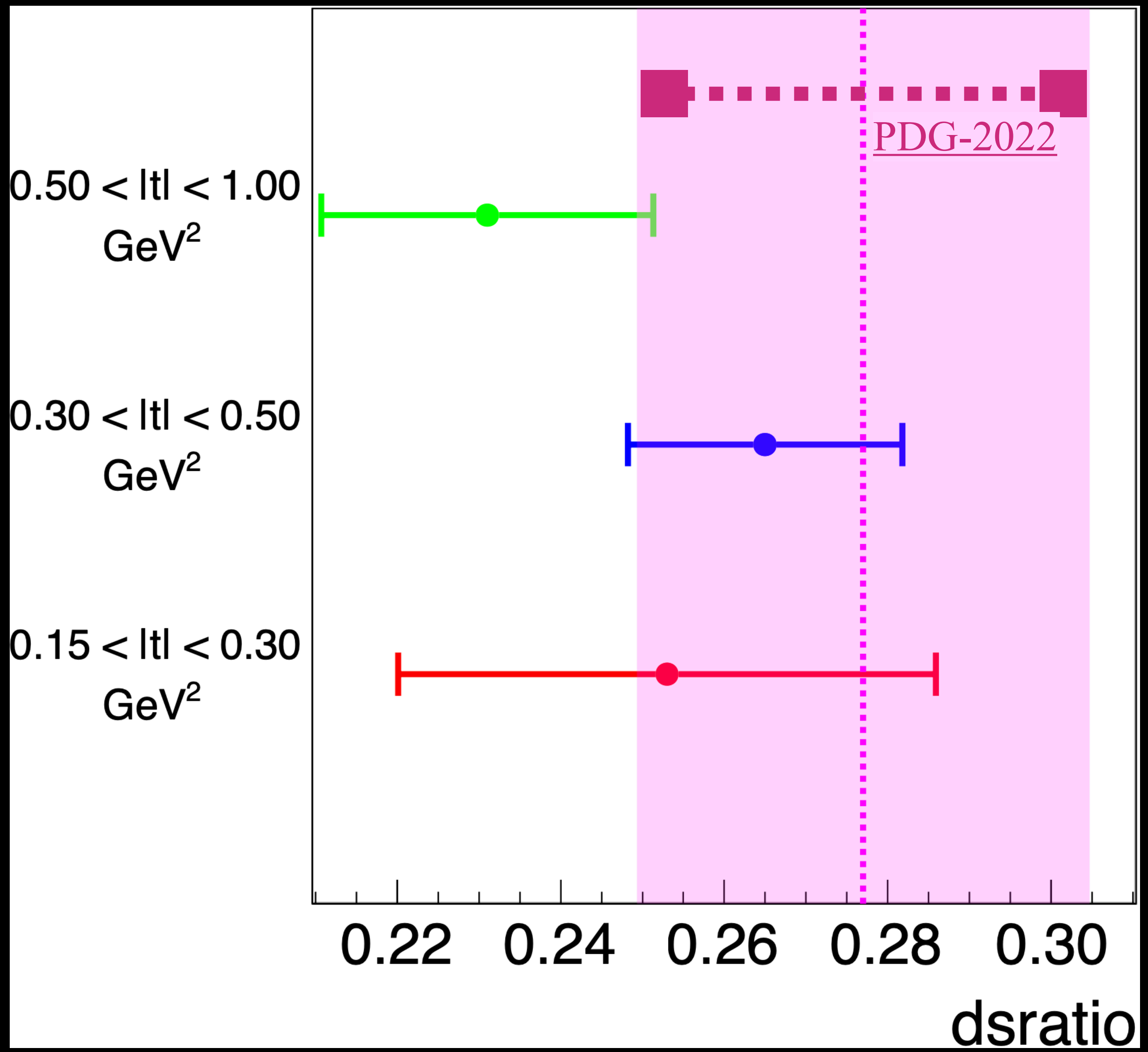
Partial Wave Analysis : Results

Extracted b_1 properties

Consistent across four orientations



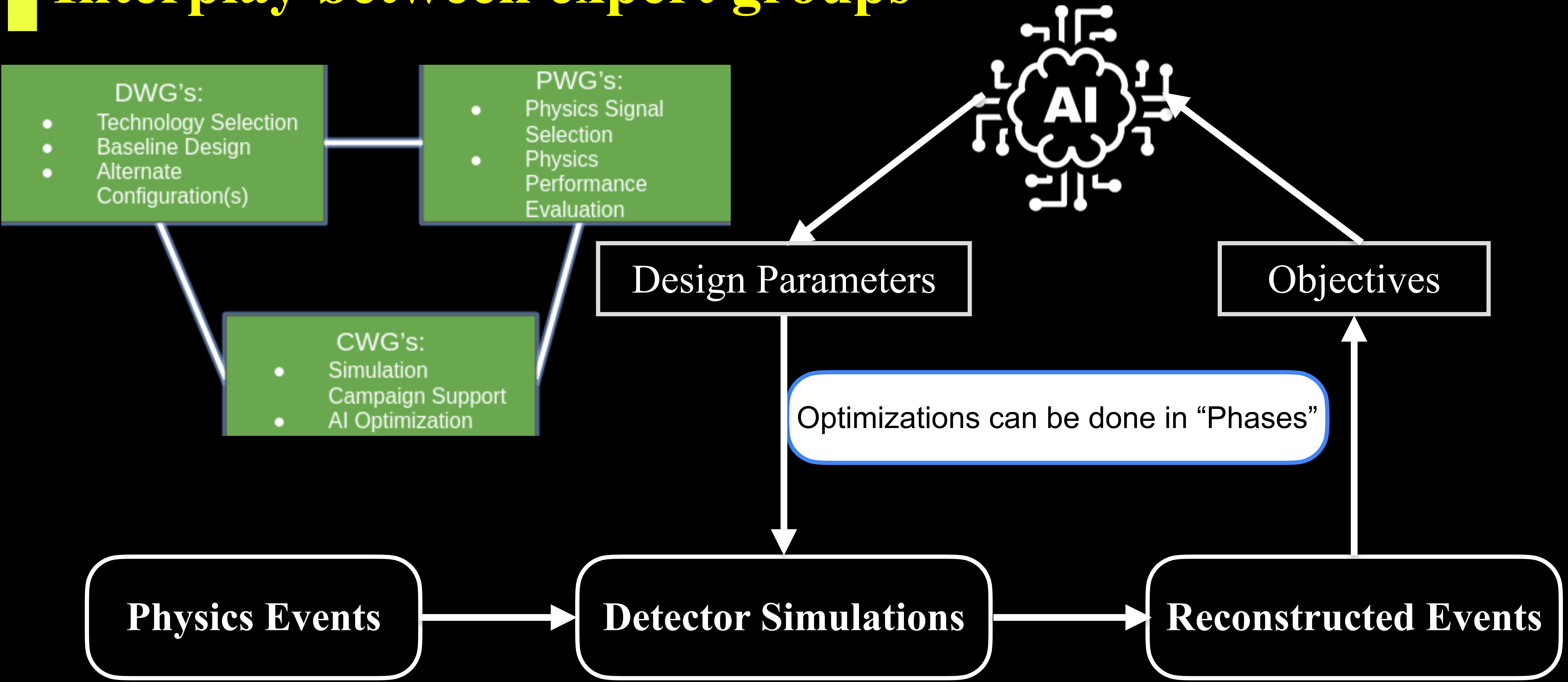




Cut Name	$\lvert t\rvert$ bins GeV^2		
	$0.15 < \lvert t\rvert < 0.30$	$0.30 < \lvert t\rvert < 0.50$	$0.50 < \lvert t\rvert < 1.00$
Fit Wave combos	0.0325	0.0165	0.0173
Mass bin	0.0048	0.0025	0.0104
Beam Energy	0.0012	0.0015	0.0019
Dalitz Parameter	0.0007	0.0007	0.0007
Benchmark DS Ratio	0.2530	0.2650	0.2310
Statistical Uncertainty Δ_{stat}	0.0011 0.0012	0.0008 0.0008	0.0013 0.0014
Systematic Uncertainty Δ_{sys}	**0.0329**	**0.0168**	**0.0203**

$[1^+]^{(+)}$ dominant → b_1 decays through **Natural** exchange

Interplay between expert groups



DWG's:

- Technology Selection
- Baseline Design
- Alternate Configuration(s)

PWG's:

- Physics Signal Selection
- Physics Performance Evaluation

CWG's:

- Simulation Campaign Support
- AI Optimization

AI

Design Parameters

Objectives

Optimizations can be done in “Phases”

Physics Events

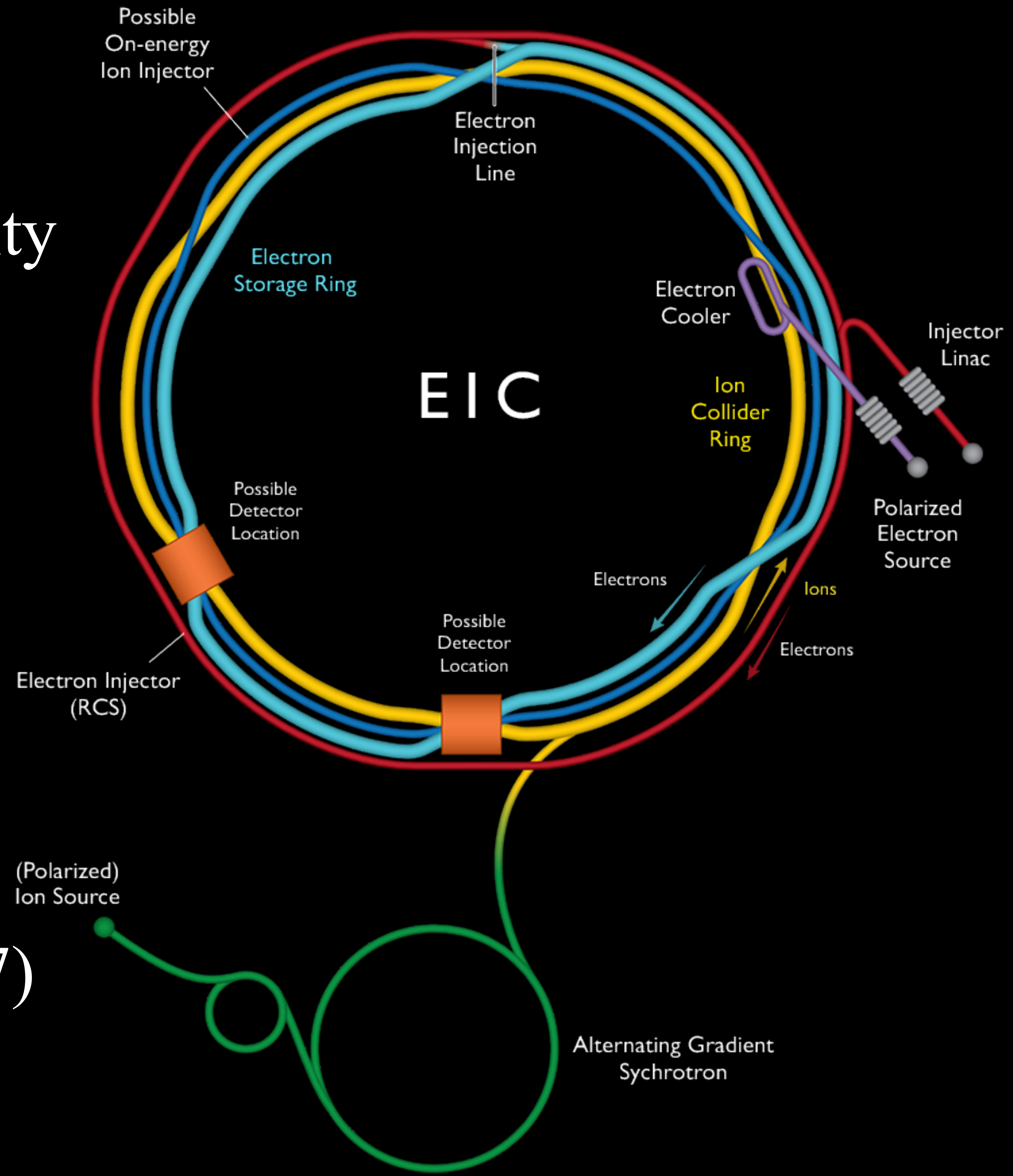
Detector Simulations

Reconstructed Events

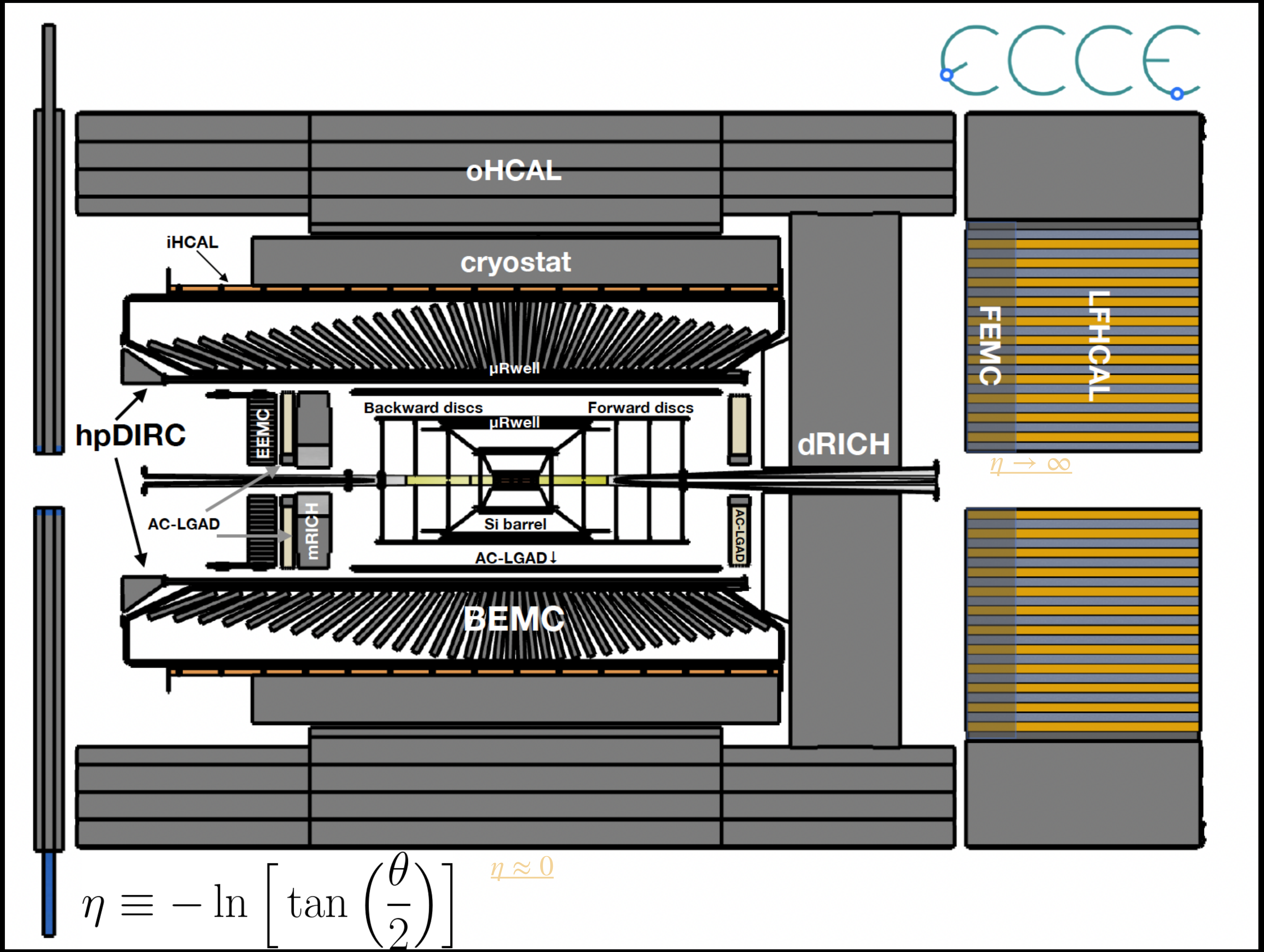
Desired kinematic range

Electron Ion Collider

- To be built at BNL (Brookhaven National Laboratory) . Use existing infrastructure of RHIC.
- Physics Goal : Structure and dynamics of matter at high luminosity and energy using polarized beams. Wide range of nuclei [arXiv:1212.1701]
- The Machine will be capable to perform
  - High luminosity measurements **(10^{33} cm^{-2} s^{-1} - 10^{34} cm^{-2} s^{-1})**
  - Flexible center-of-mass energy range. $\sqrt{s} = \sqrt{4E_eE_p}$
  - Deliver highly polarized electron (0.8) and proton/ light ion (0.7)
  - Almost a 4***π*** detector to measure particles scattering in all directions and at wide range of energies

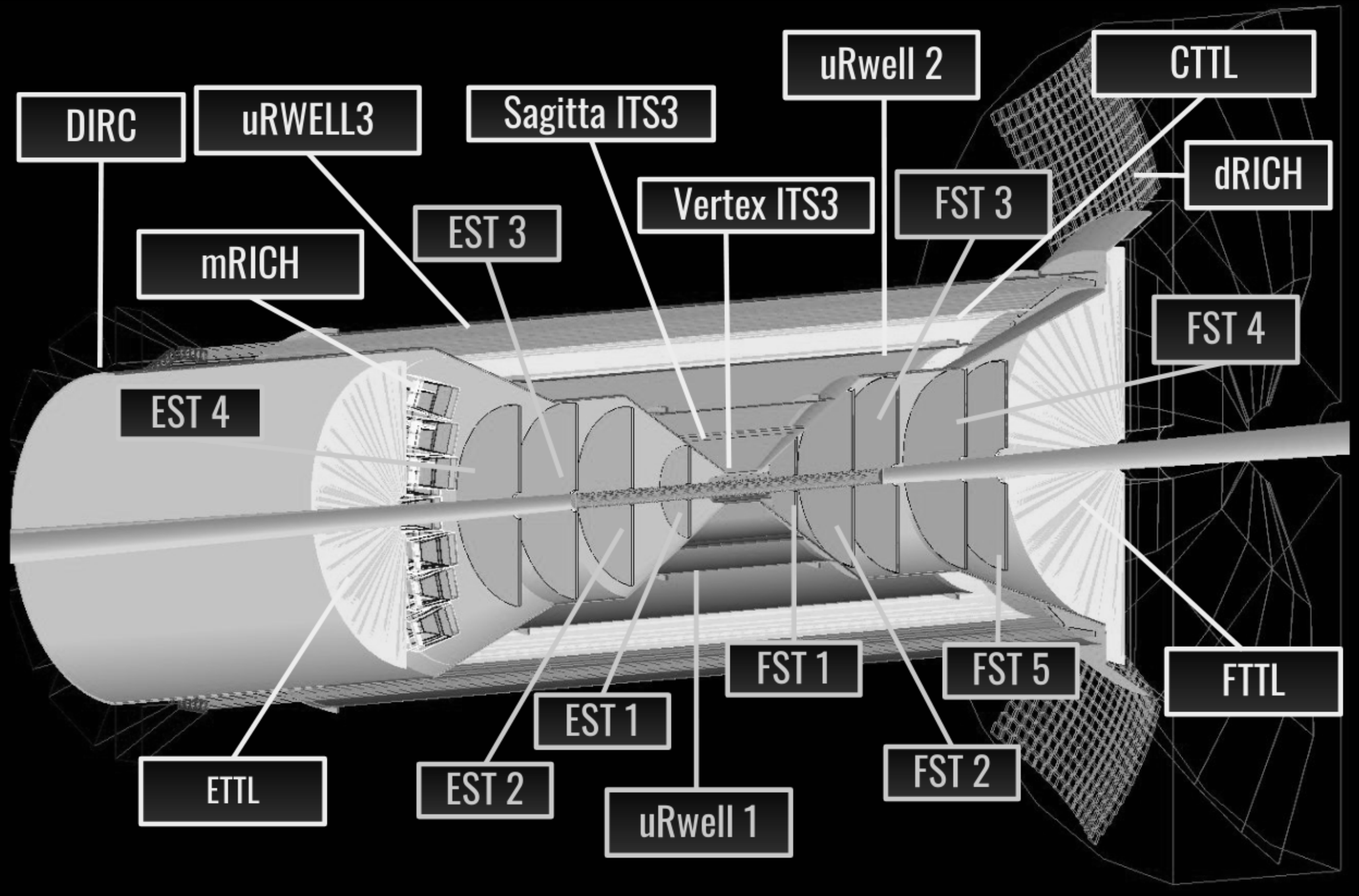


Example: The ECCE Detector - the Tracking System



$$\eta \equiv -\ln\left[\tan\left(\frac{\theta}{2}\right)\right]$$

Tracker System

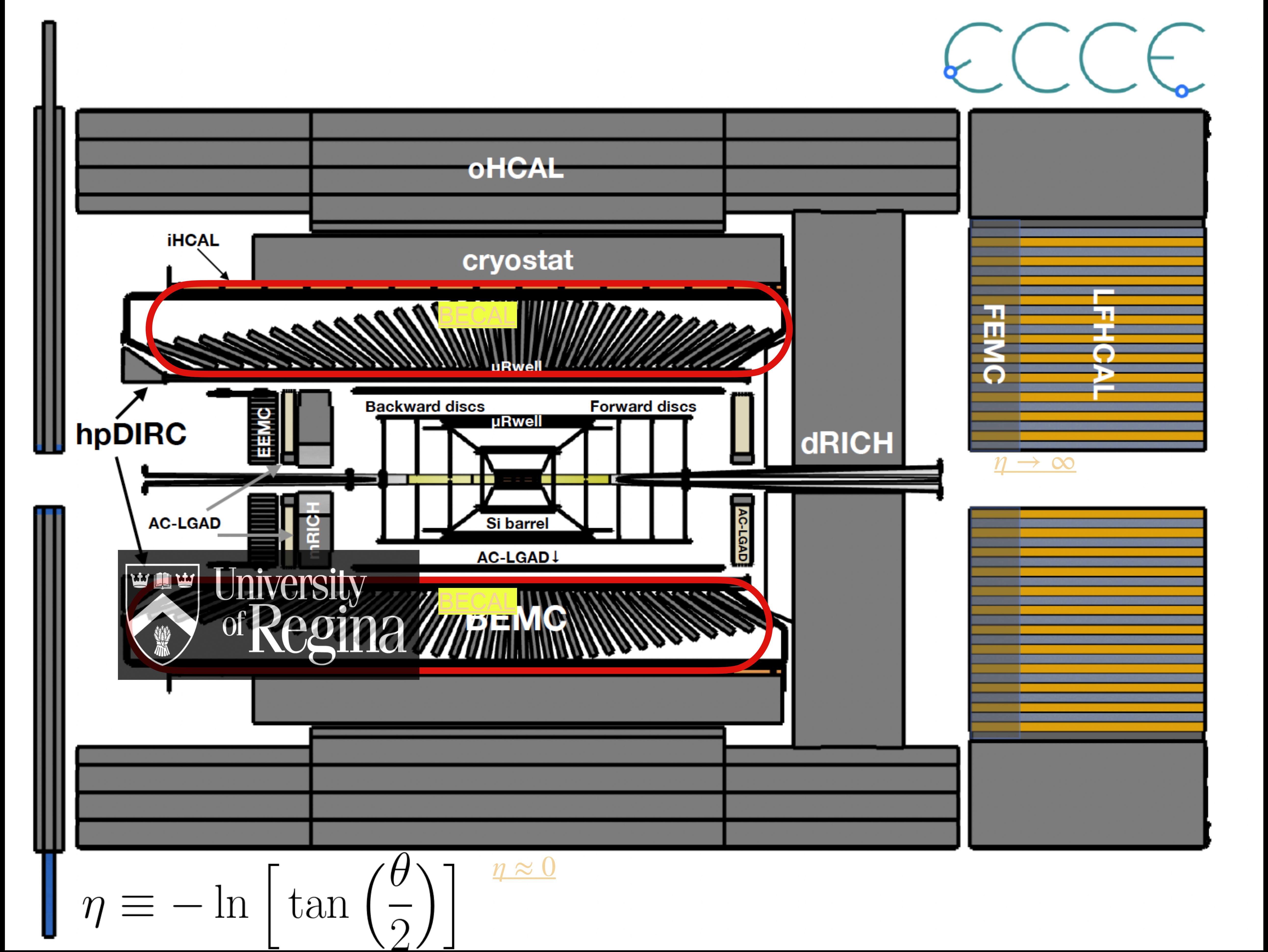


AI been used to steer the design

arxiv:2205.09185, arxiv:2203.04530

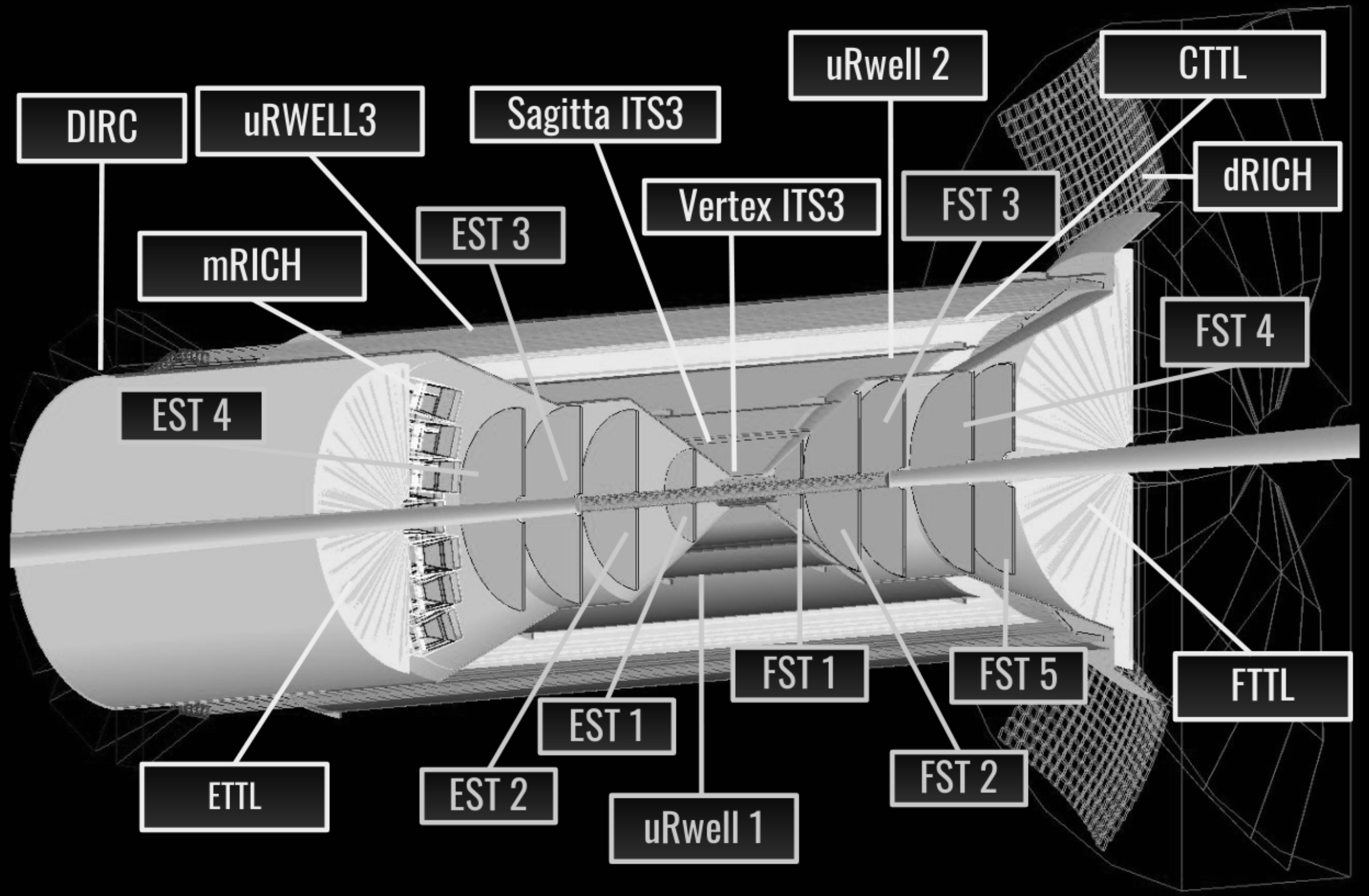
ECCE design was chosen as reference. Lots of updates/progress from Tracking WG (ePIC) since then.

Example: The ECCE Detector - the Tracking System



$$\eta \equiv -\ln\left[\tan\left(\frac{\theta}{2}\right)\right]$$

Tracker System

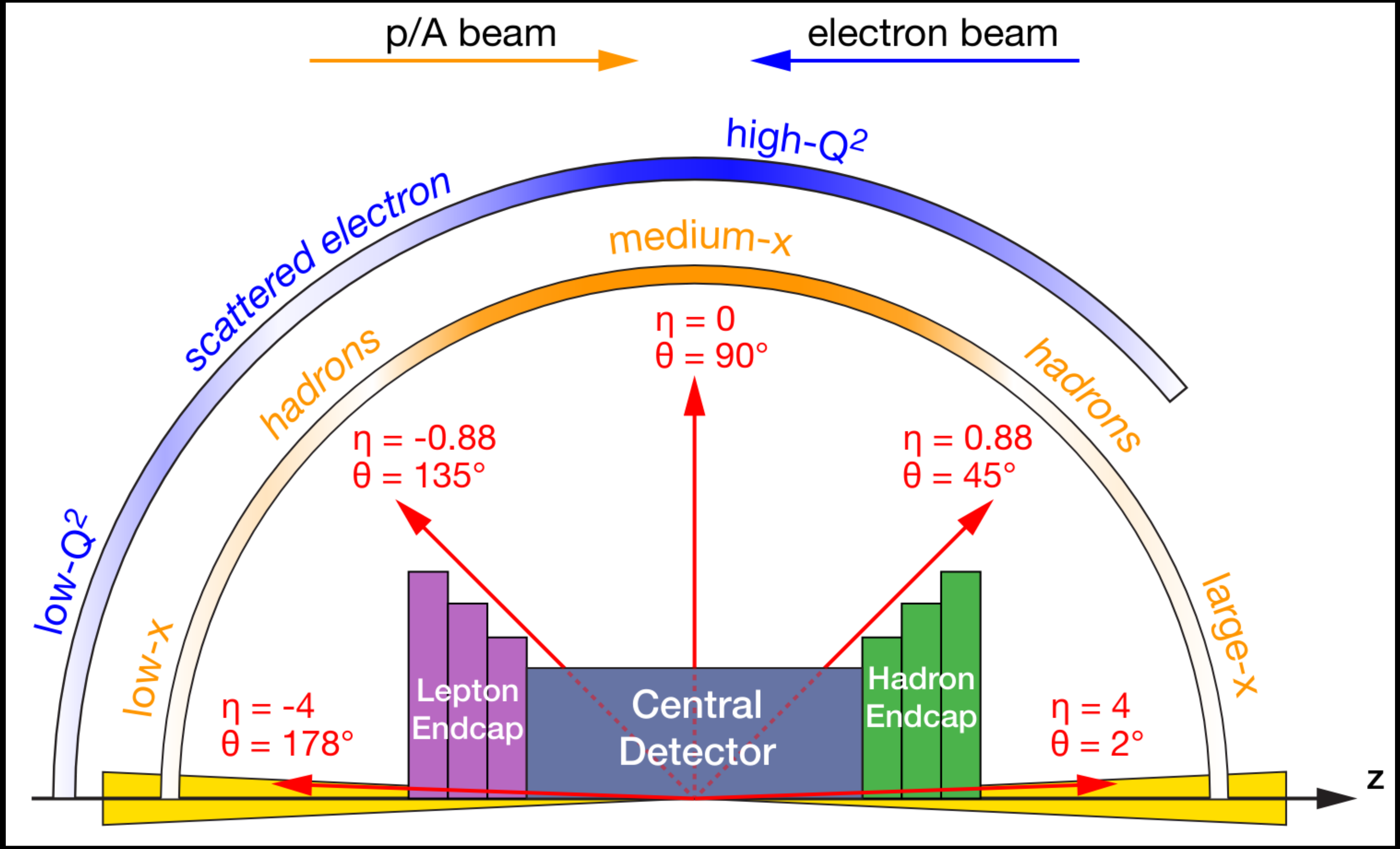


AI been used to steer the design

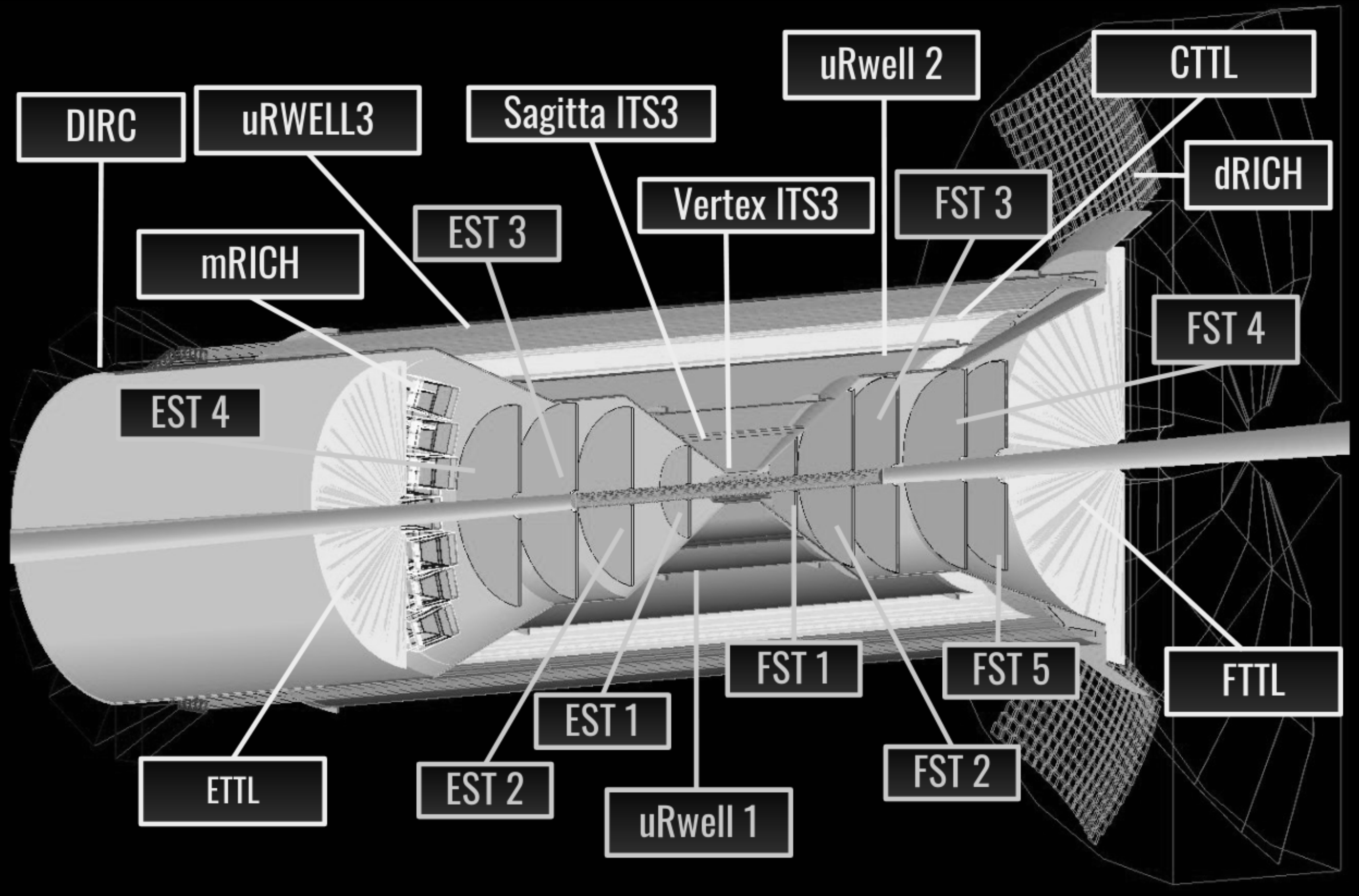
arxiv:2205.09185, arxiv:2203.04530

Major change — BECAL — UofR significant contributor — Expertise from BCAL @ GlueX

Example: The ECCE Detector - the Tracking System



Tracker System



AI been used to steer the design

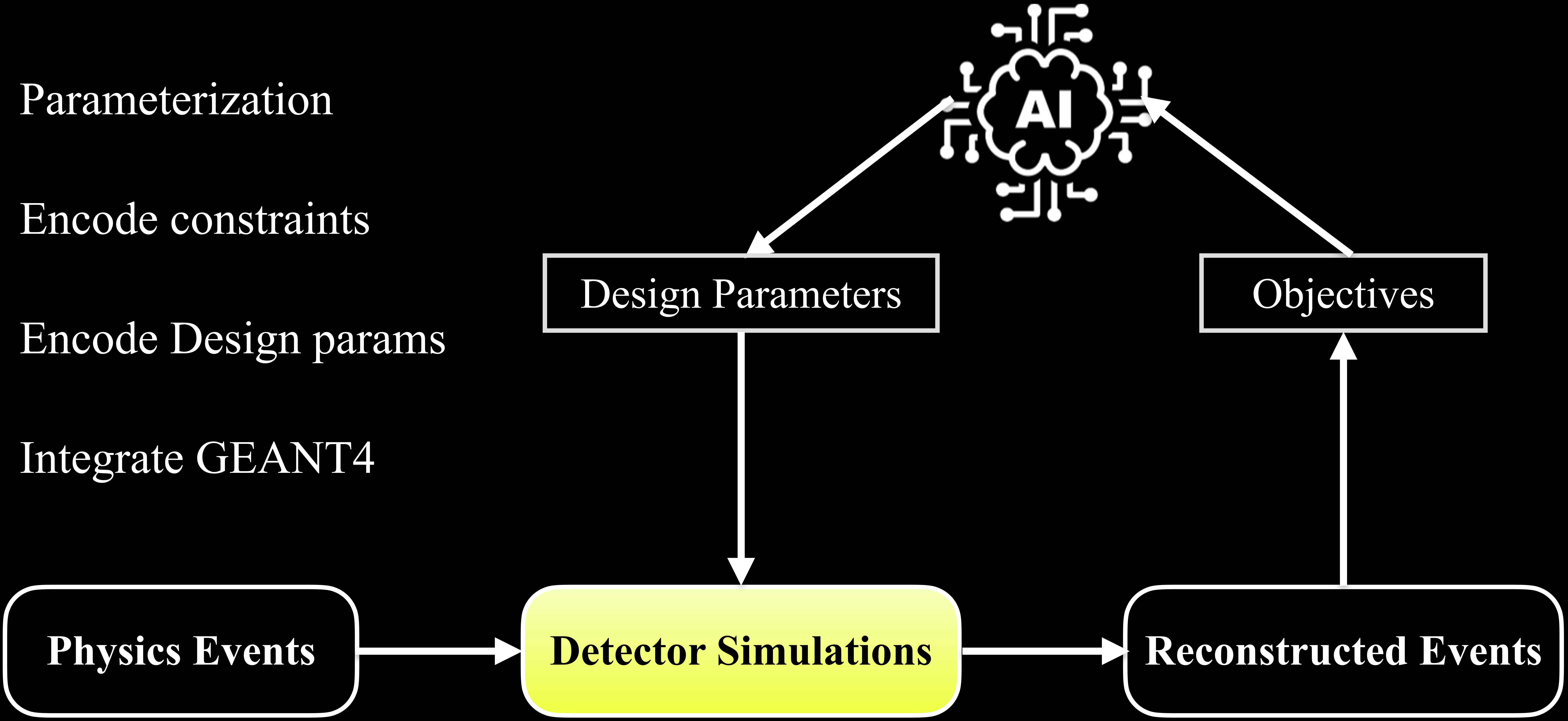
arxiv:2205.09185, arxiv:2203.04530

The tracking system reconstructs charged particle tracks. It combines different technologies.

For the entire study 120-600k π^- tracks are simulated across η and p ‘bins’

Detector simulation

- Parameterization
- Encode constraints
- Encode Design params
- Integrate GEANT4



Design Parameters

Objectives

Physics Events

Detector Simulations

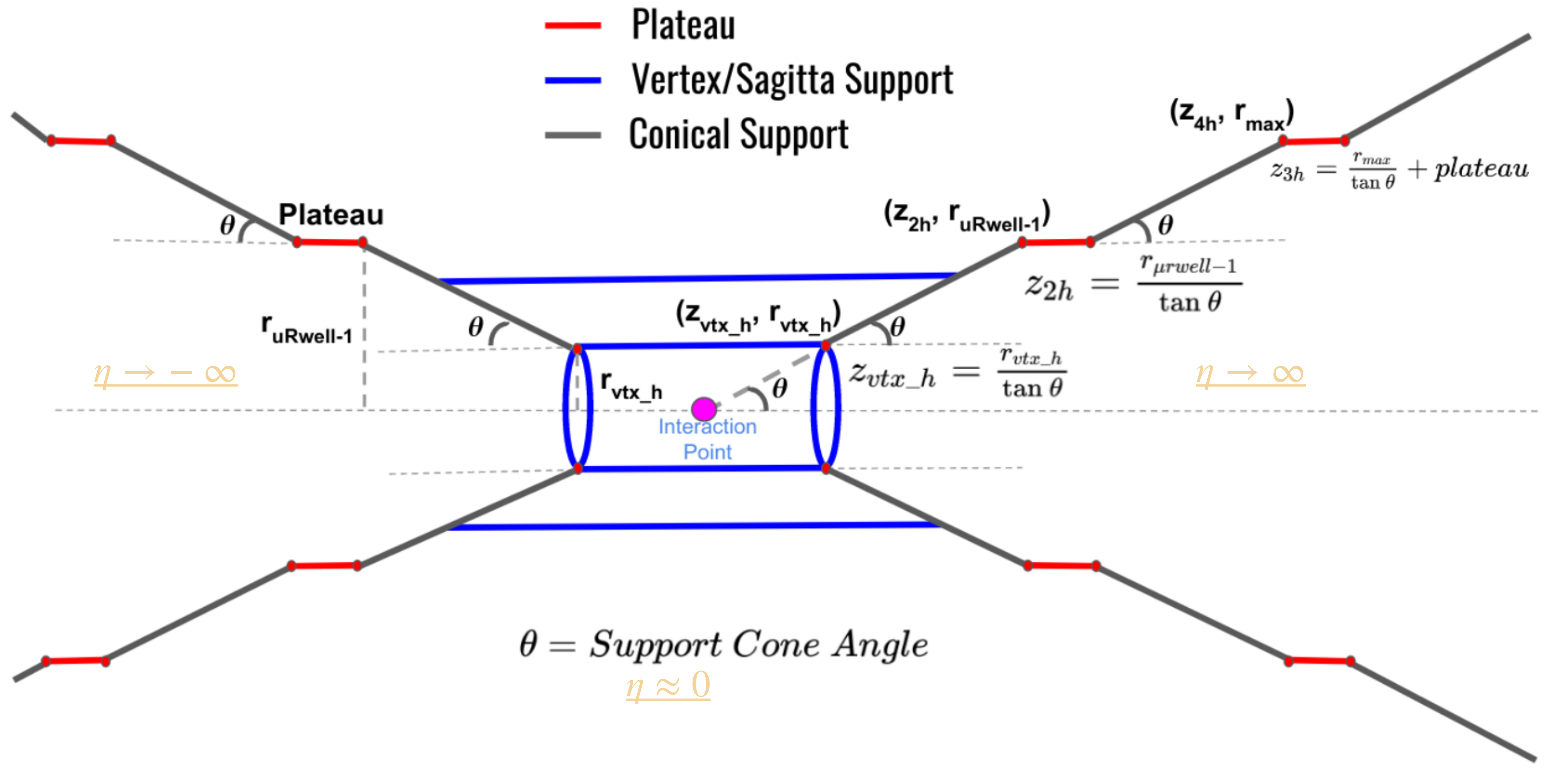
Reconstructed Events

Desired kinematic range

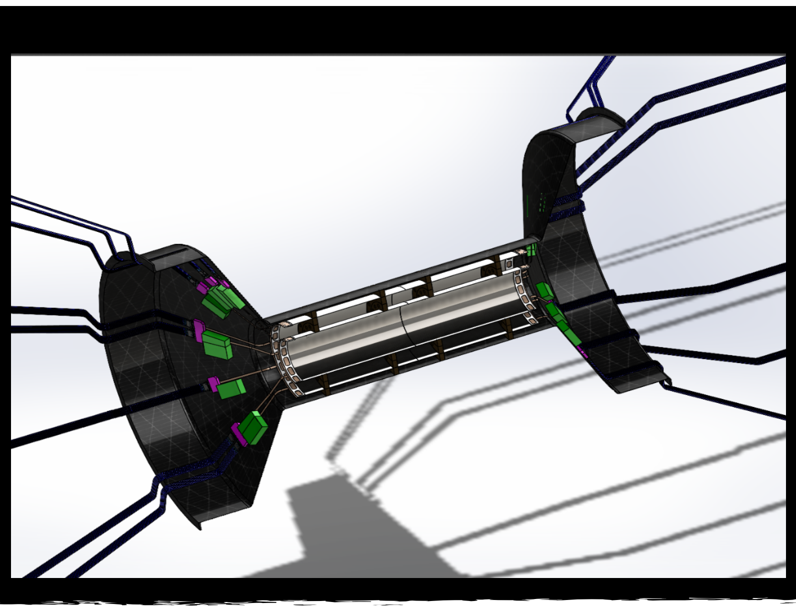
Parametrization

Parametrization is an essential part of an automated optimization:

- explores different designs
- avoids overlaps of volumes
- encodes constraints

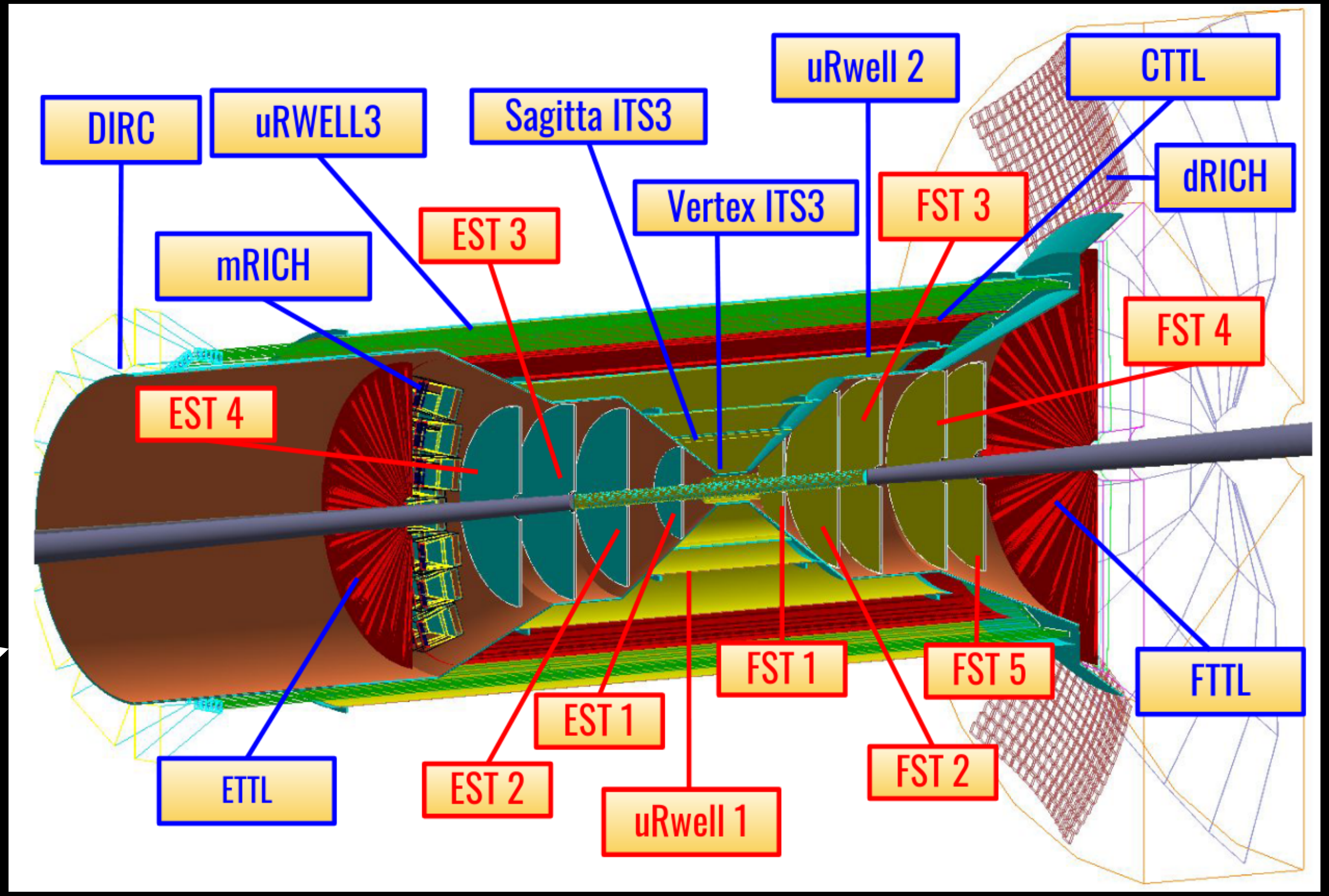


$$\eta \equiv -\ln\left[\tan\left(\frac{\theta}{2}\right)\right]$$

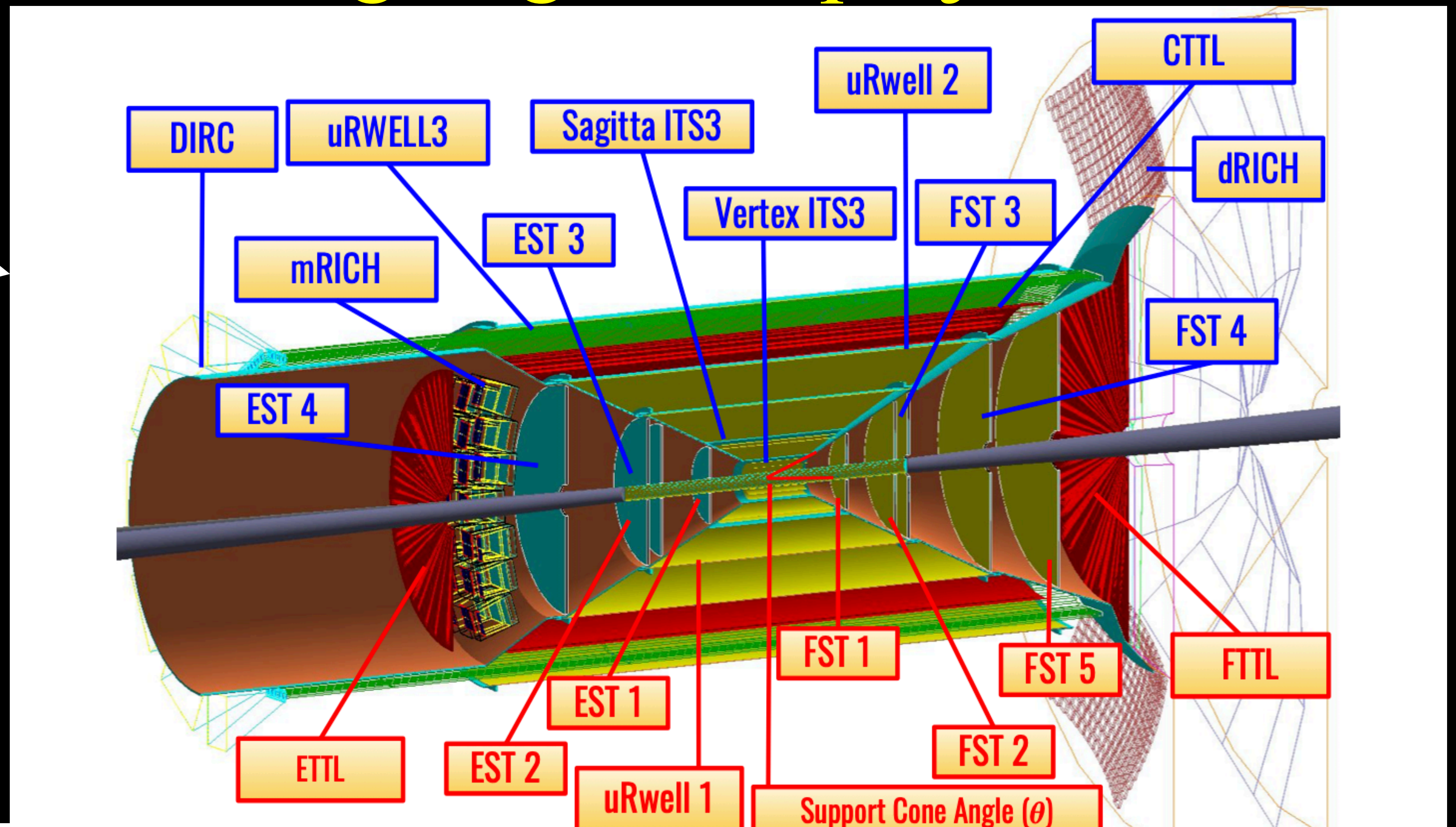


Implementation of support structures with realistic material budgets

Reference design

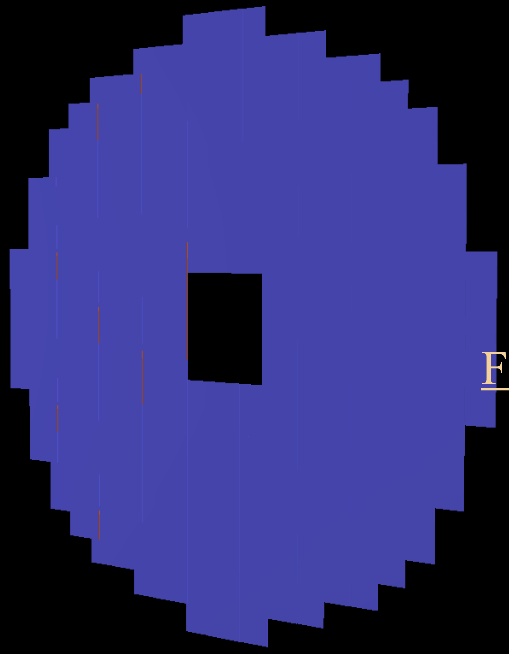


Ongoing R&D projective

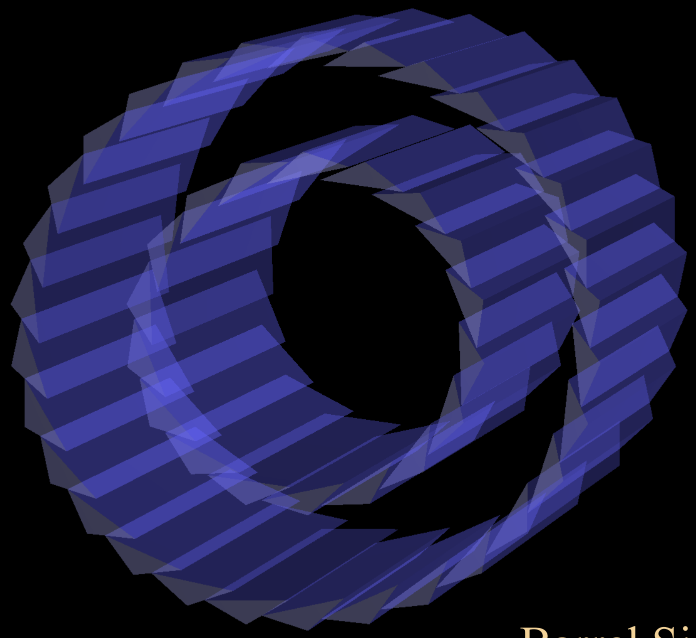


Variable pars; Fixed pars

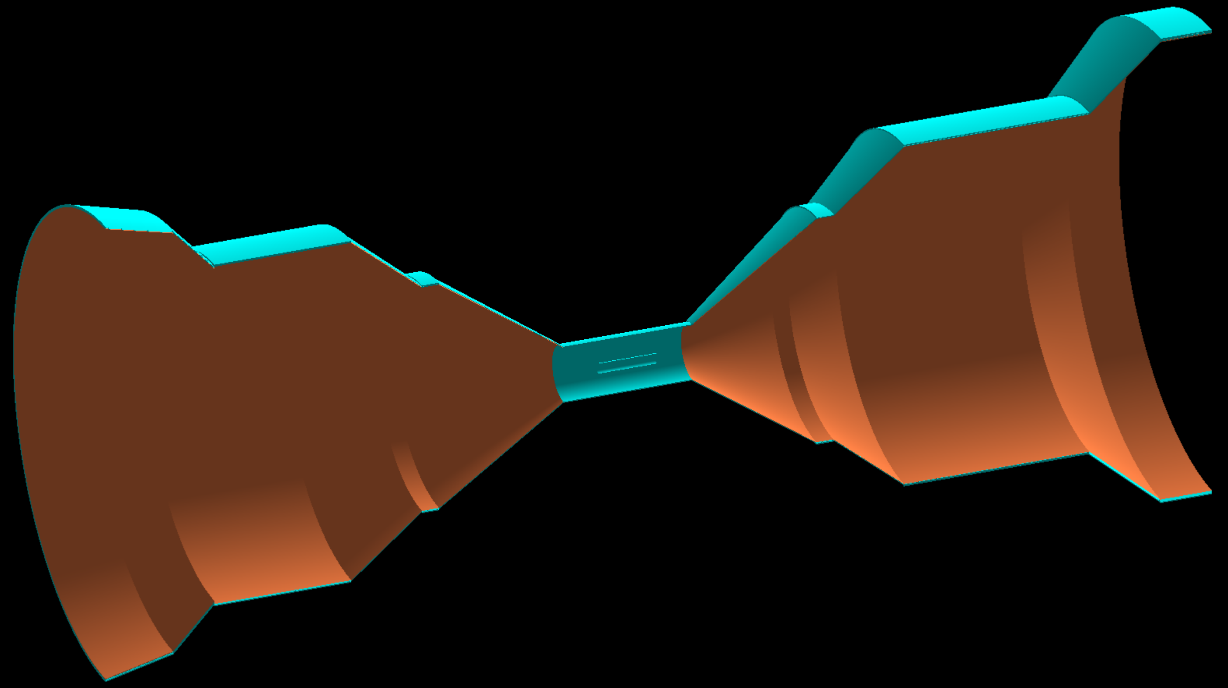
Constraints



FST/EST Disks



Barrel Si Layer

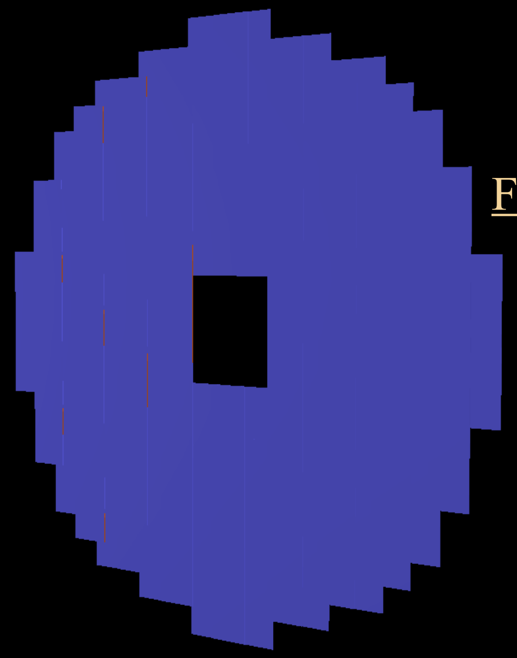


- **Design Parameters** (O(N) ≈ 10)
    - Based on an extensive parameterization.
- **Constraints** being used (n_const ≥ 3)
    - HARD The minimum distance between 2 disks should be >= 10 cm (giving room for services)
    - SOFT The Rmax-Rmin for the disks have to be multiple of 3.00 cms and 1.8 cms (Tiling of pixels)
- **Overlaps checks**
    - GEANT4 unstable when overlaps are detected in volumes.
    - Overlaps are checked for every design explored and penalized.

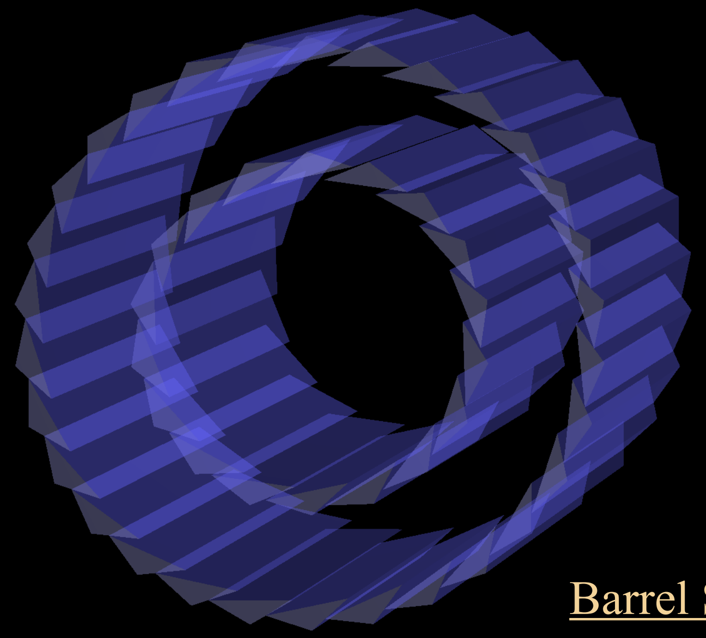
sub-detector	**constraint**	**description**
EST/FST disks	$min\left\{\sum_{i}^{disks}\left\lvert\frac{R^{l}_{out}-R^{l}_{in}}{d}-\left\lfloor\frac{R^{l}_{out}-R^{l}_{in}}{d}\right\rfloor\right\rvert\right\}$	**soft constraint**: sum of residuals in sensor coverage for disks; sensor dimensions: d = 17.8 (30.0) mm
EST/FST disks	$z_{n+1}-z_{n}$ >= 10.0 cm	**strong constraint**: minimum distance between 2 consecutive disks
sagitta layers	$min\left\{\left\lvert\frac{2\pi r_{sagitta}}{w}-\left\lfloor\frac{2\pi r_{sagitta}}{w}\right\rfloor\right\rvert\right\}$	**soft constraint**: residual in sensor coverage for every layer; sensor strip width: w = 17.8 mm
μRWELL	$r_{n+1}-r_{n}$ >= 5.0 cm	**strong constraint**: minimum distance between μRwell barrel layers

Extensive details at arXiv:2205.09185

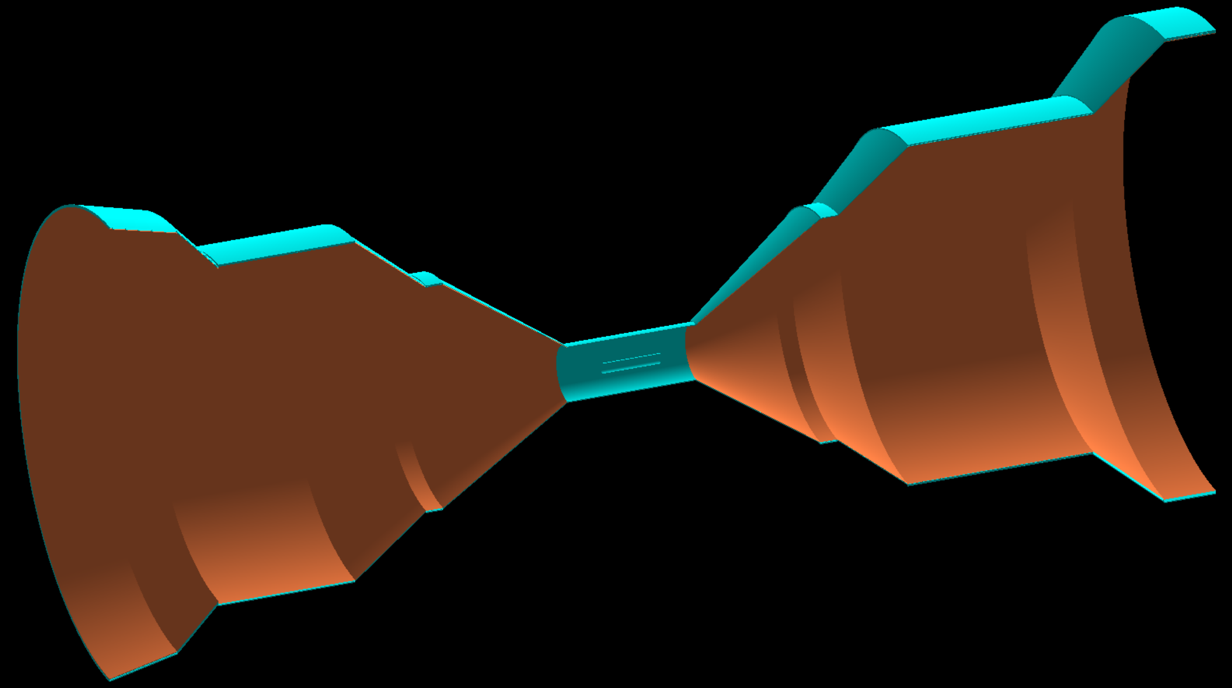
The Design params for this case

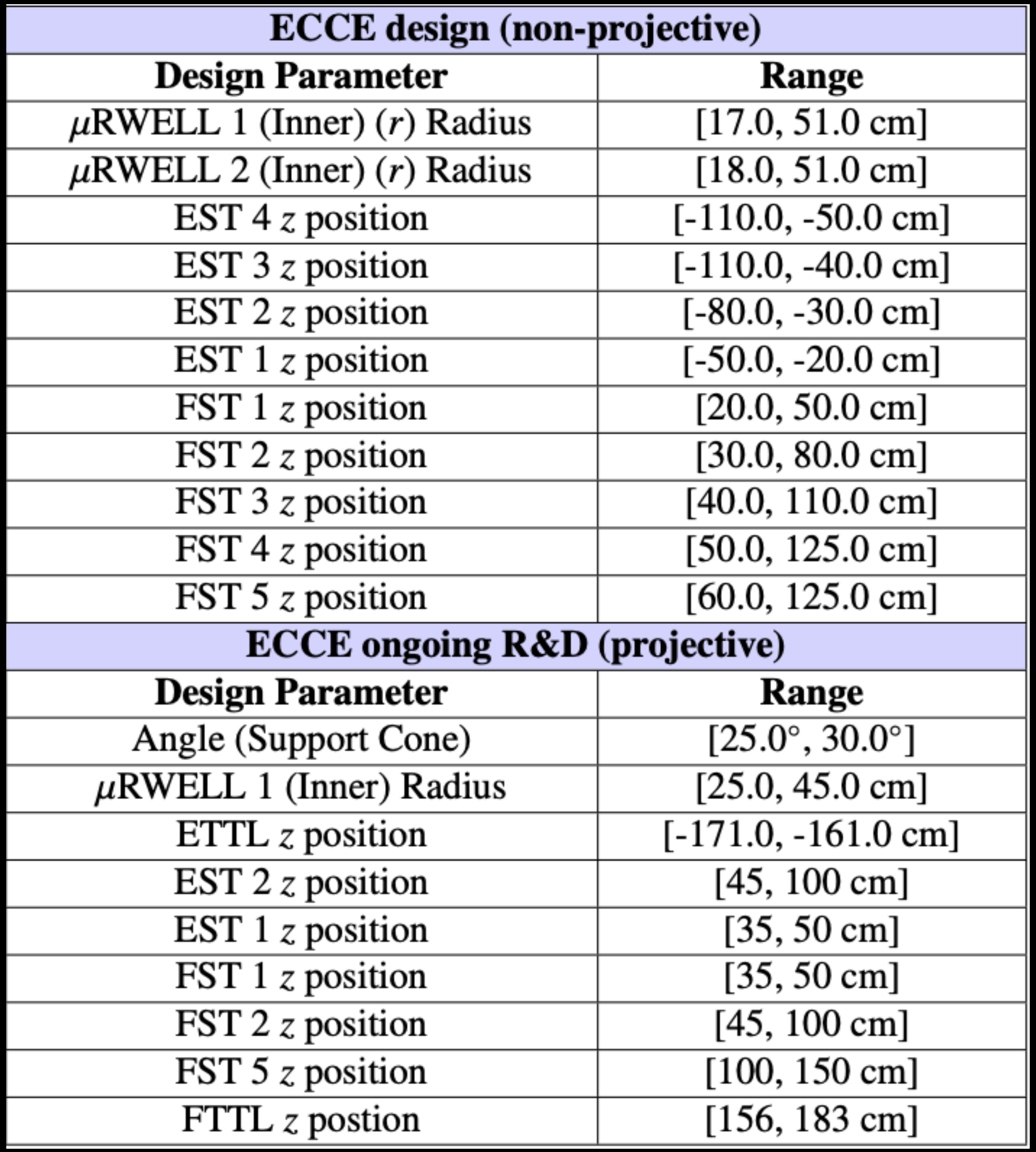


FST/EST Disks

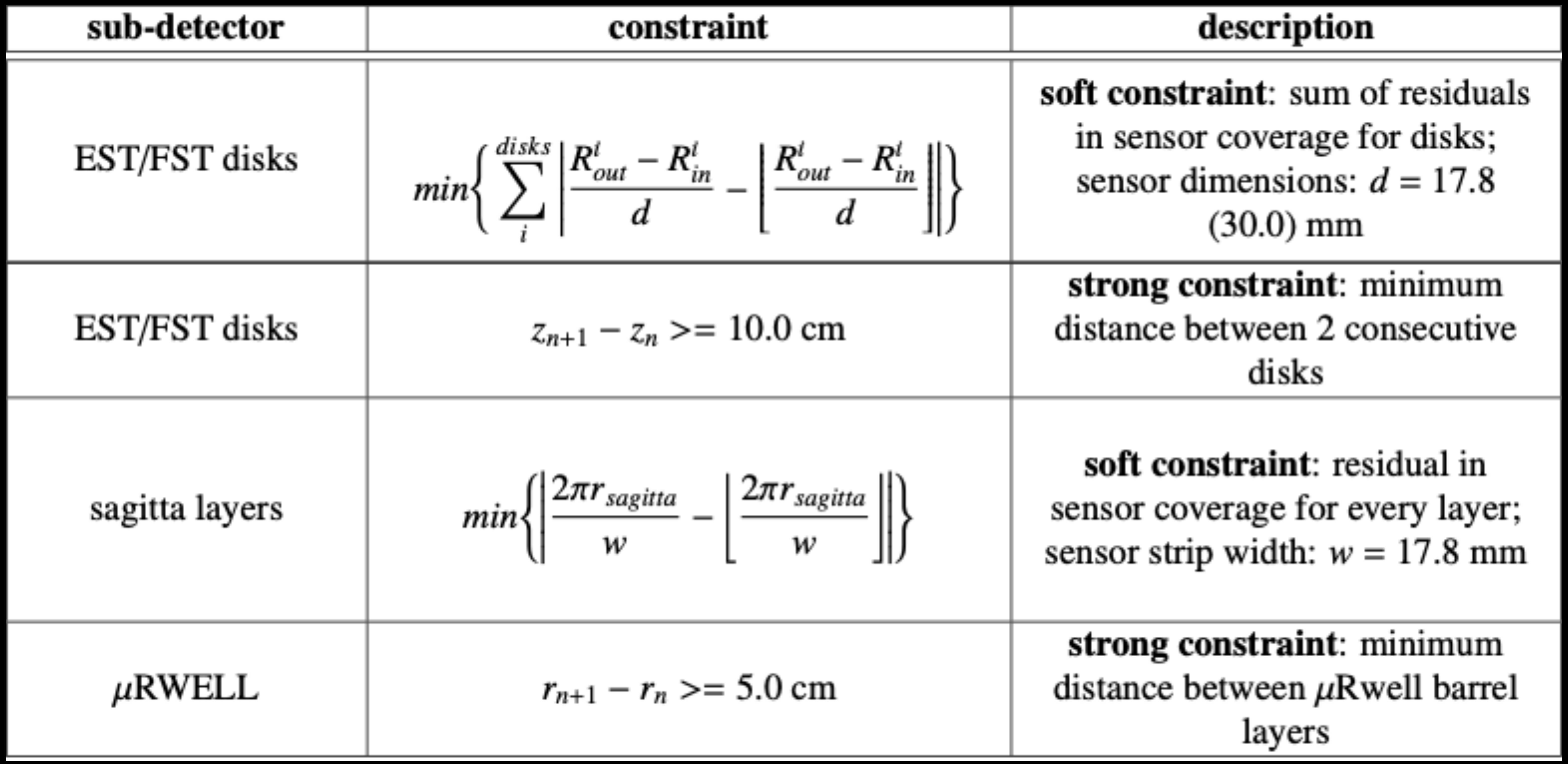


Barrel Si Layer





ECCE design (non-projective)	
Design Parameter	**Range**
μRWELL 1 (Inner) (r) Radius	[17.0, 51.0 cm]
μRWELL 2 (Inner) (r) Radius	[18.0, 51.0 cm]
EST 4 z position	[-110.0, -50.0 cm]
EST 3 z position	[-110.0, -40.0 cm]
EST 2 z position	[-80.0, -30.0 cm]
EST 1 z position	[-50.0, -20.0 cm]
FST 1 z position	[20.0, 50.0 cm]
FST 2 z position	[30.0, 80.0 cm]
FST 3 z position	[40.0, 110.0 cm]
FST 4 z position	[50.0, 125.0 cm]
FST 5 z position	[60.0, 125.0 cm]
ECCE ongoing R&D (projective)	
Design Parameter	**Range**
Angle (Support Cone)	[25.0°, 30.0°]
μRWELL 1 (Inner) Radius	[25.0, 45.0 cm]
ETTL z position	[-171.0, -161.0 cm]
EST 2 z position	[45, 100 cm]
EST 1 z position	[35, 50 cm]
FST 1 z position	[35, 50 cm]
FST 2 z position	[45, 100 cm]
FST 5 z position	[100, 150 cm]
FTTL z postion	[156, 183 cm]



sub-detector	constraint	description
EST/FST disks	$min\left\{\sum_{i}^{disks}\left\lvert\frac{R^i_{out}-R^i_{in}}{d}-\left\lfloor\frac{R^i_{out}-R^i_{in}}{d}\right\rfloor\right\rvert\right\}$	**soft constraint**: sum of residuals in sensor coverage for disks; sensor dimensions: d = 17.8 (30.0) mm
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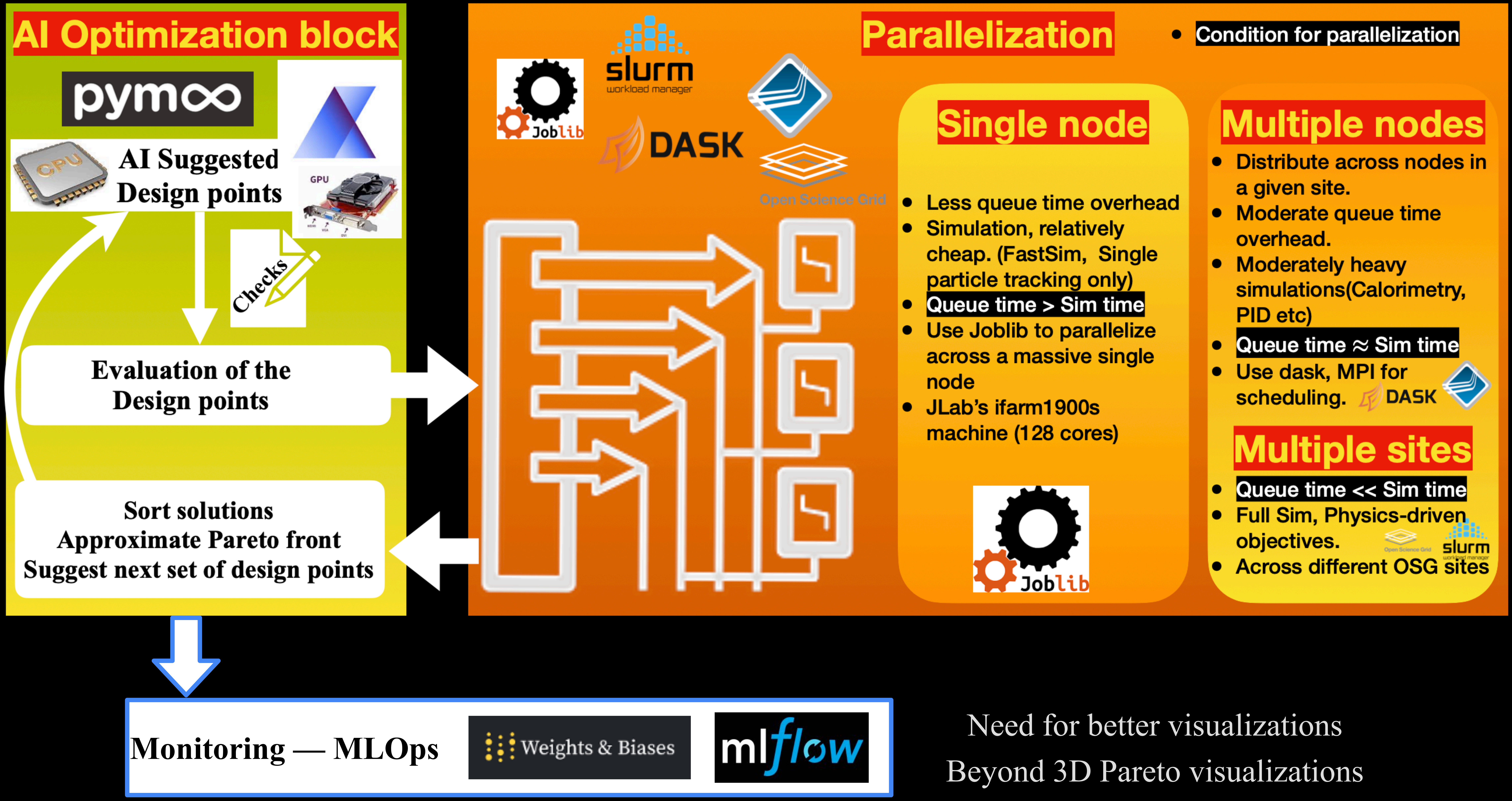
μRWELL	$r_{n+1} - r_n >= 5.0$ cm	**strong constraint**: minimum distance between μRwell barrel layers

Extensive details at arXiv:2205.09185

How a distributed Optimization pipeline will look like?



AI Optimization block

AI Suggested Design points

Evaluation of the Design points

Sort solutions
Approximate Pareto front
Suggest next set of design points

Parallelization

- Condition for parallelization

Single node

- Less queue time overhead
- Simulation, relatively cheap. (FastSim, Single particle tracking only)
- Queue time > Sim time
- Use Joblib to parallelize across a massive single node
- JLab's ifarm1900s machine (128 cores)

Multiple nodes

- Distribute across nodes in a given site.
- Moderate queue time overhead.
- Moderately heavy simulations(Calorimetry, PID etc)
- Queue time ≈ Sim time
- Use dask, MPI for scheduling.

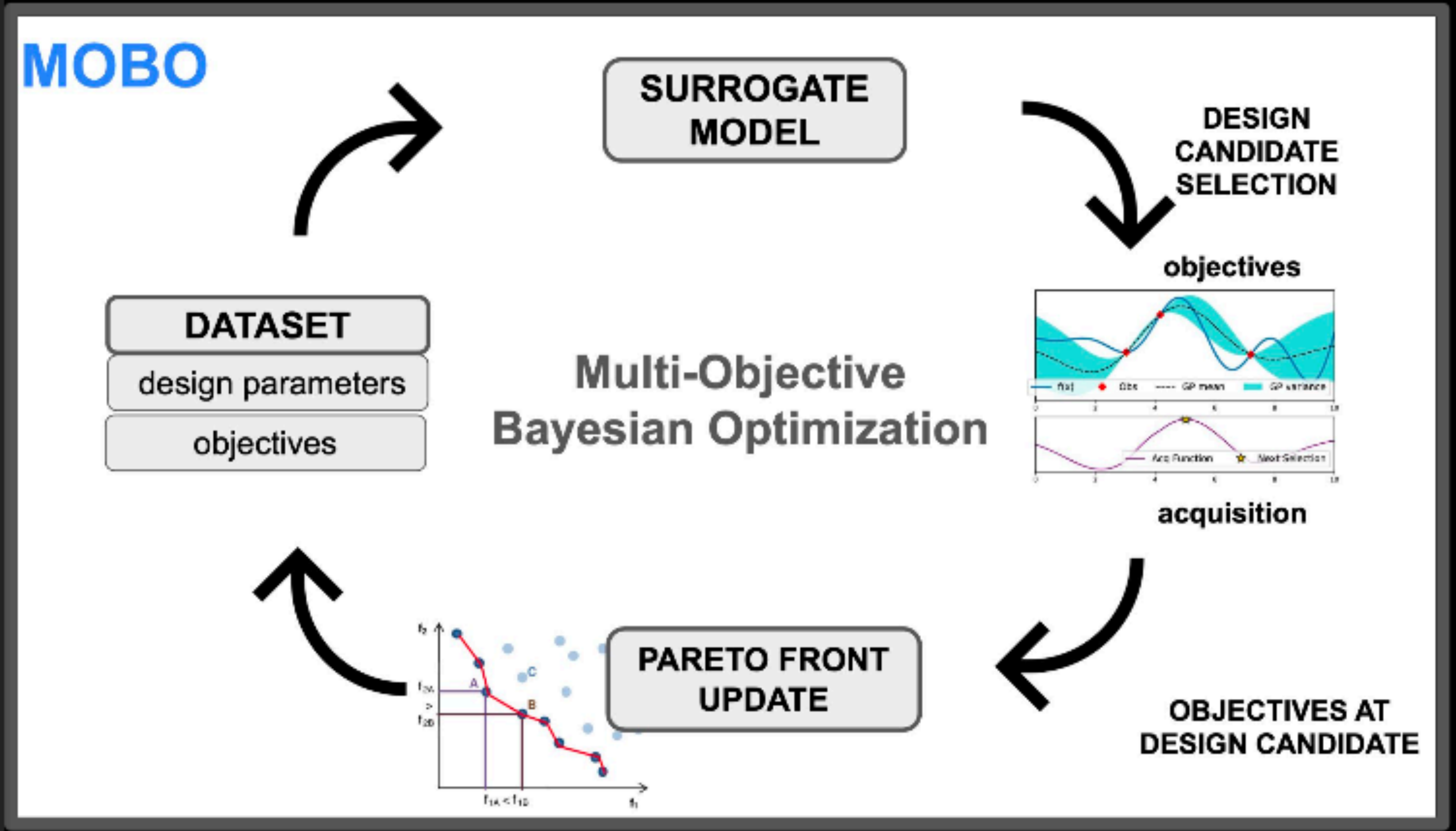
Multiple sites

- Queue time << Sim time
- Full Sim, Physics-driven objectives.
- Across different OSG sites

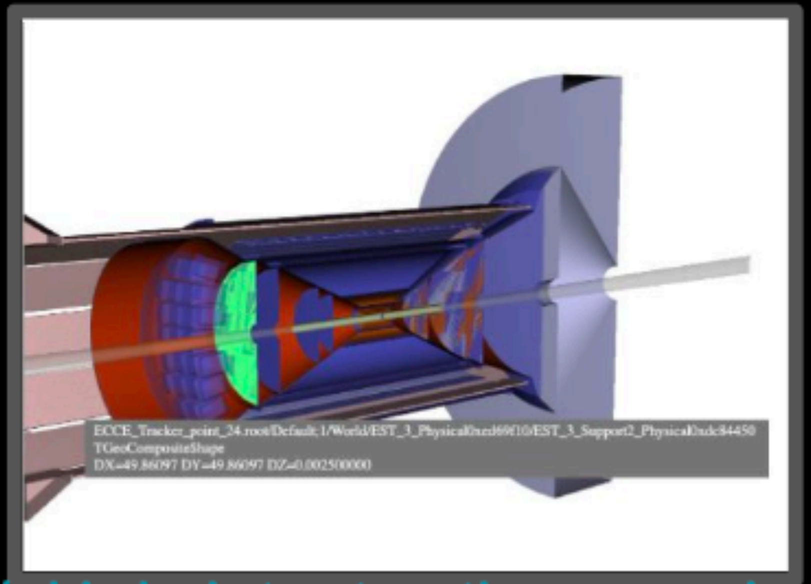
Monitoring — MLOps

Need for better visualizations
Beyond 3D Pareto visualizations

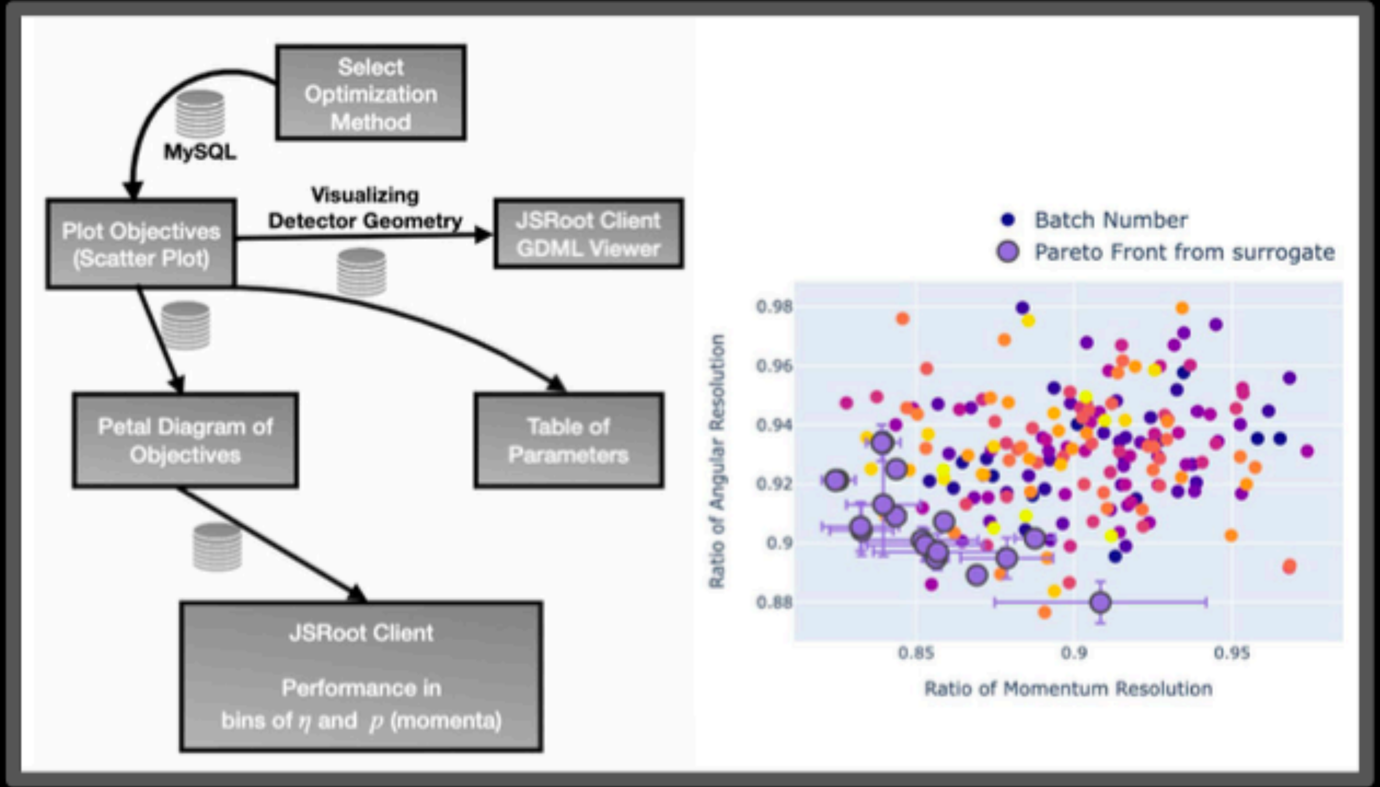
The AIDE Project



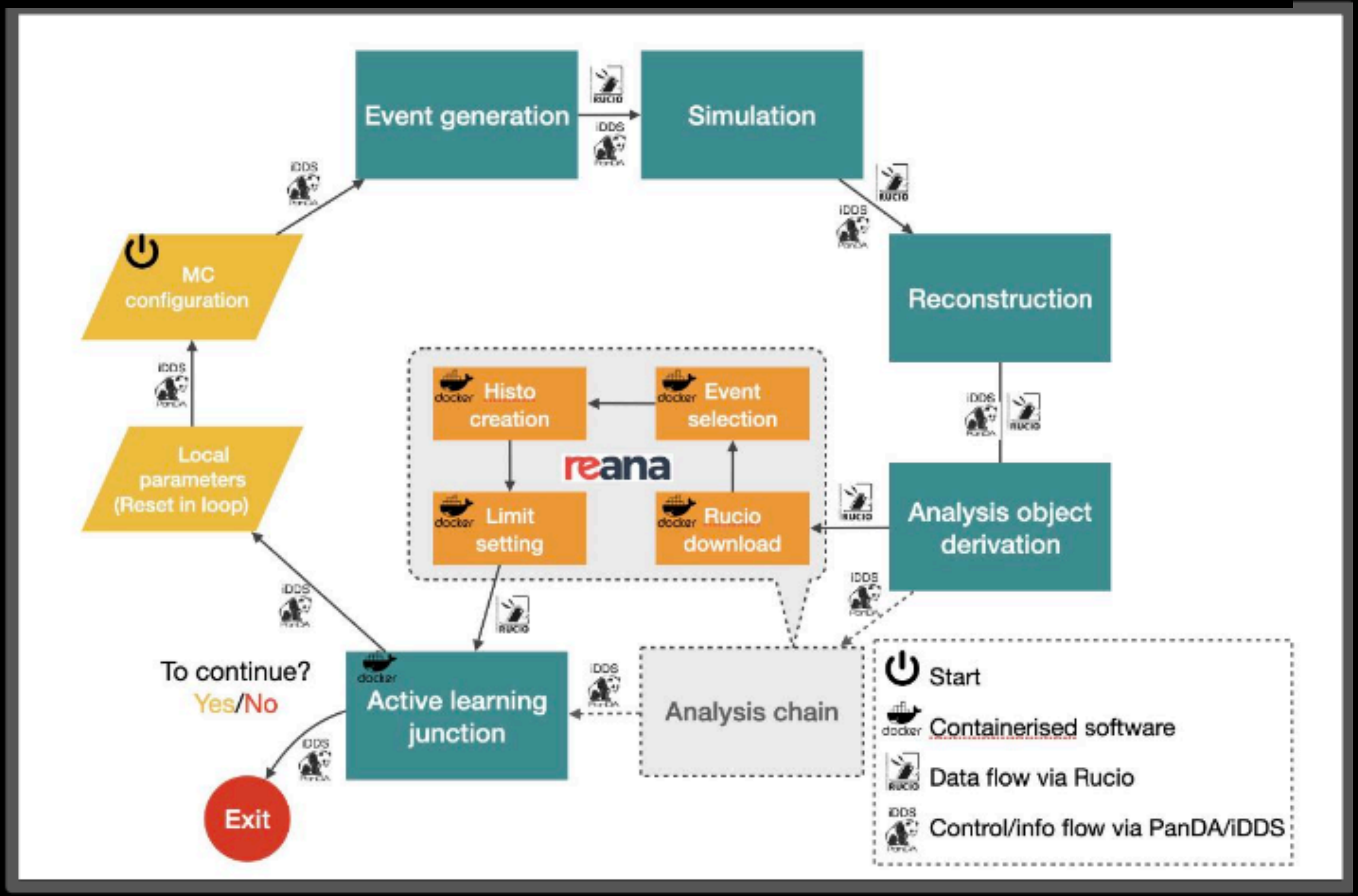
(i) Will contribute to advance the undaries of MOBO complexity to accommodate a large number of ectives and will explore usage of physics-inspired approaches



https://ai4eicdetopt.pythonanywhere.com/



(ii) Development of suite of data science tools for interactive navigation of Pareto front (multi-dim design with multiple objectives)



(iii) Will leverage cutting-edge workload management systems capable of operating at massive data and handle complex workflows

Examining solutions on the Pareto front of ePIC at different values of the budget can have great cost benefits

A fractional improvement in the objectives translates to a more efficient use of beam time which will make up a majority of the cost of the EIC over its lifetime

Implementing Objectives

- Objective functions Average of Weighted Averages (n_obj ≥ 2)
    - Momentum resolution dp/p
    - Theta resolution dθ/θ
    - Projected dθ/θ at PID location.
    - Kalman Filtering inefficiency (improving the tracking reconstruction ability of the algorithm)

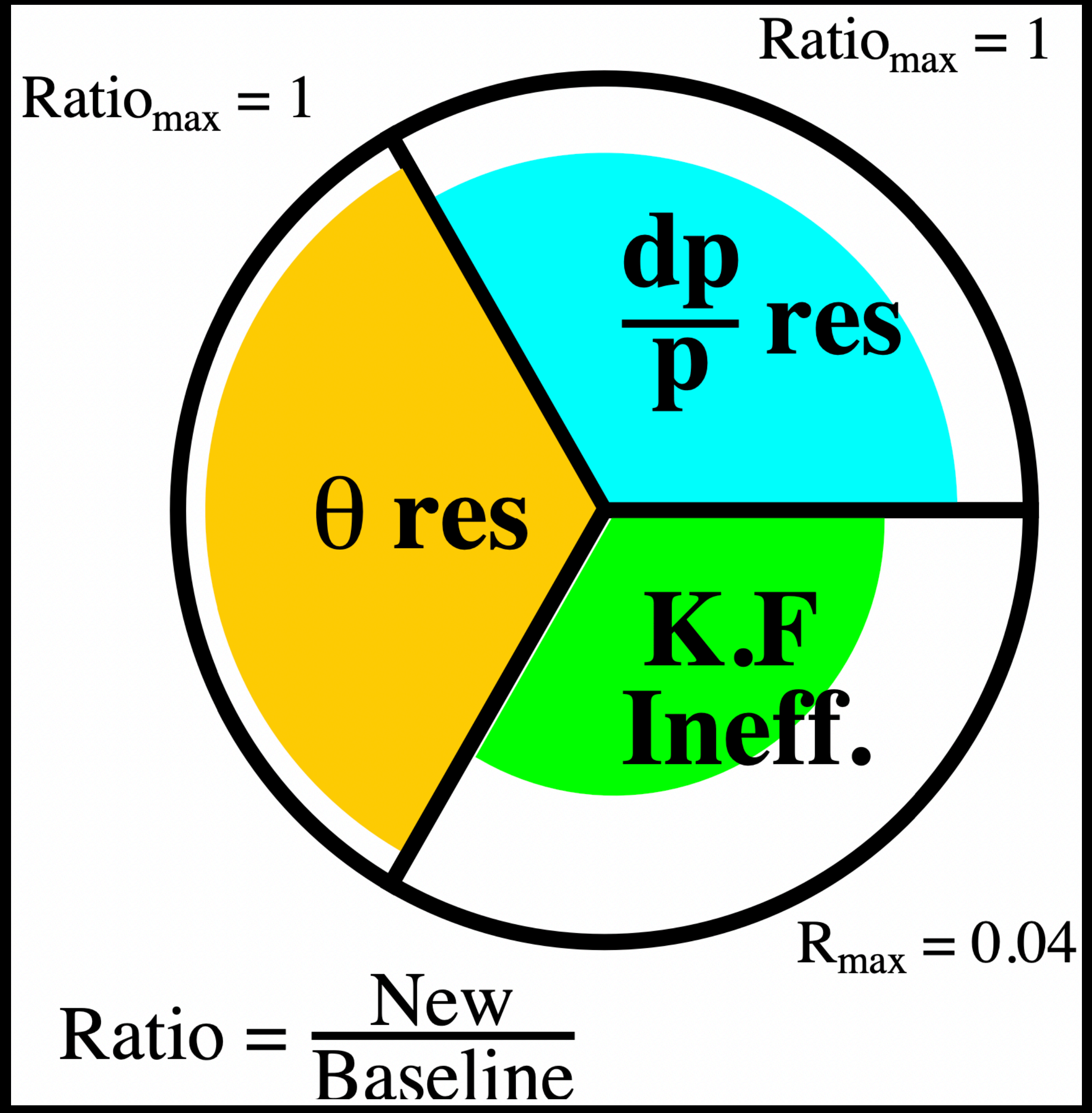
- Validation of the solutions
    - Validate by comparing optimal vs baseline dφ resolution, vertex resolution and reconstruction efficiency

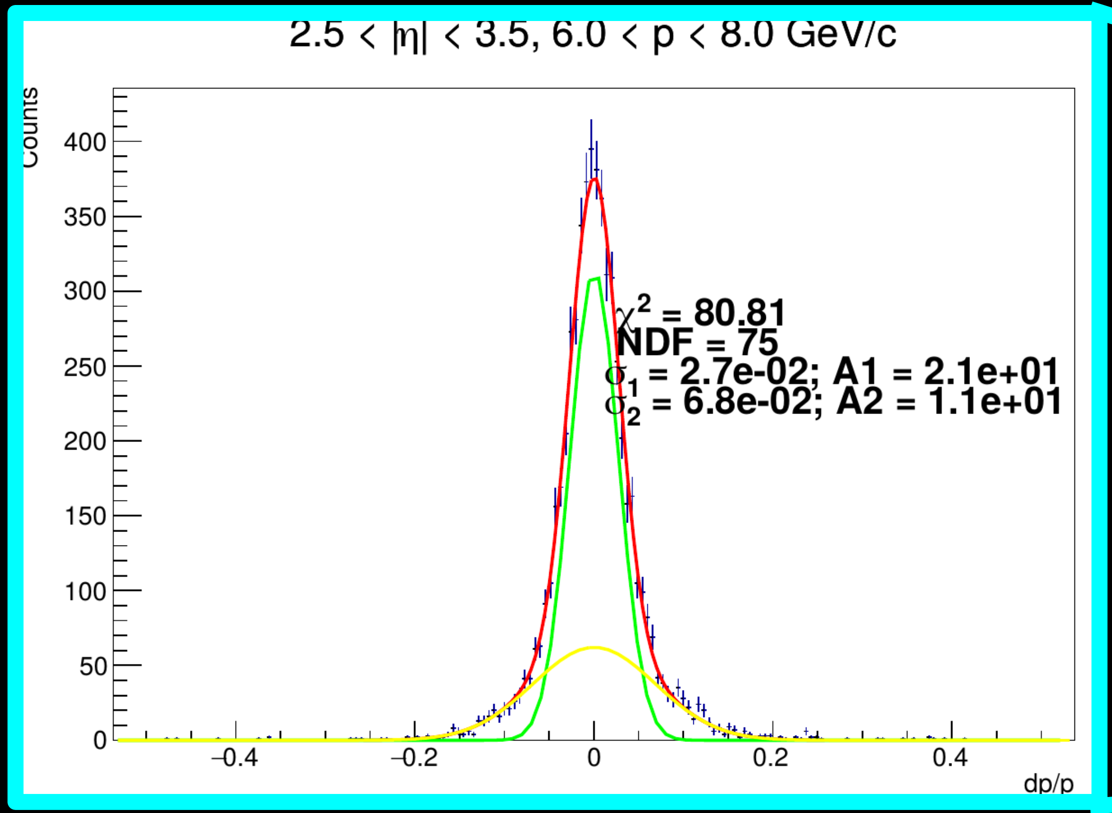
Implementing Objectives

Weighted sum with errors along η

Robust fitting procedure in fine-grained phase-space

Propagate uncertainties in fits throughout





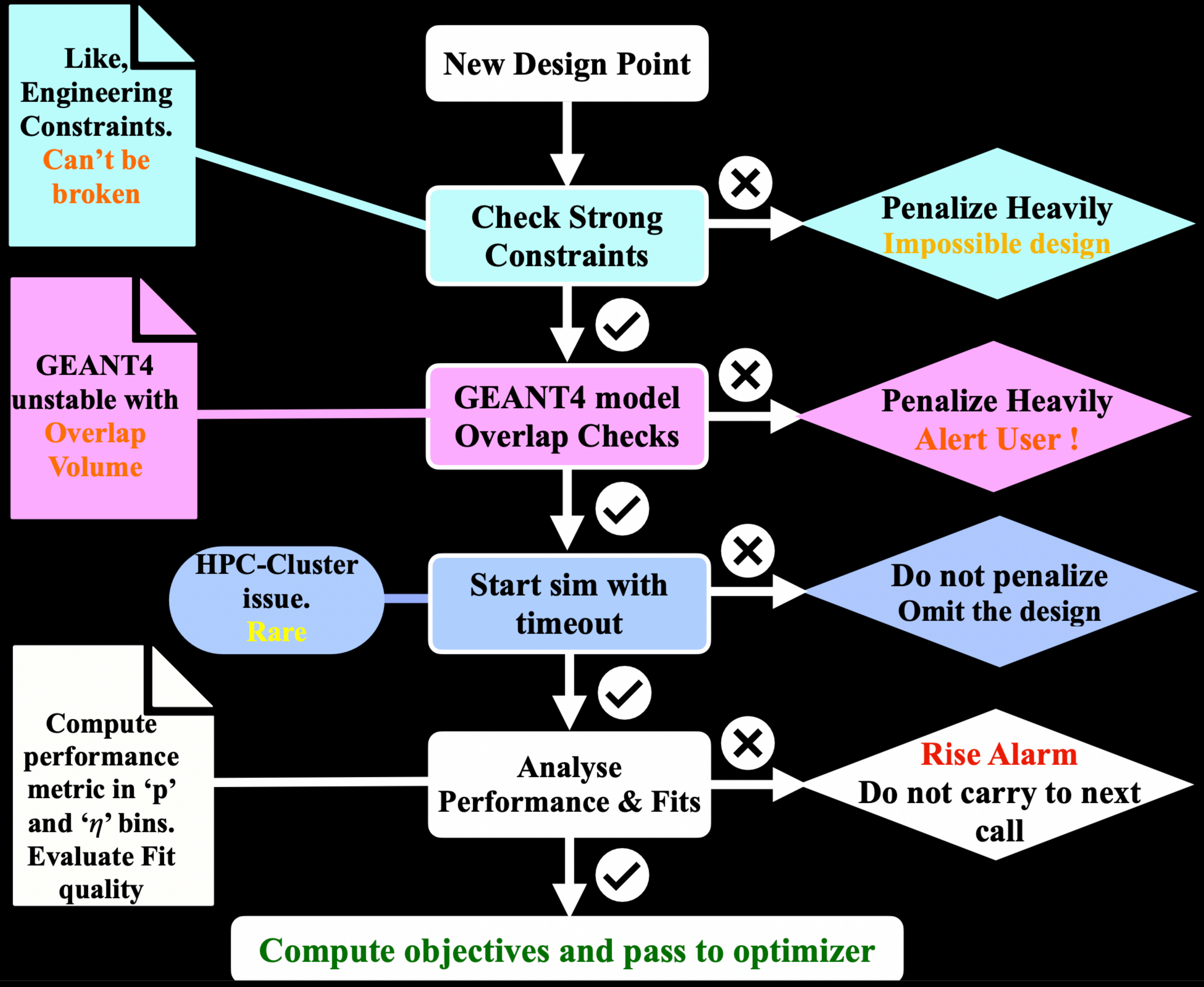
$$\bar{x}_\eta = \frac{\Sigma_p x_p w_p}{\Sigma_p w_p}$$

Avg in a η bin

Weighted sum with errors along η

$$\bar{x} = \frac{\Sigma_\eta^{N_\eta} \bar{x}_\eta}{N_\eta}$$

Checks performed



New Design Point

Check Strong Constraints

Like, Engineering Constraints. Can't be broken

✗ Penalize Heavily
Impossible design

✓

GEANT4 model Overlap Checks

GEANT4 unstable with Overlap Volume

✗ Penalize Heavily
Alert User !

✓

Start sim with timeout

HPC-Cluster issue. Rare

✗ Do not penalize
Omit the design

✓

Analyse Performance & Fits

Compute performance metric in 'p' and 'η' bins. Evaluate Fit quality

✗ Rise Alarm
Do not carry to next call

✓

Compute objectives and pass to optimizer

Multi Objective Evolutionary Algorithms

- Inspired by Biological Systems.
- Semi heuristic in nature.
- Quite successful in solving MOO problems.
- Embedding constraints relatively easier

Swarm Algorithms

Ant Colony optimization
Bees algorithm
Particle swarm optimization
Cuckoo search

Genetic Algorithms

Default Genetic Algorithm
NSGA
NSGA-II
U-NSGA-III

Differential Evolution

Cellular Automata

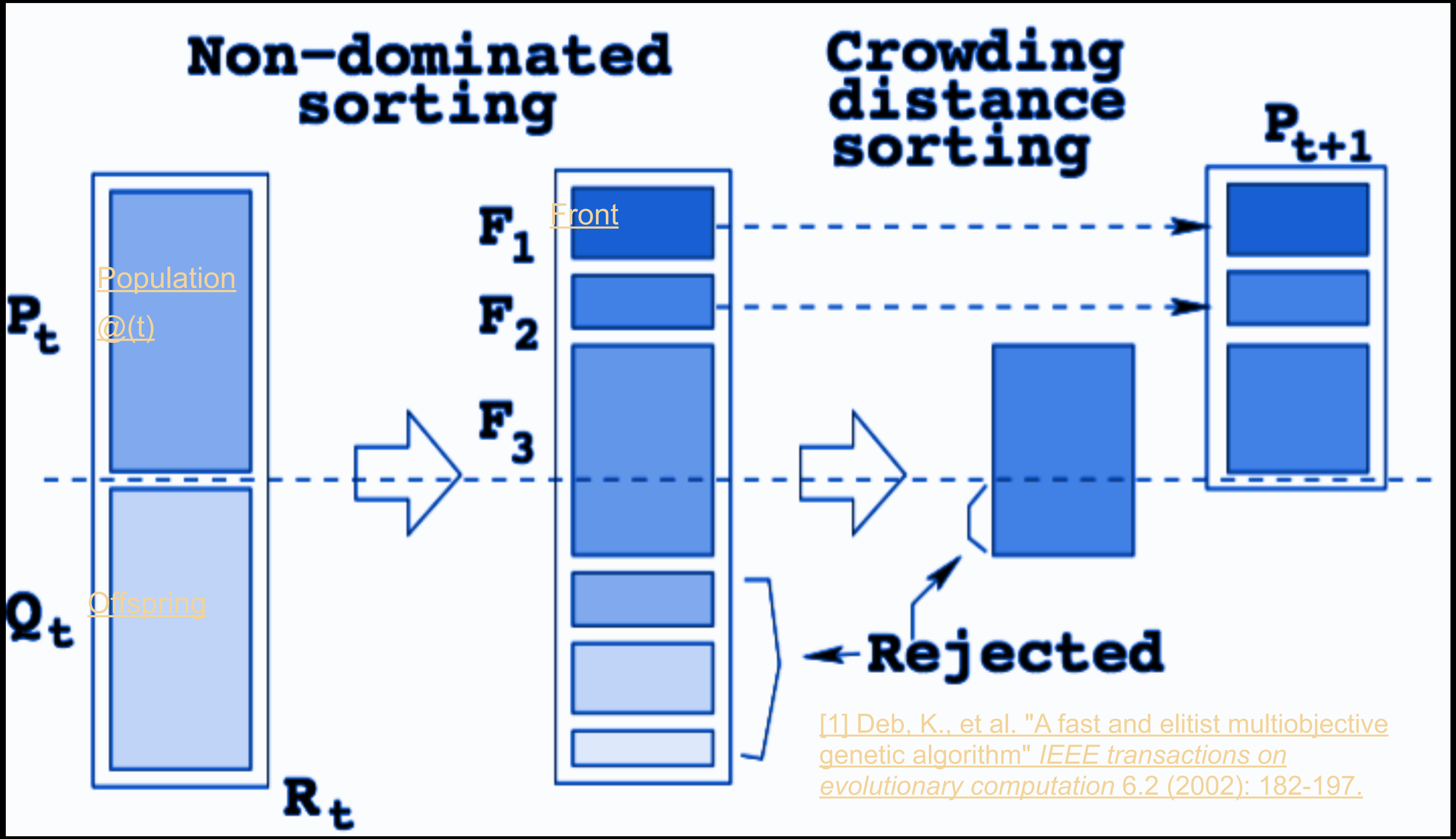
PyGMO

Multi-objective Optimization in Python
pymoo

jMetalPy

TMVA

Elitist Non-Dominated Sorting Genetic (NSGA)



[1] Deb, K., et al. "A fast and elitist multiobjective genetic algorithm" *IEEE transactions on evolutionary computation* 6.2 (2002): 182-197.

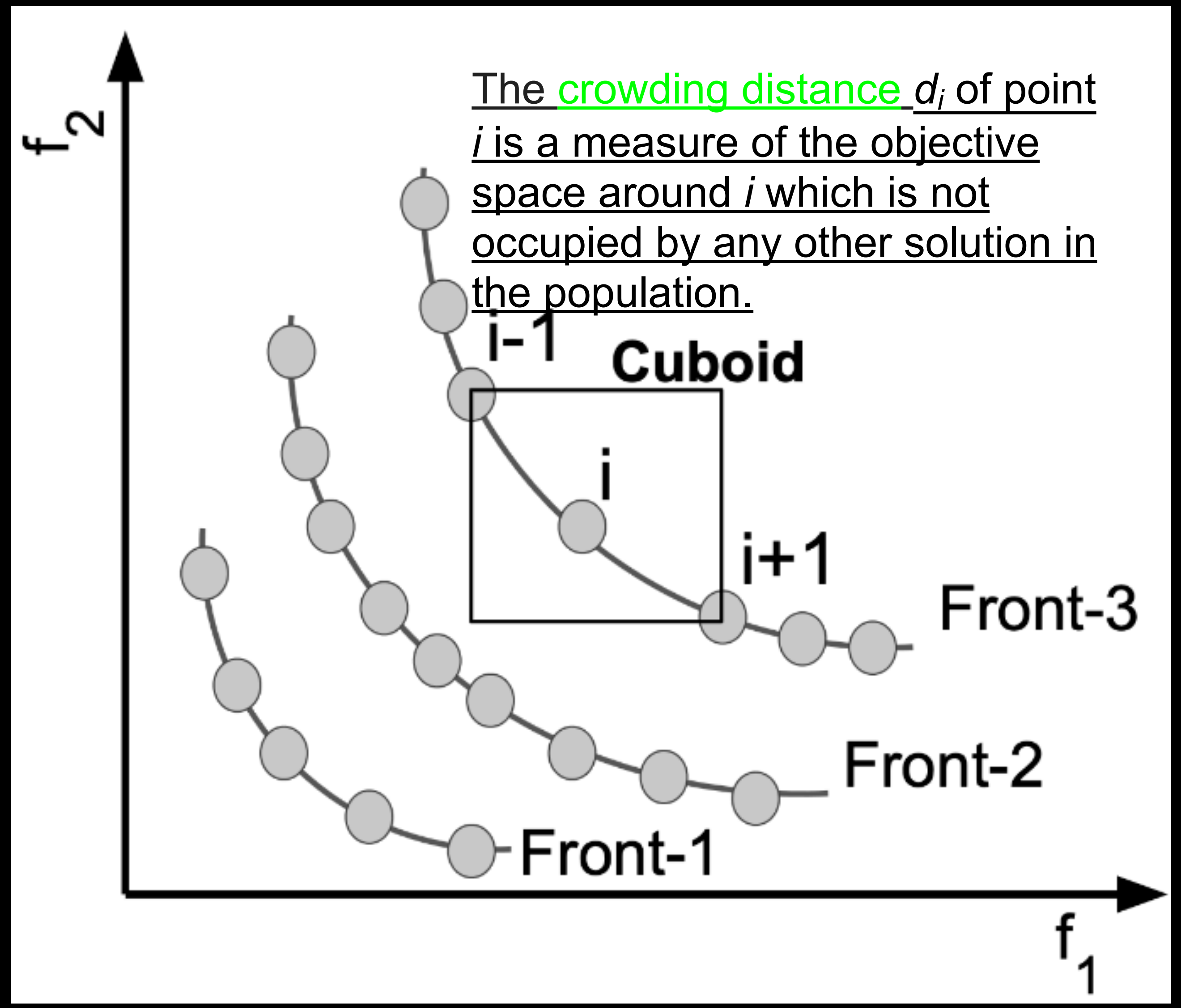
This is one of the most popular approach

(>35k citations on google scholar), characterized by:

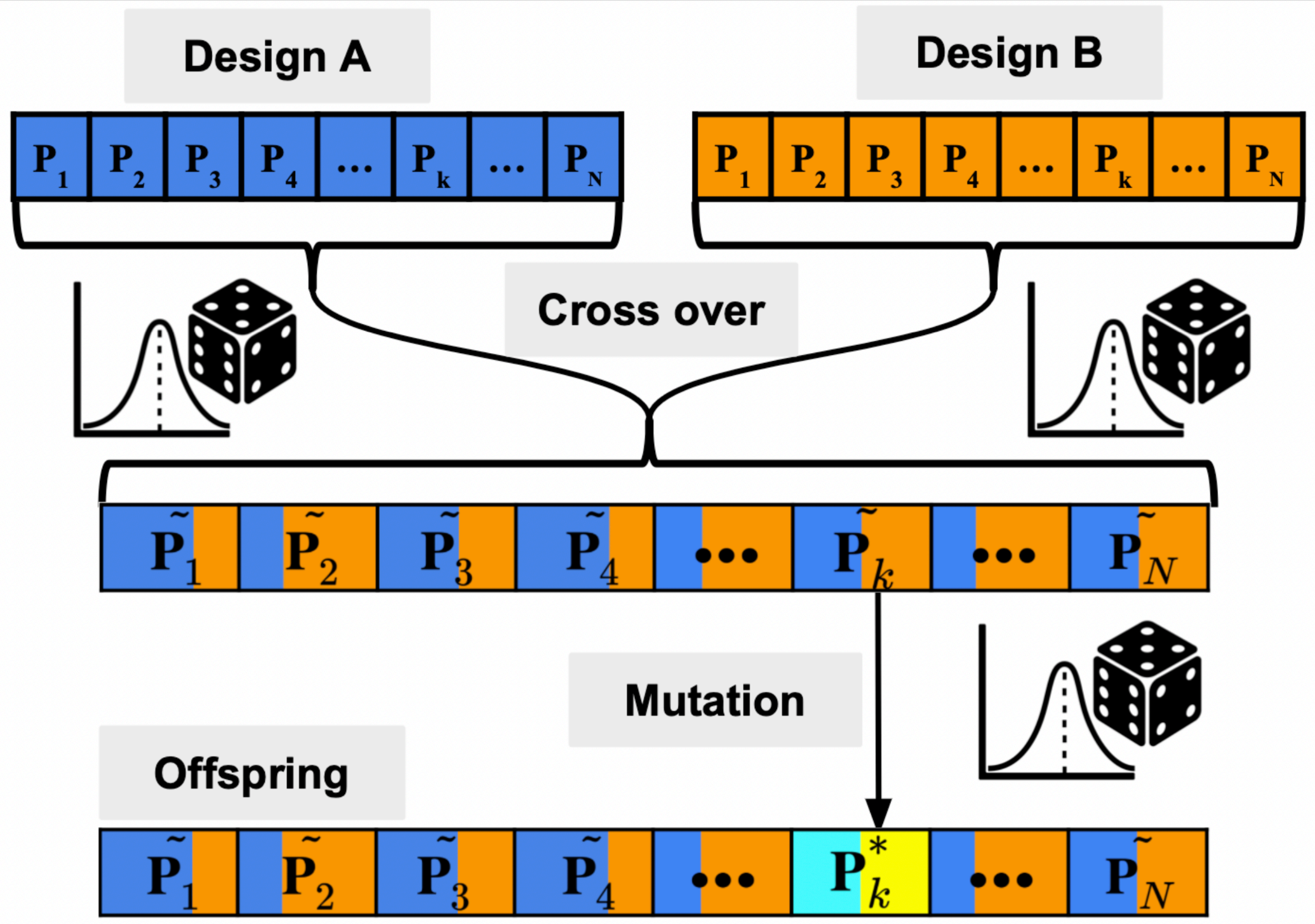
- Use of an elitist principle
- Explicit diversity preserving mechanism
- Emphasis in non-dominated solutions

The population R_t is classified in non-dominated fronts.

Not all fronts can be accommodated in the N slots of available in the new population P_{t+1}. We use **crowding distance** to keep those points in the last front that contribute to the highest diversity.


The crowding distance d_i of point i is a measure of the objective space around i which is not occupied by any other solution in the population.

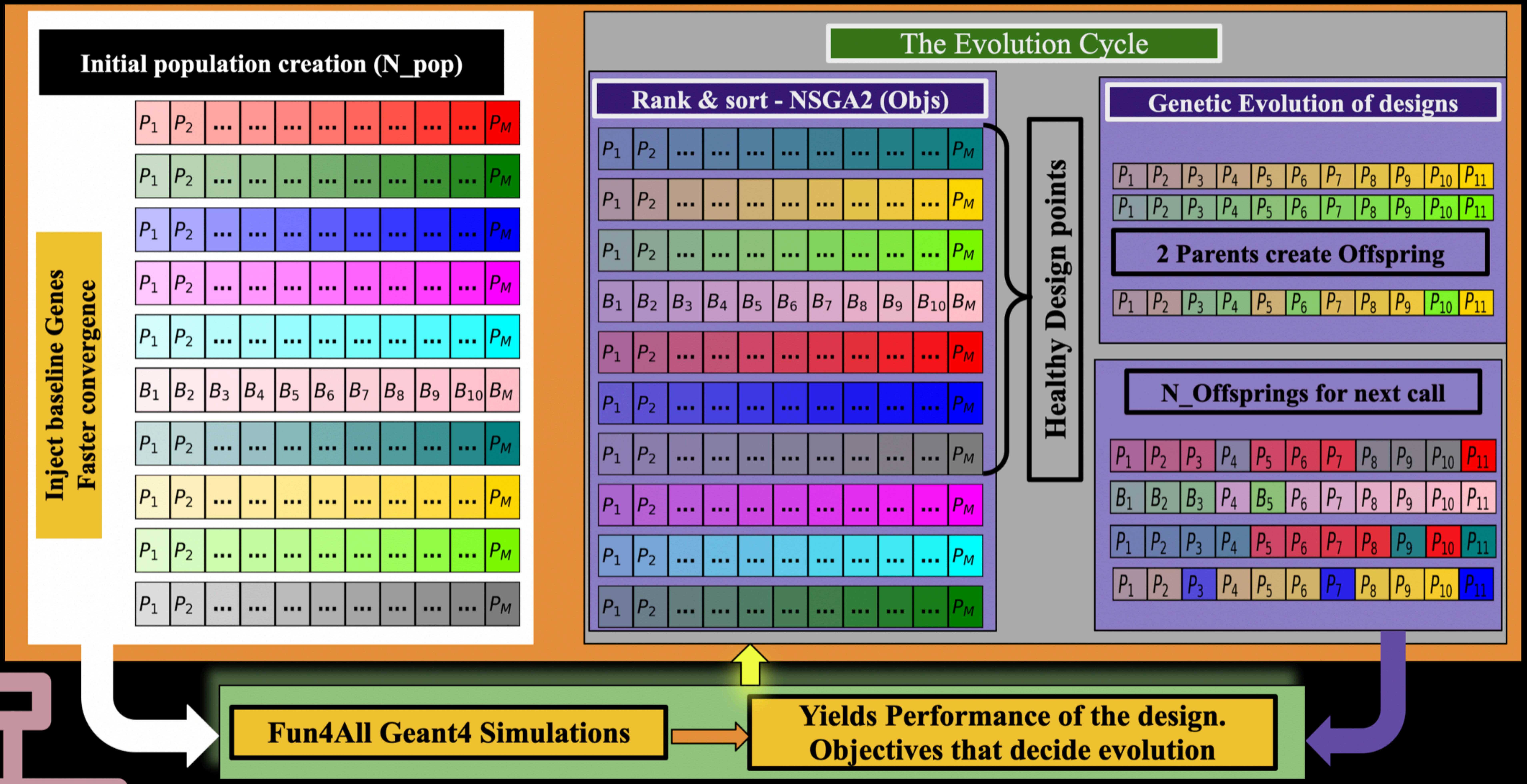
Population @(t+1)



This is to illustrate Binary Cross-over

AI assisted Detector design

MOEA Pipeline



Initial population creation (N_pop)

Inject baseline Genes
Faster convergence

The Evolution Cycle

Rank & sort - NSGA2 (Objs)

Healthy Design points

Genetic Evolution of designs

2 Parents create Offspring

N_Offsprings for next call

Fun4All Geant4 Simulations

Yields Performance of the design.
Objectives that decide evolution

2 Level Parallelization

Comprehensive checks ensures feasibility of design

Multi Objective Bayesian Optimization

BoTorch

BAYESIAN OPTIMIZATION IN PYTORCH

nextorch NEXTorch latest

Ax

GPflow

Bayesian Optimization

- Compute max/min (f) with minimum evaluations
- Build up f to query — Estimation of distribution

f

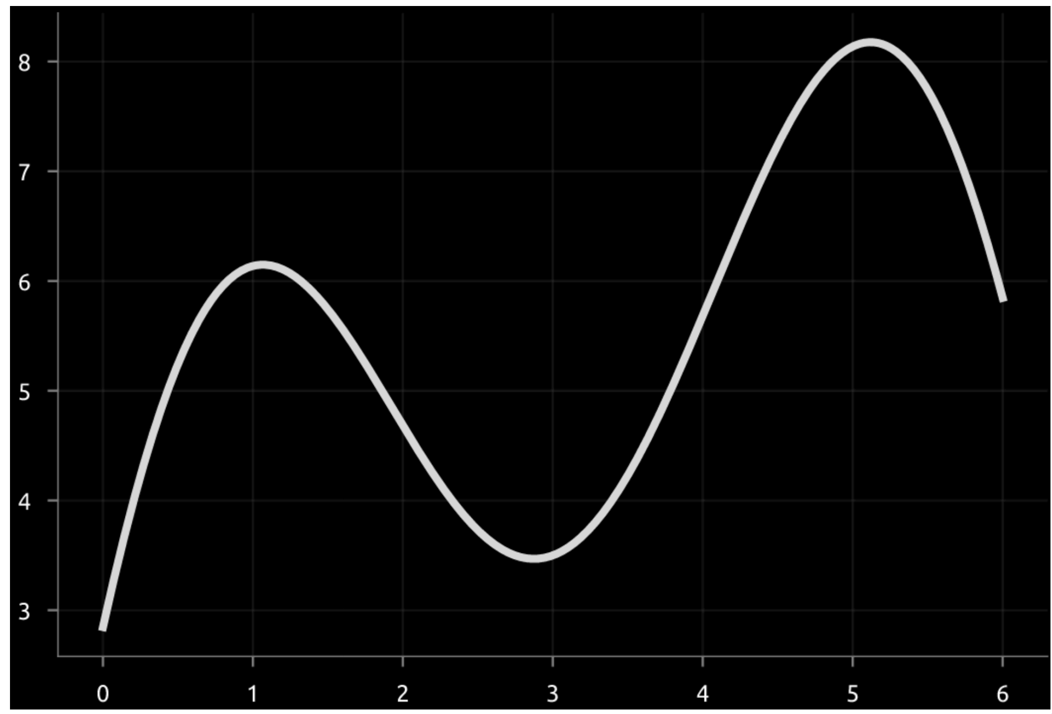
- f - continuous
- f - may be noisy

x

Design Parameters

- Black Box Function
- Too expensive to compute

True Function



Y

Objectives

Multi Objective Bayesian Optimization

A brief explanation (extends to Multiple Dimensions)

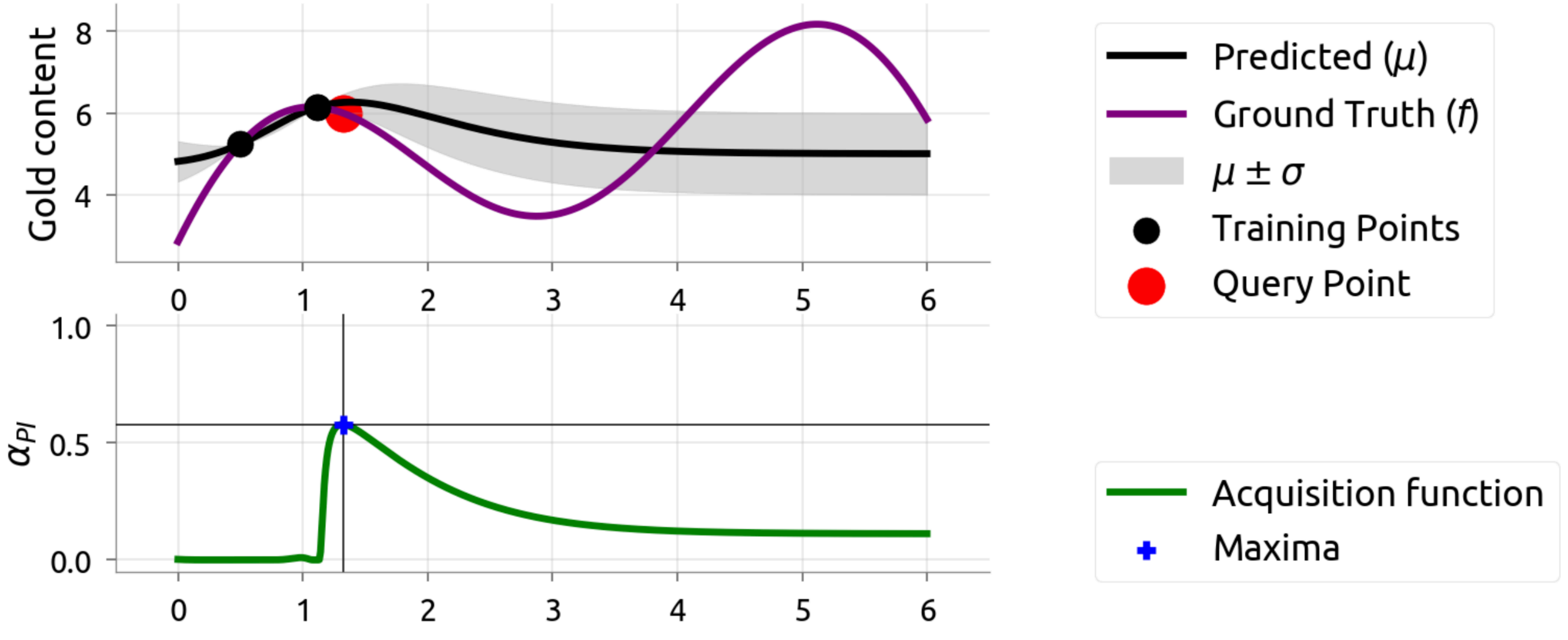
The Surrogate model

Posterior predictions

Usually based on GP

The Acquisition Function —$F(\text{posteriors}) = \alpha(x)$

Predicts "Improvement" when $x \rightarrow x + \epsilon$



1. Choose a surrogate model
2. Use Ground truth to update the surrogate model
3. Using Acq. Function to predict next point for query
4. Go to 1. Until Convergence

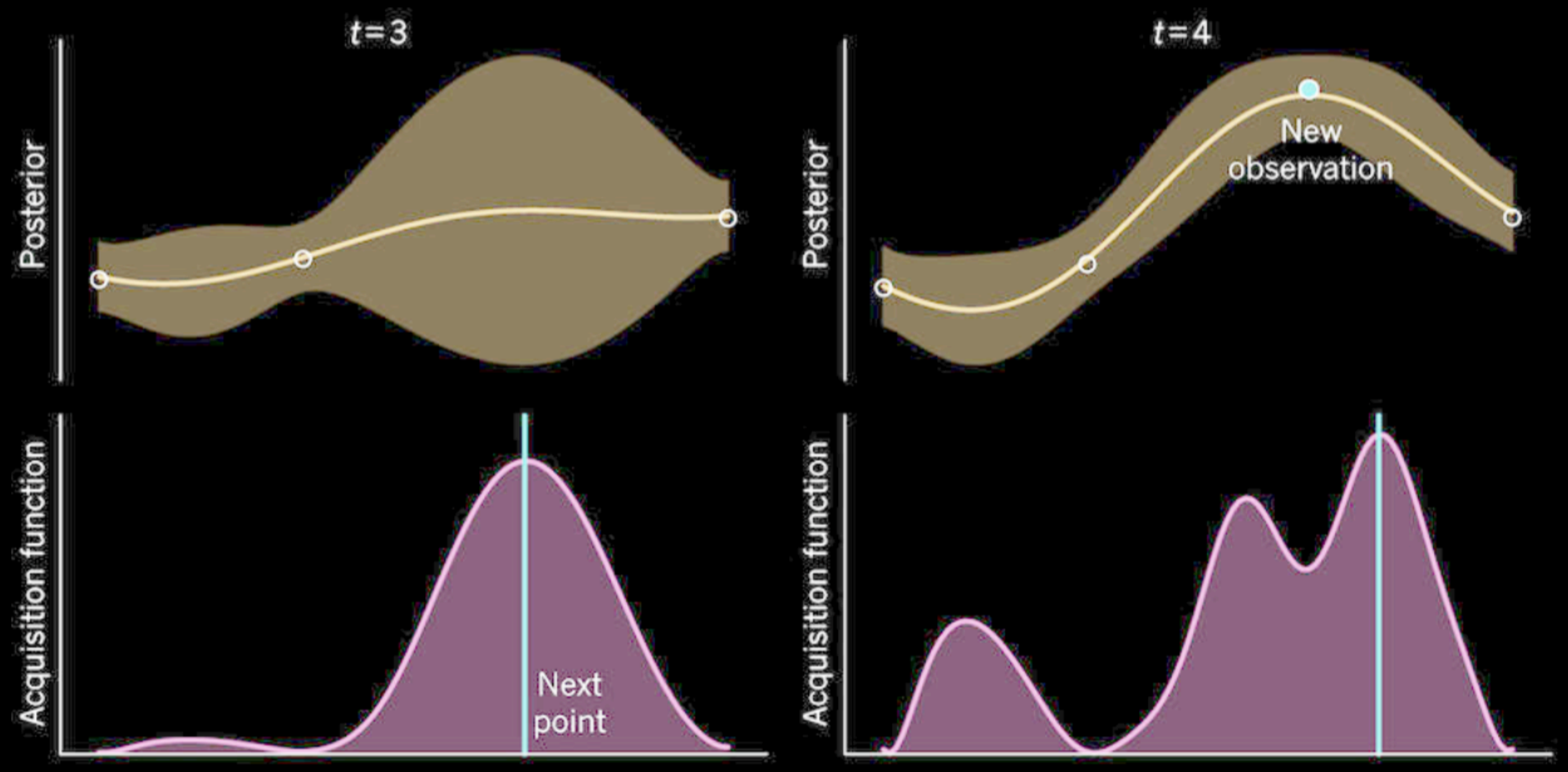
Agnihotri & Batra, "Exploring Bayesian Optimization", Distill, 2020.

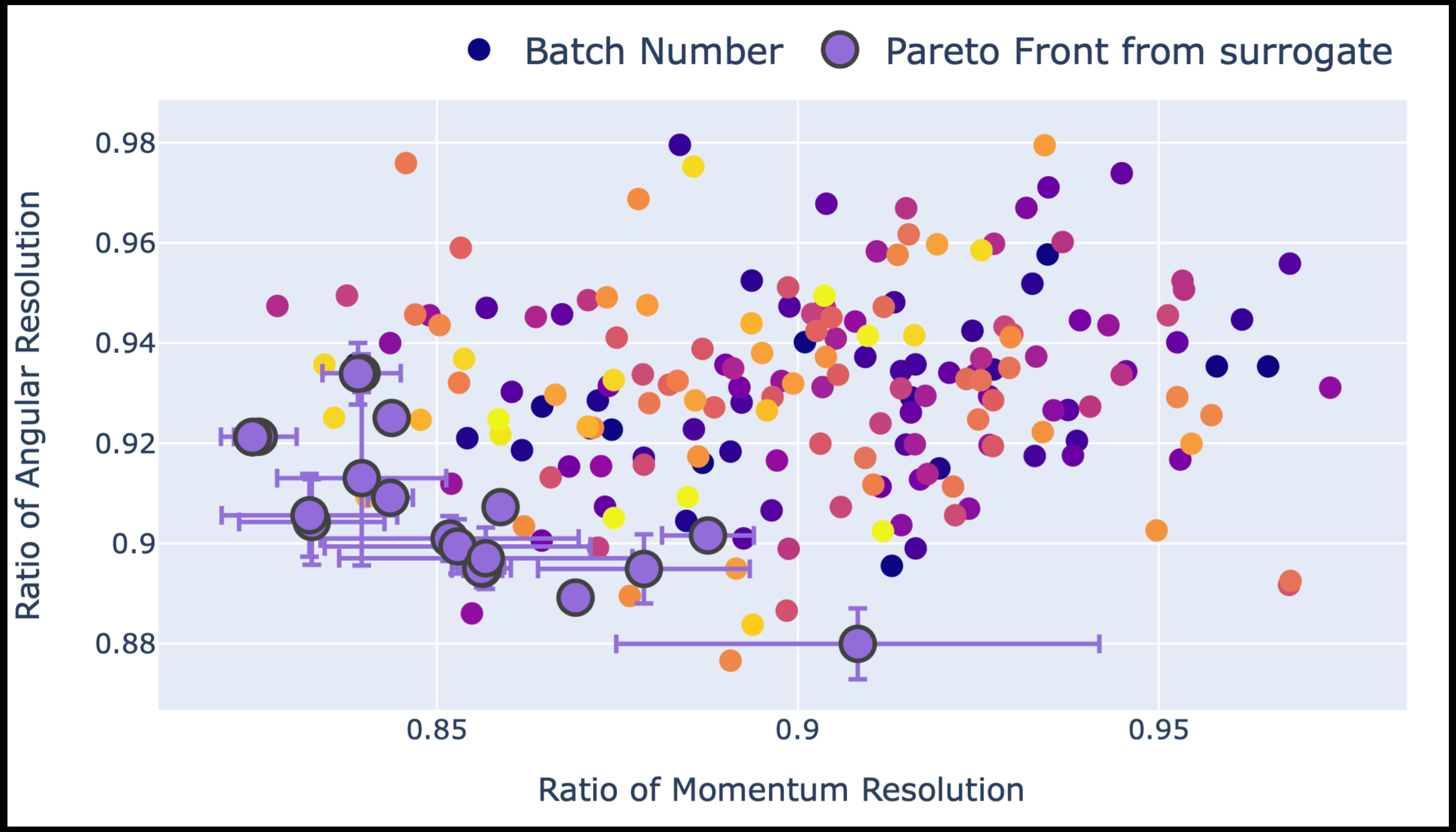
Multi Objective Bayesian Optimization

- **Ax - BoTorch**
    - Apt when evaluations of objectives are costly. Typical for the problem in hand.
    - Builds surrogate models that maps objective space to design parameter space.
    - Uses novel qNEHVI acq. function with reduced computational complexity arxiv:2105.08195.

- **Implementation**
    - 1 Level Parallelization (≈ 120cores)
    - N_objectives = 2
    - BATCH_SIZE - 3 (q)
    - N_BATCH - 50
    - qNEHVI + SAASBO*

*SAASBO ~ O(N^3)
good for high design dimensions but
not recommended beyond a few hundred evaluations





Interactive Visualization of the result

Proof of concept

MOEA or MOBO ?

MOEA

- Has been widely used for solving MOO problems
- ↑ population /off spring — ↑ diversity — ↓
- Relatively easier to implement
- Complexity relatively easy to compute
- Ideal — Cost of computing “cheap”
- Successful with large Design and Objective parameters
- No Map : “Design” ↔ “Objectives”

MOBO

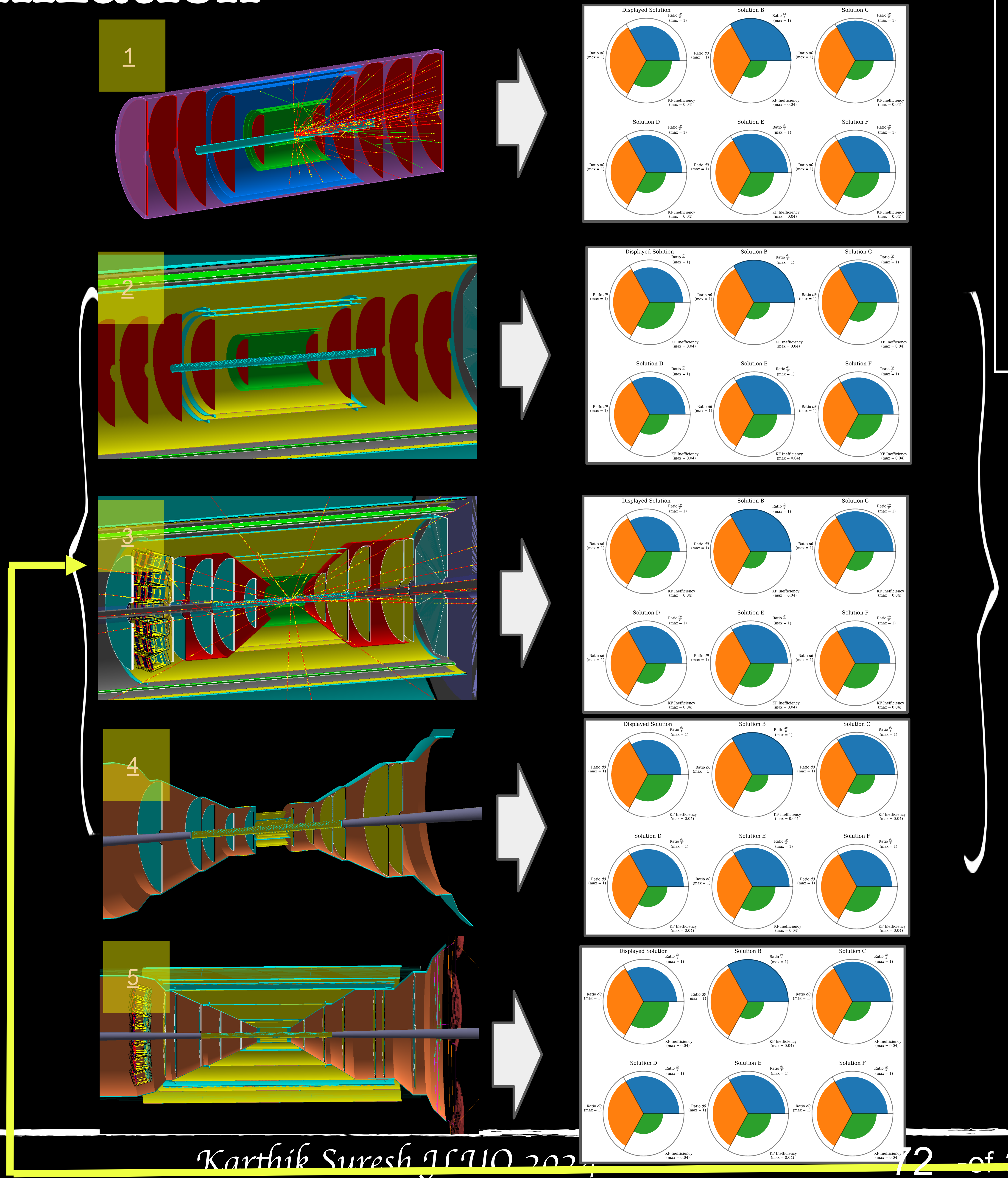
- Has been around for a while, gaining popularity
- Sequential Strategy — global minimization
- Relatively harder to implement
- Complexity relatively easy to compute
- Ideal — simulations can be heavily parallelized
- Currently, Not recommended beyond 4-5 Objective parameters
- Can Map : “Design” → “Objectives” — Fast simulator can be built

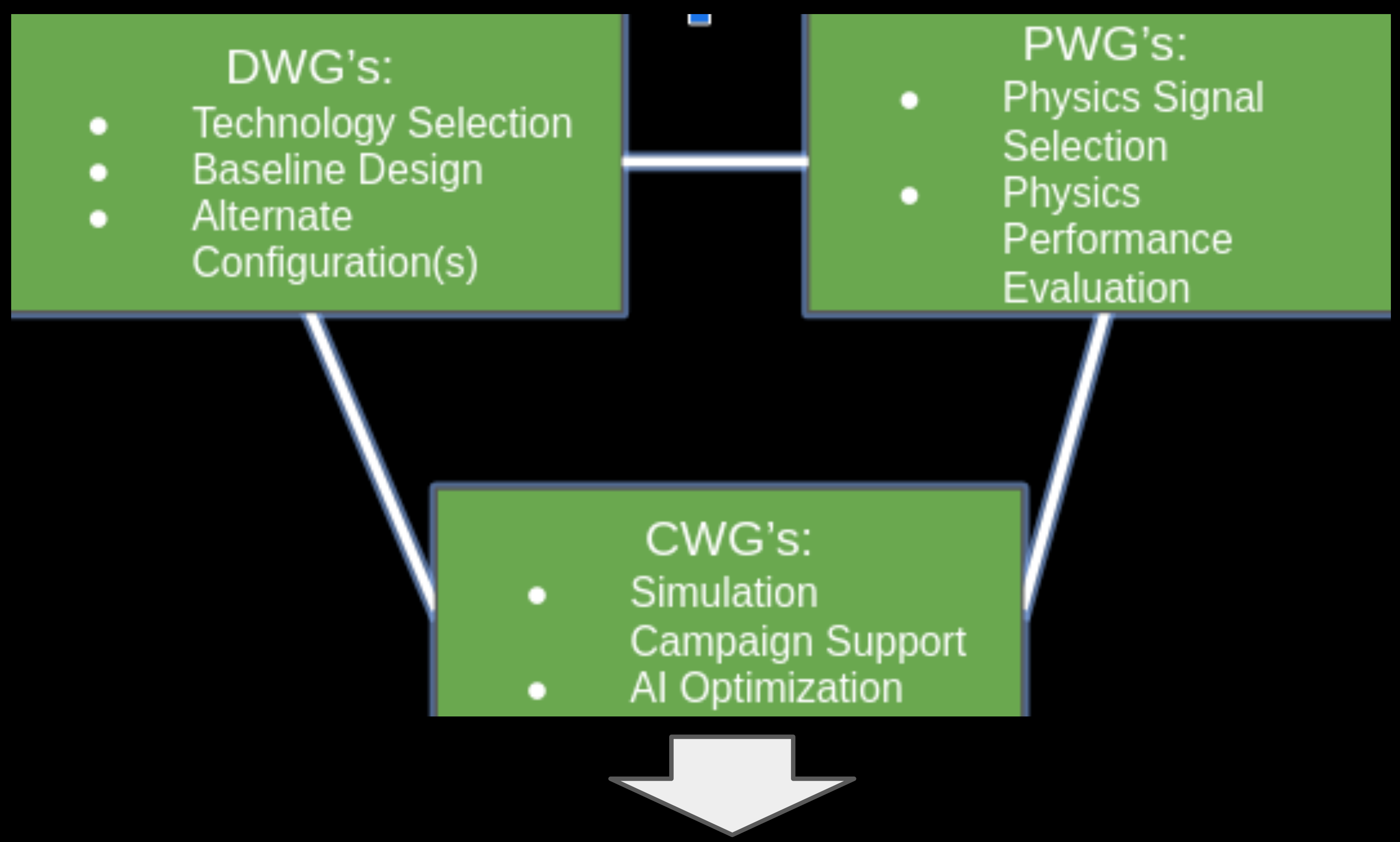
ECCE Results :Phases of Optimization

Tracker Optimisation timeline.

- 1: Barrel + technological choices. - Chose technologies
- 2: Barrel+Disks. W/O support structures. - Identified holes in Disks, Cylinder rearranged — no double layers
- 3. Barrel+Disks. With **fixed** support structures. - Disks rearranged
- 4. Barrel+Disks and support structure. - Projective Geometry
- 5. Full tracking system optimization. - Removing Tracking after Hadron - PID

Phases of Optimisation





DWG's:
- Technology Selection
- Baseline Design
- Alternate Configuration(s)

PWG's:
- Physics Signal Selection
- Physics Performance Evaluation

CWG's:
- Simulation Campaign Support
- AI Optimization

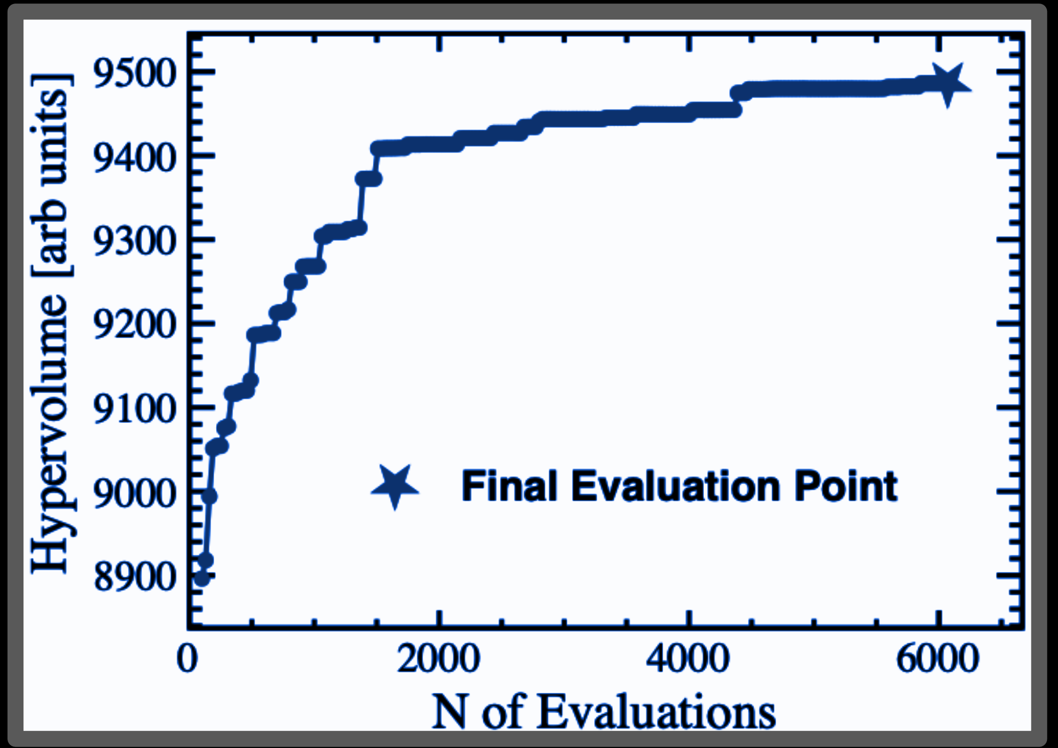
updated configurations with any additional requirements

Optimisation phases

ECCE Results : Analyzing results

1

Can take a snapshot any time during evaluation

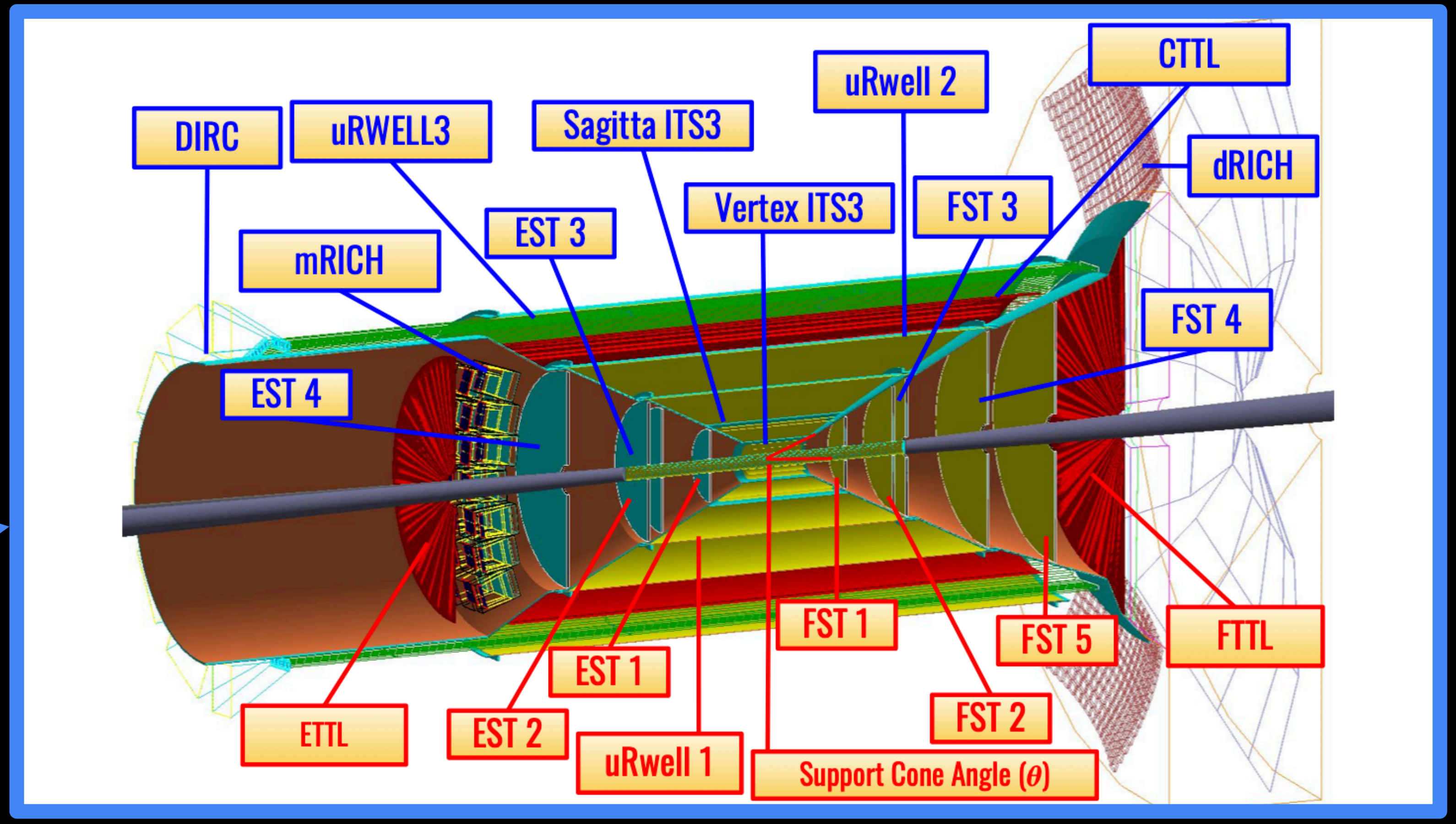


2

Updated Pareto Front at time t

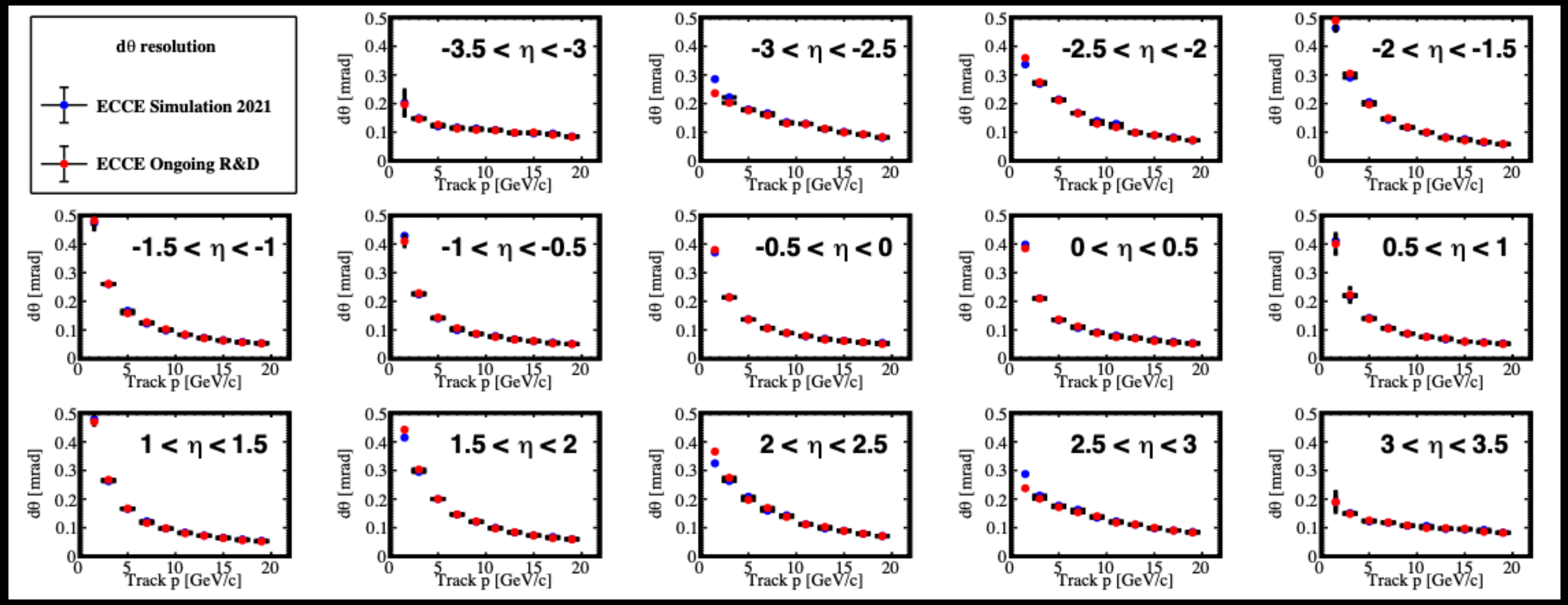
3

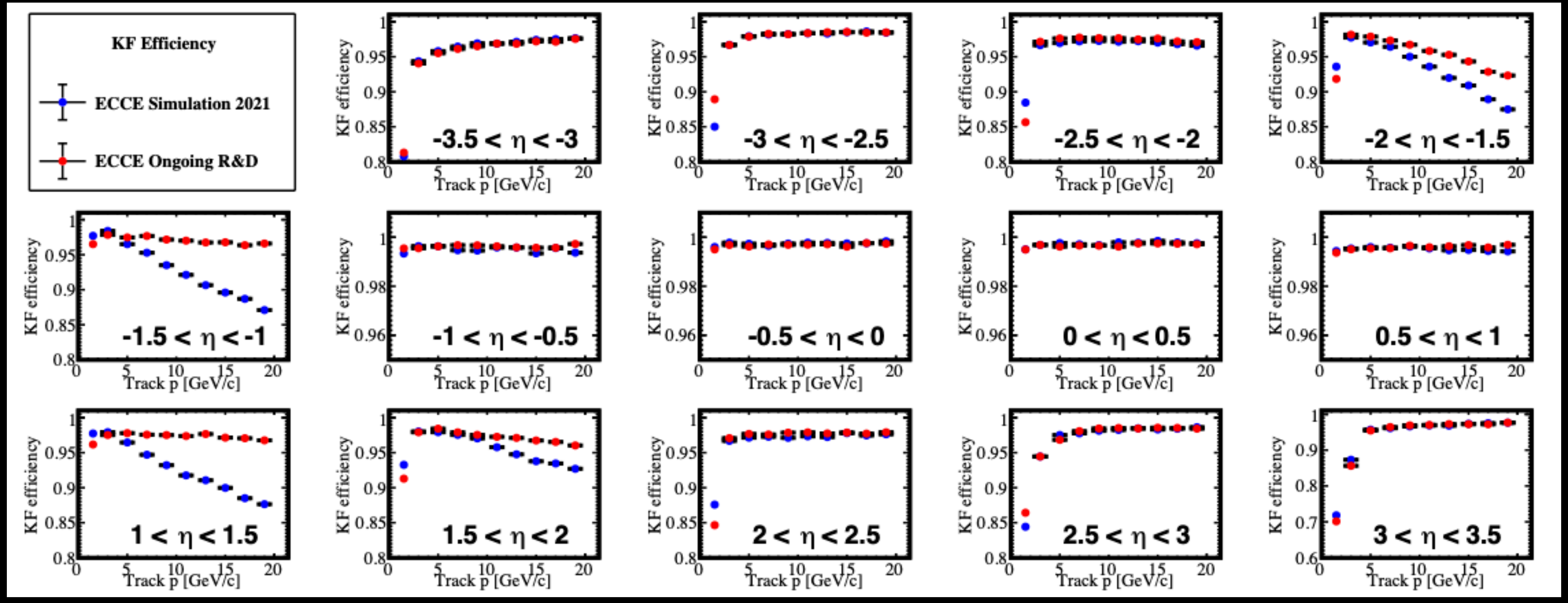
Each point is a design



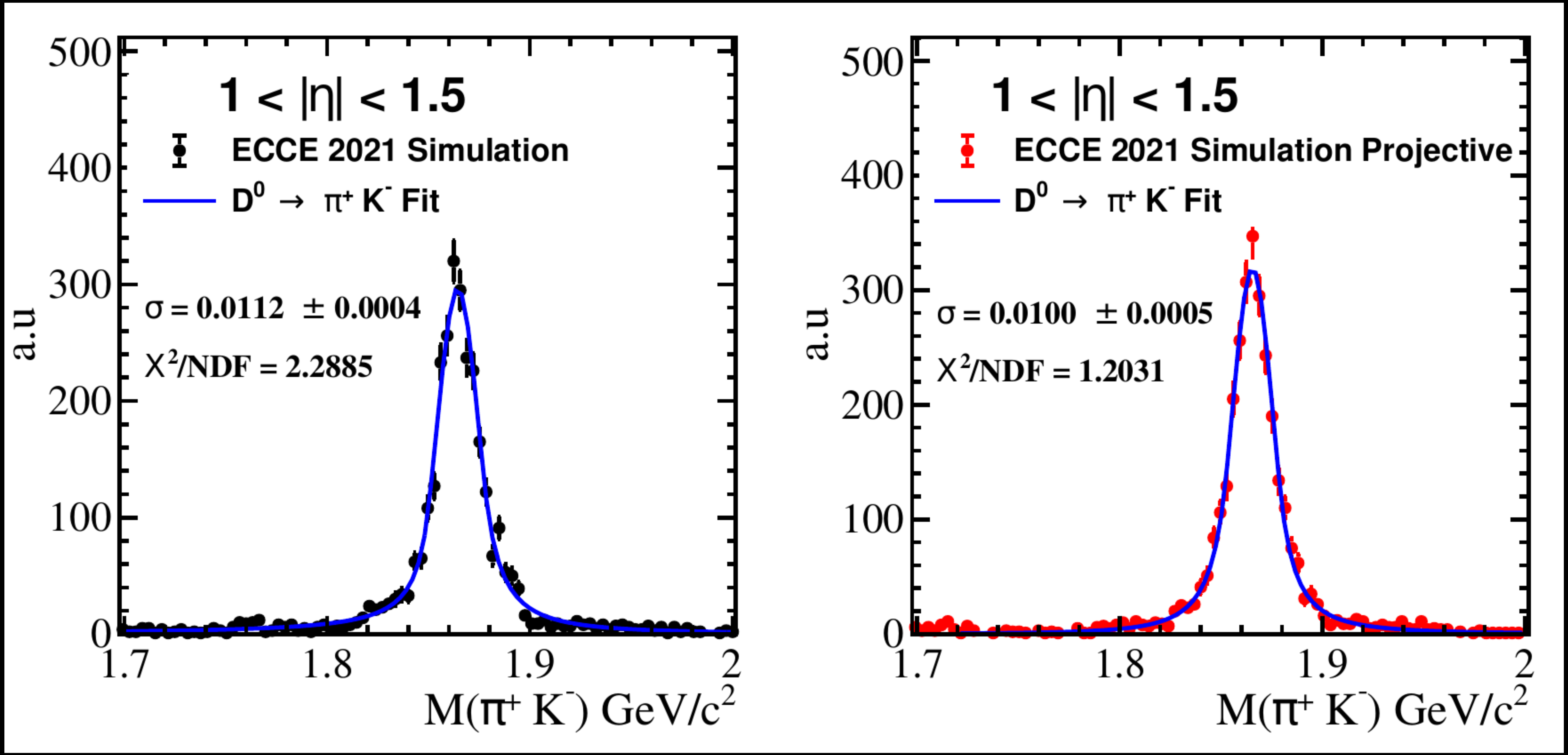
4

Analysis of Objectives (momentum resolution, angular resolution, KF Efficiency)





Post-hoc validation on physics observables



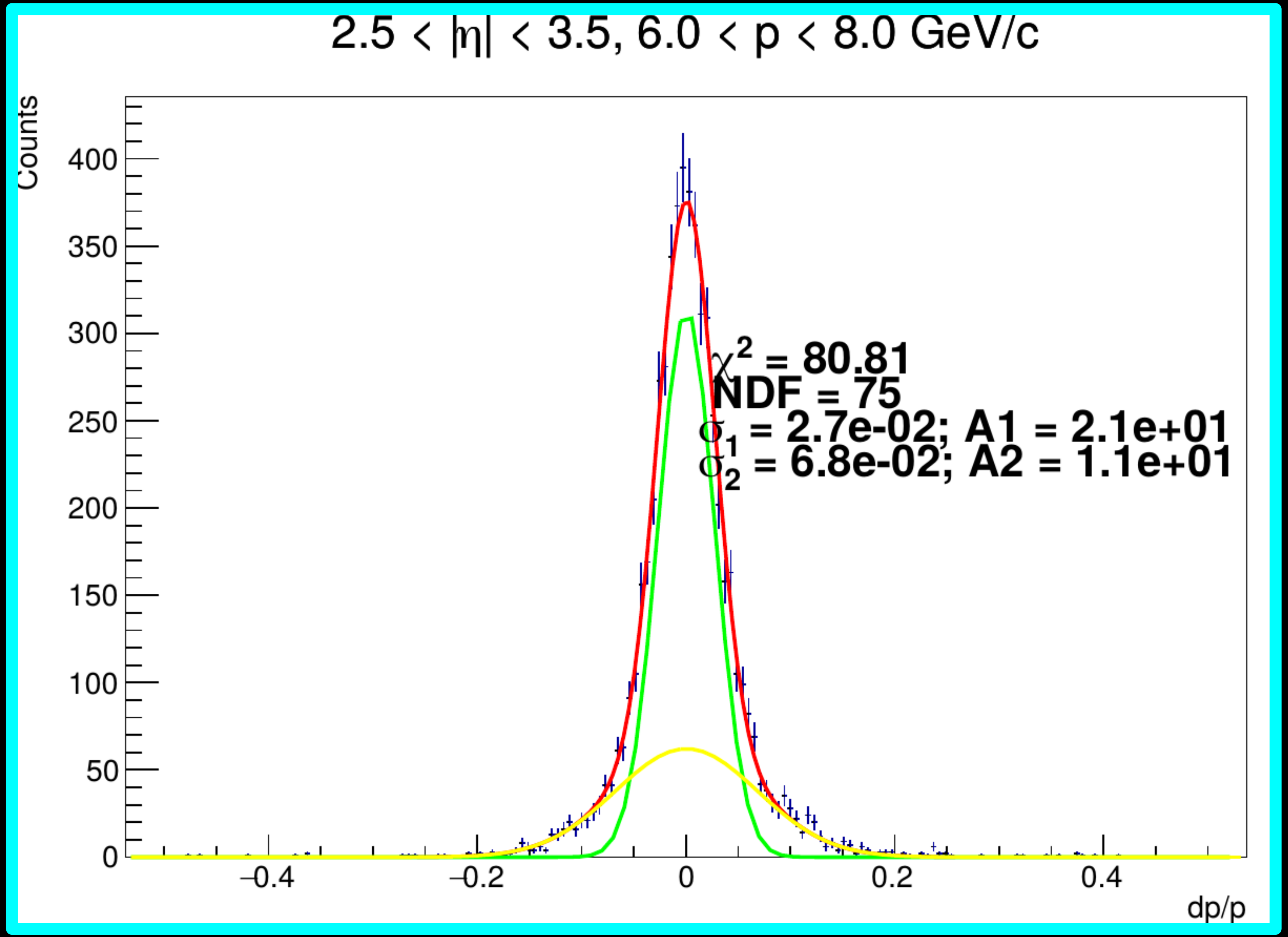
The $\pi^{+}K^{-}$ invariant mass obtained from the SIDIS events with updated baseline and optimized projective geometry. A region of eta that is sensitive due to considerable materials for support structure was also taken in to account for this optimization.

Fitting Procedure

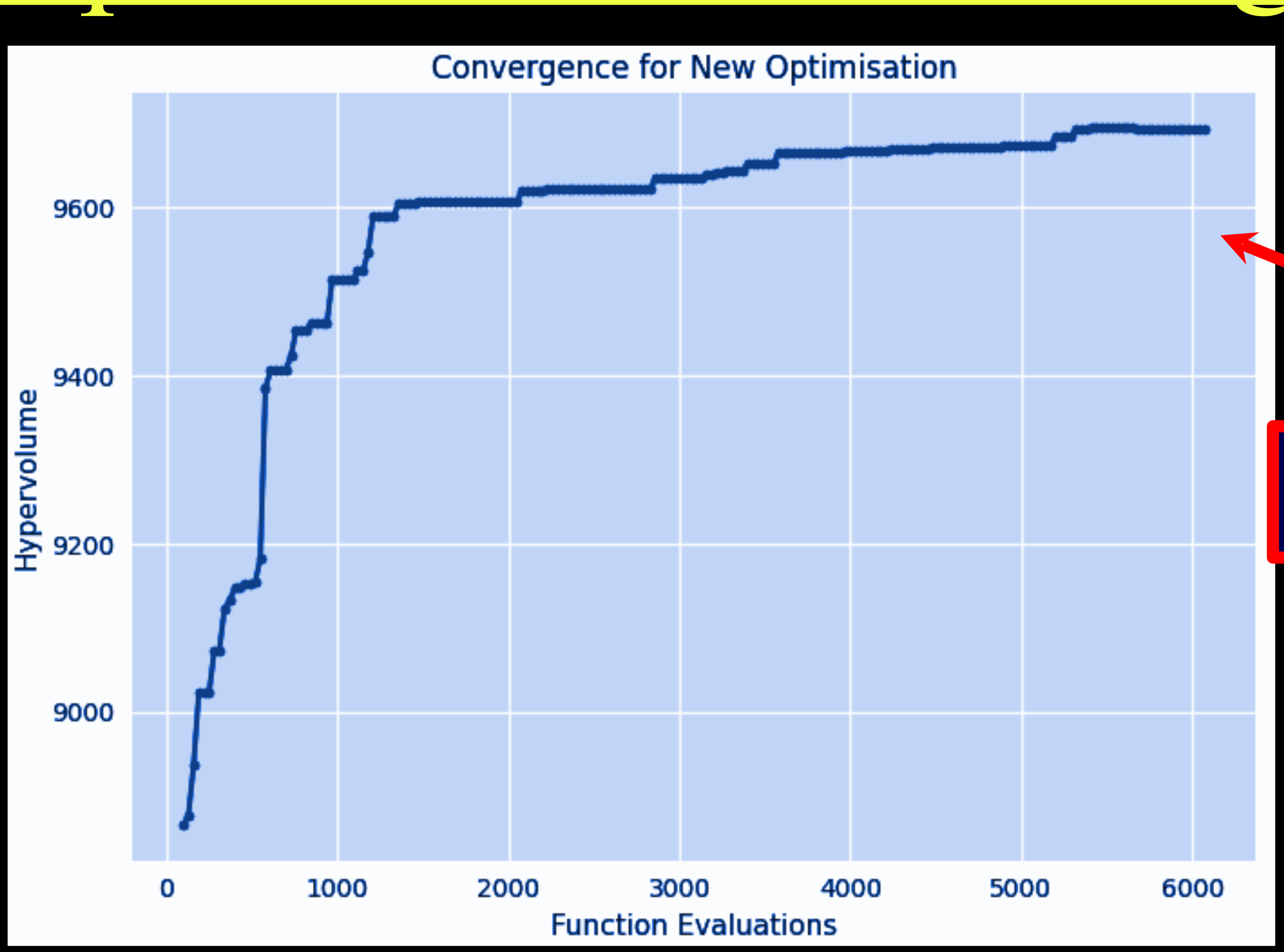
$$D_1e^{(x-\mu)^2/\sigma_1^2)} + D_2e^{(x-\mu)^2/\sigma_2{}^2)}$$

$$\sigma = \frac{\sigma_1 A_1 + \sigma_2 A_2}{A_1 + A_2}$$

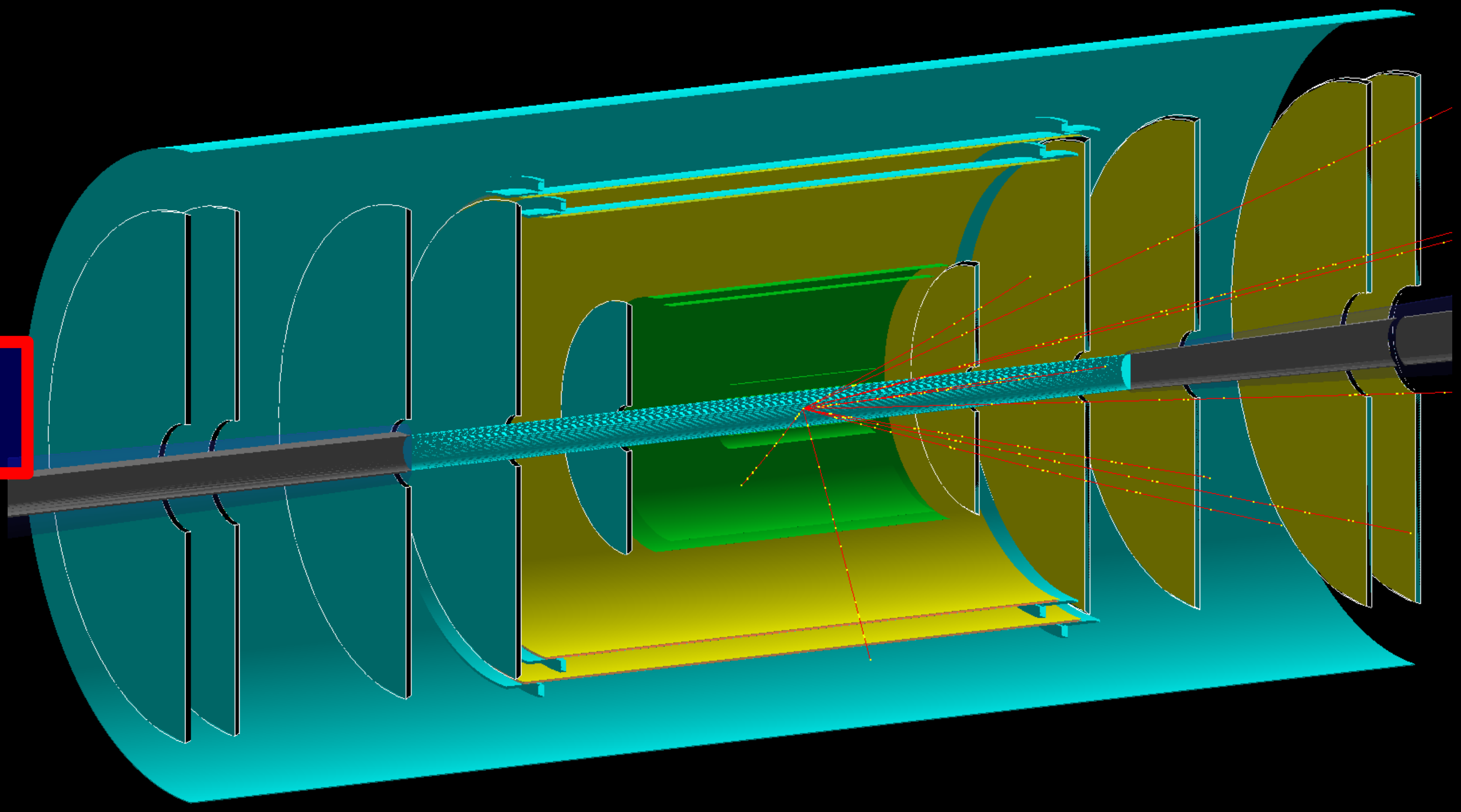
- For resolutions
  - Plot distributions of resolution in bins of eta and p
  - Fit with a double gaussian function
  - Set $A_{1 \text{ or } 2}$ (Amplitude) to 0 if the fit value of A is less than 1% of the $A_{2 \text{ or } 1}$
  - Set $\sigma_{1 \text{ or } 2}$ to 0 if it is greater than the x axis extent of the histogram
  - Calculate the weighted sigma of the fit function and its associated errors.
- For Global KF Inefficiency
  - Calculate the total number of tracks with trackID<0 for the entire simulation
  - Global_KF_Inefficiency = No_of_tracks(trackID<0)/Total_Events

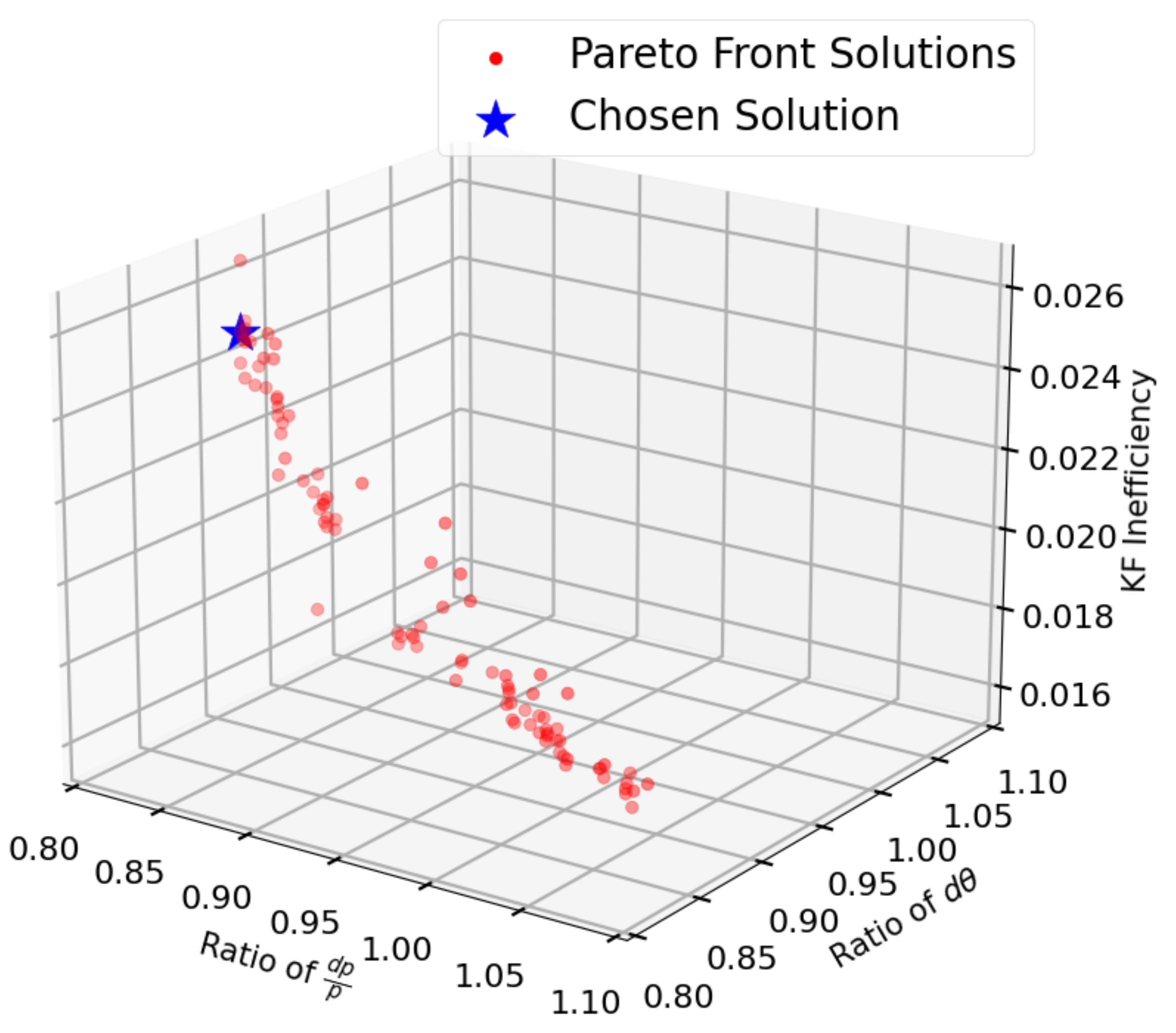


Optimal Detector Design Solutions



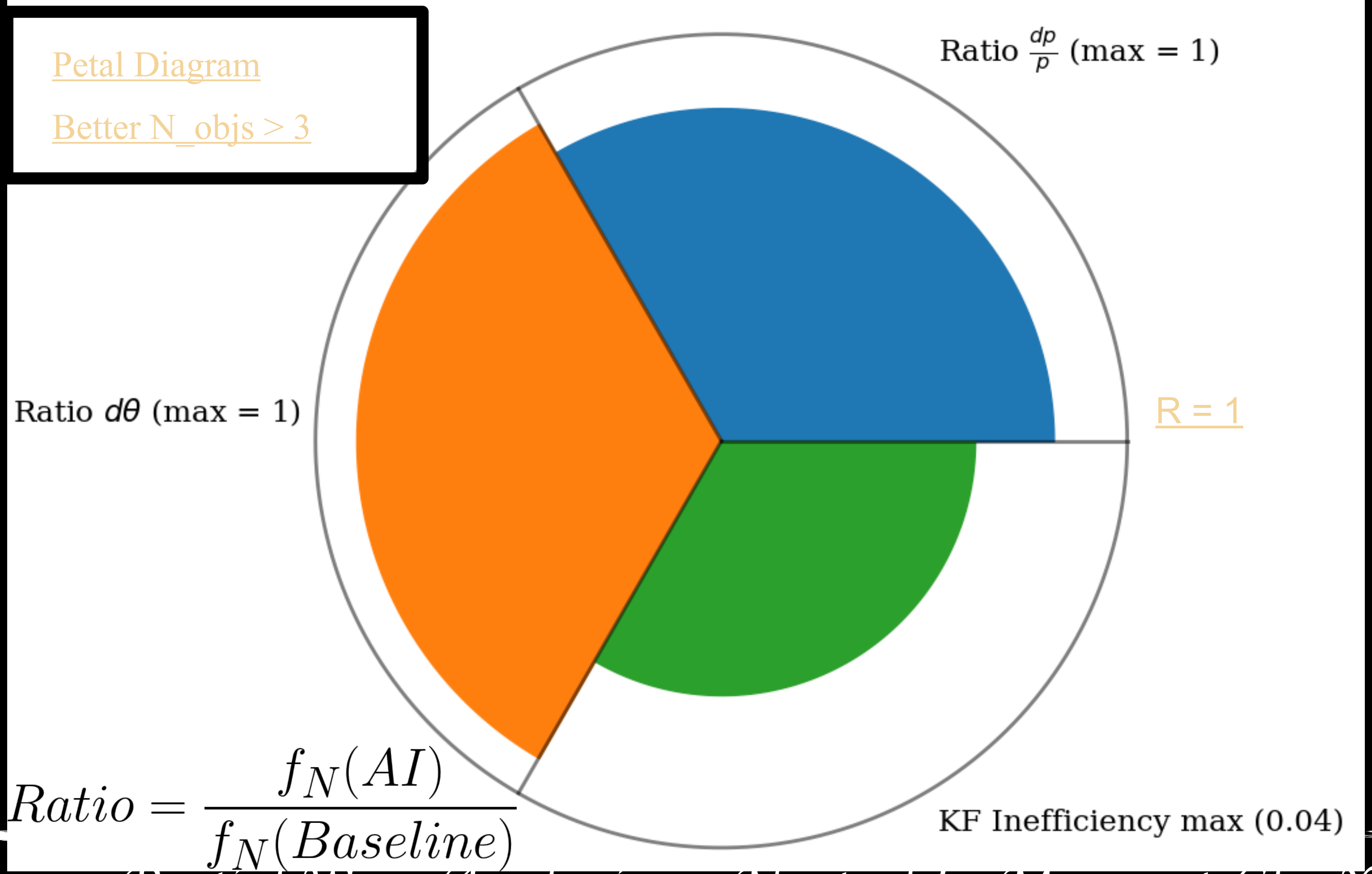
Inferring solutions at any stage of optimization





Example of solution

rformance of the
osen Solution

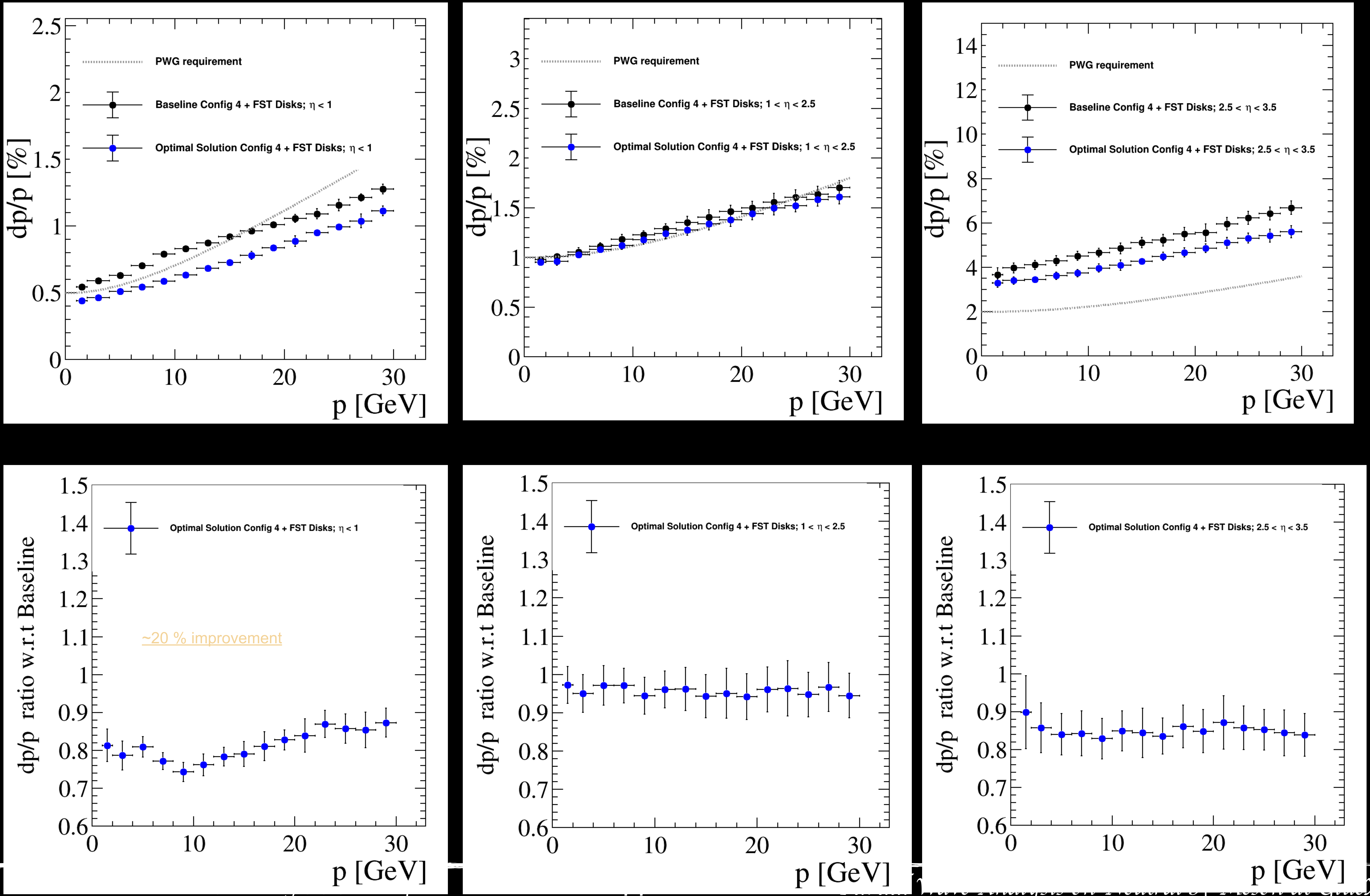


Petal Diagram

Better N_objs > 3

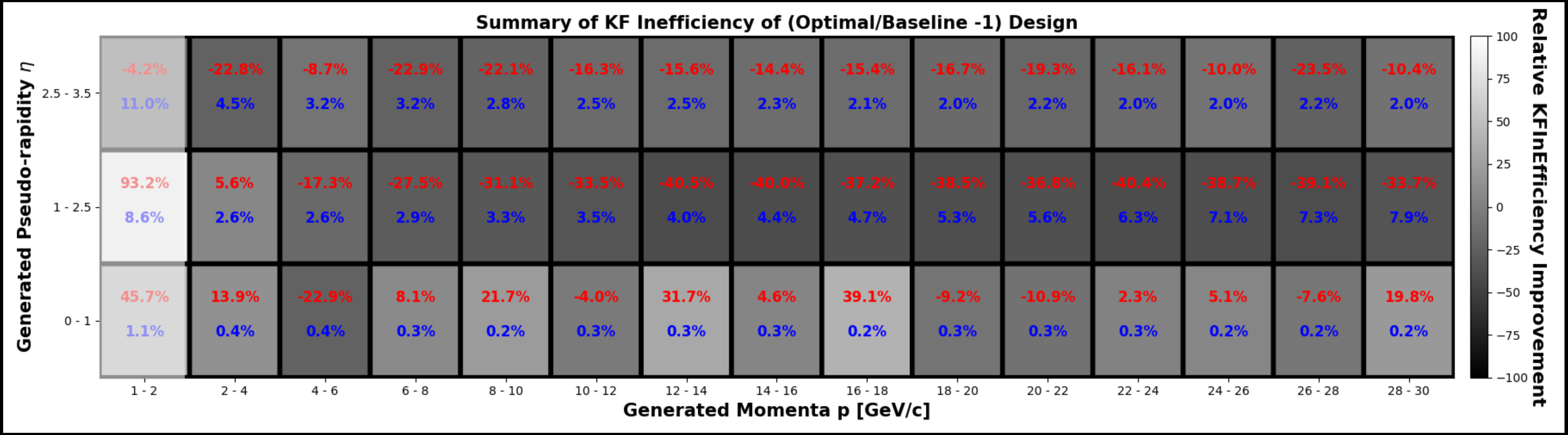
$$Ratio = \frac{f_N(AI)}{f_N(Baseline)}$$

Momentum Resolution



KF Inefficiency Improvement

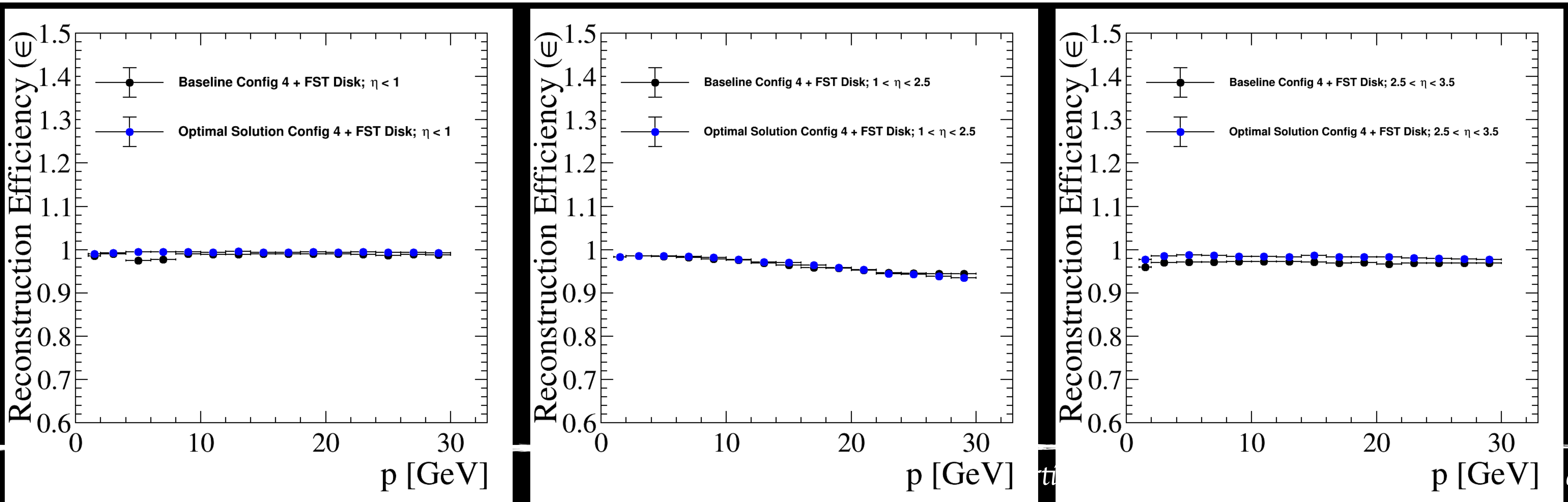
- 🔴 Optimal/baseline -1
- 🔵 Baseline Ineff



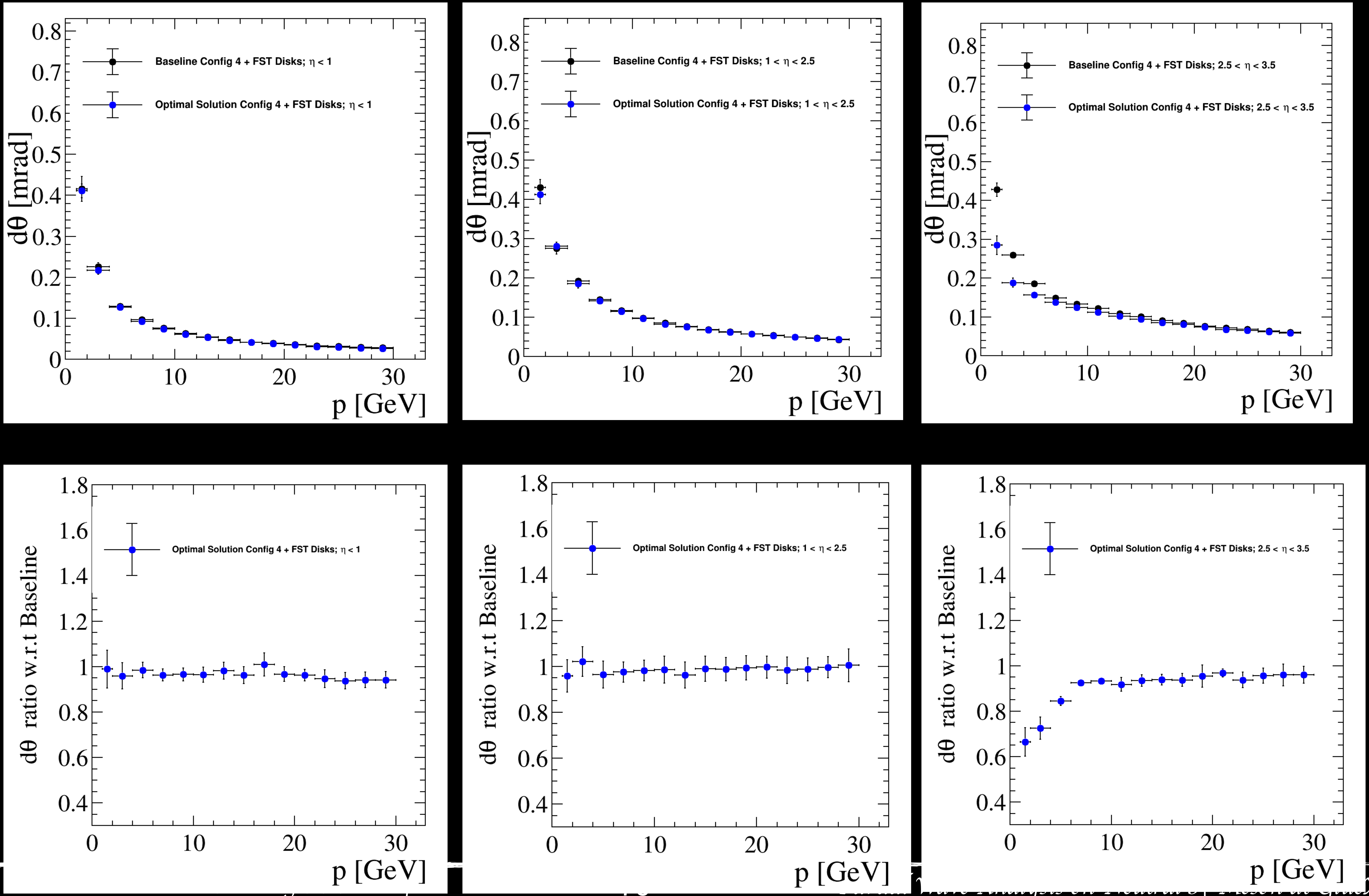
Summary of KF Inefficiency of (Optimal/Baseline -1) Design

Generated Pseudo-rapidity η \ Generated Momenta p [GeV/c]	1 - 2	2 - 4	4 - 6	6 - 8	8 - 10	10 - 12	12 - 14	14 - 16	16 - 18	18 - 20	20 - 22	22 - 24	24 - 26	26 - 28	28 - 30
2.5 - 3.5	-4.2% 11.0%	-22.8% 4.5%	-8.7% 3.2%	-22.9% 3.2%	-22.1% 2.8%	-16.3% 2.5%	-15.6% 2.5%	-14.4% 2.3%	-15.4% 2.1%	-16.7% 2.0%	-19.3% 2.2%	-16.1% 2.0%	-10.0% 2.0%	-23.5% 2.2%	-10.4% 2.0%
1 - 2.5	93.2% 8.6%	5.6% 2.6%	-17.3% 2.6%	-27.5% 2.9%	-31.1% 3.3%	-33.5% 3.5%	-40.5% 4.0%	-40.0% 4.4%	-37.2% 4.7%	-38.5% 5.3%	-36.8% 5.6%	-40.4% 6.3%	-38.7% 7.1%	-39.1% 7.3%	-33.7% 7.9%
0 - 1	45.7% 1.1%	13.9% 0.4%	-22.9% 0.4%	8.1% 0.3%	21.7% 0.2%	-4.0% 0.3%	31.7% 0.3%	4.6% 0.3%	39.1% 0.2%	-9.2% 0.3%	-10.9% 0.3%	2.3% 0.3%	5.1% 0.2%	-7.6% 0.2%	19.8% 0.2%

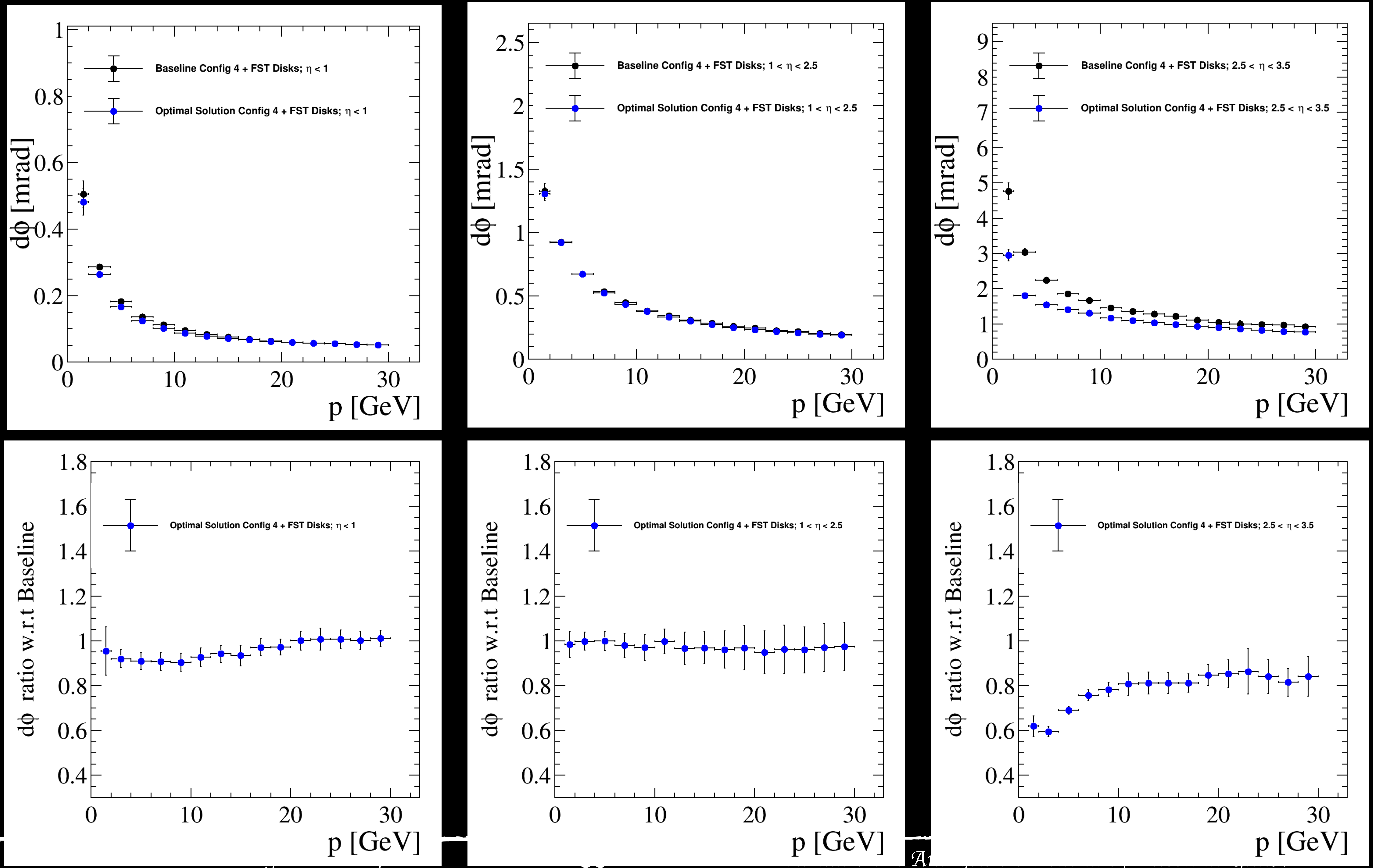
Validation Reconstruction Efficiency



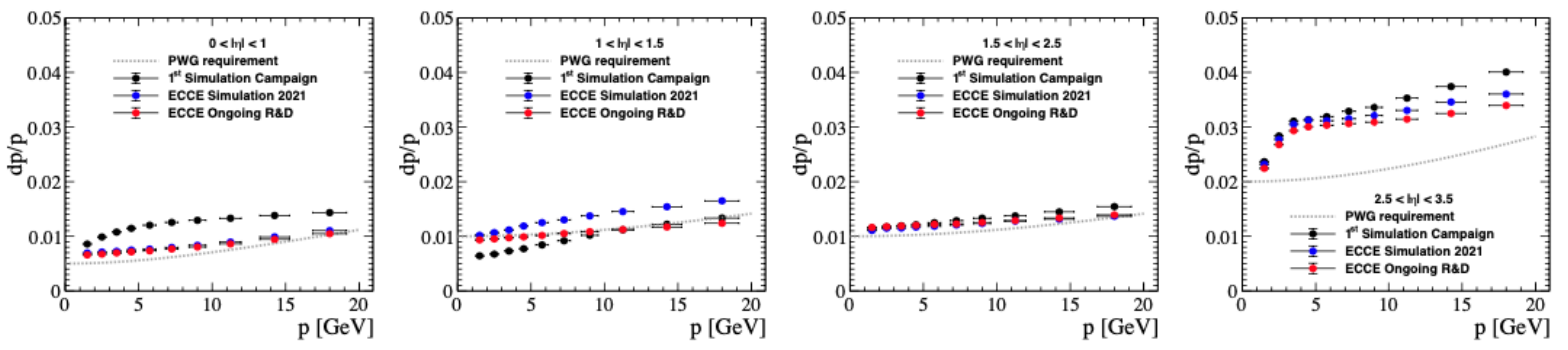
θ Resolution [mrad]

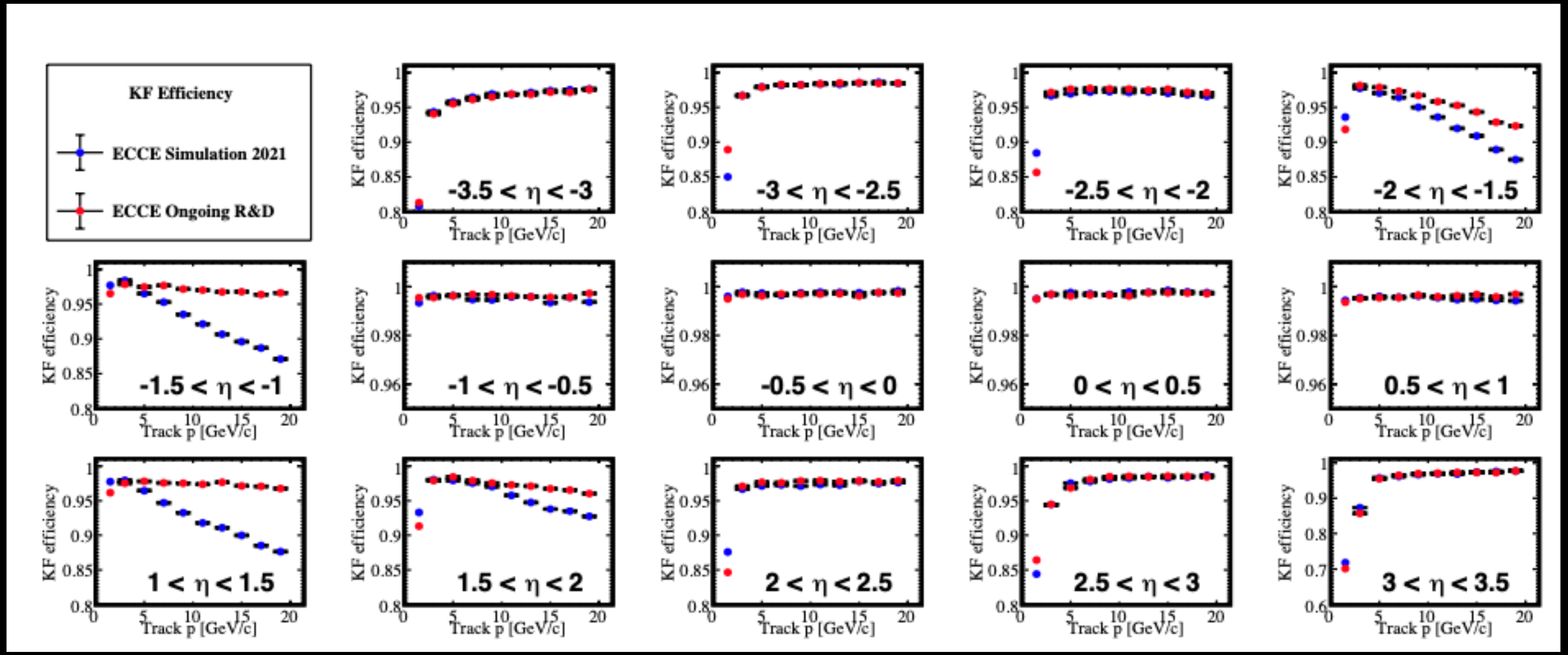


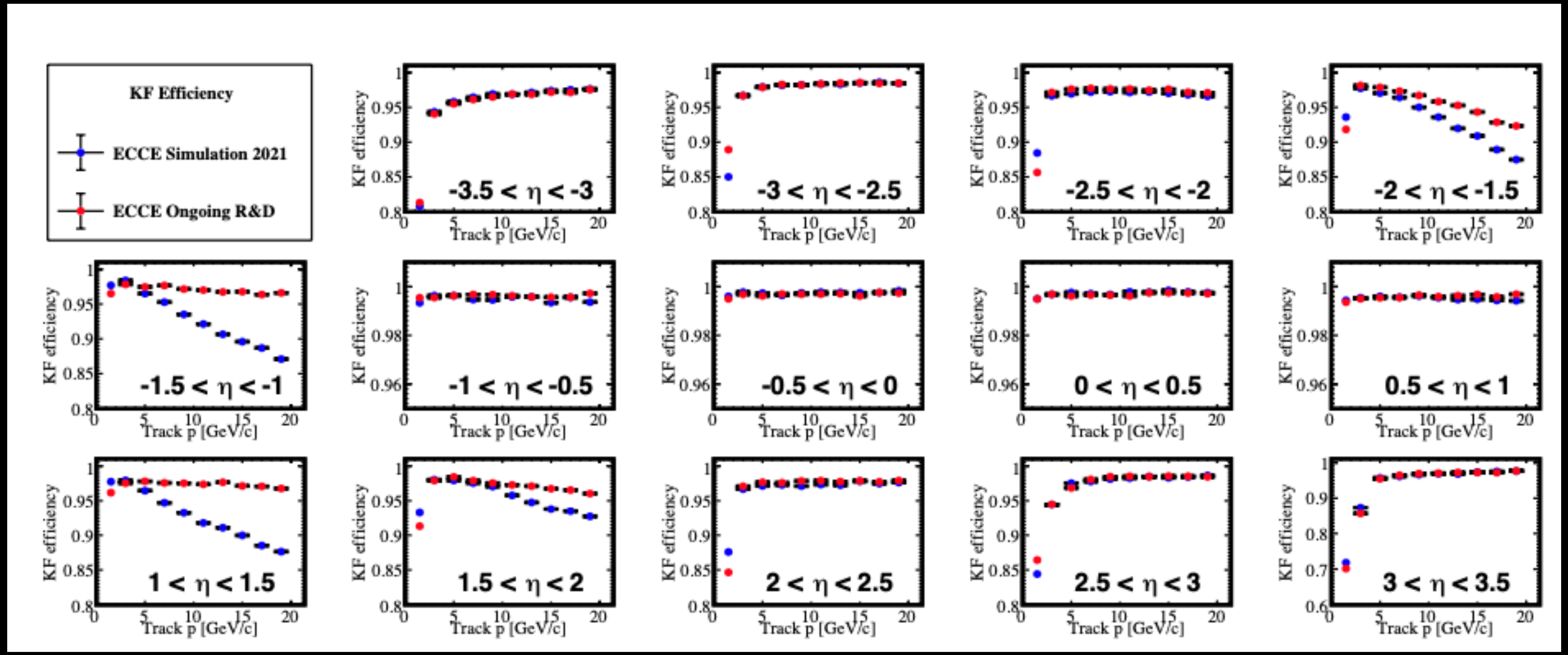
alidation φ Resolution [mrad]



Evolution of Detector Performance (ECCE)



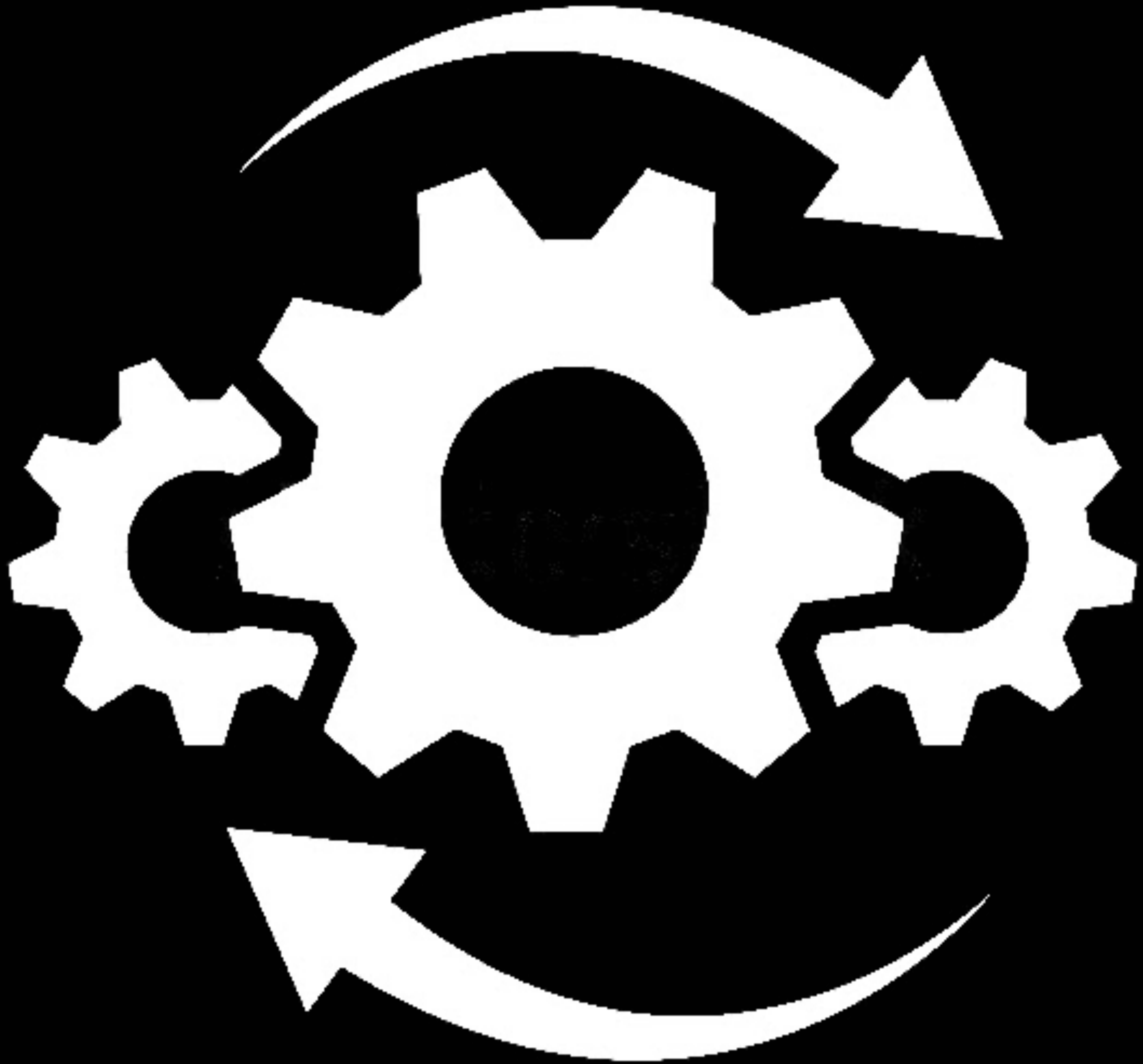


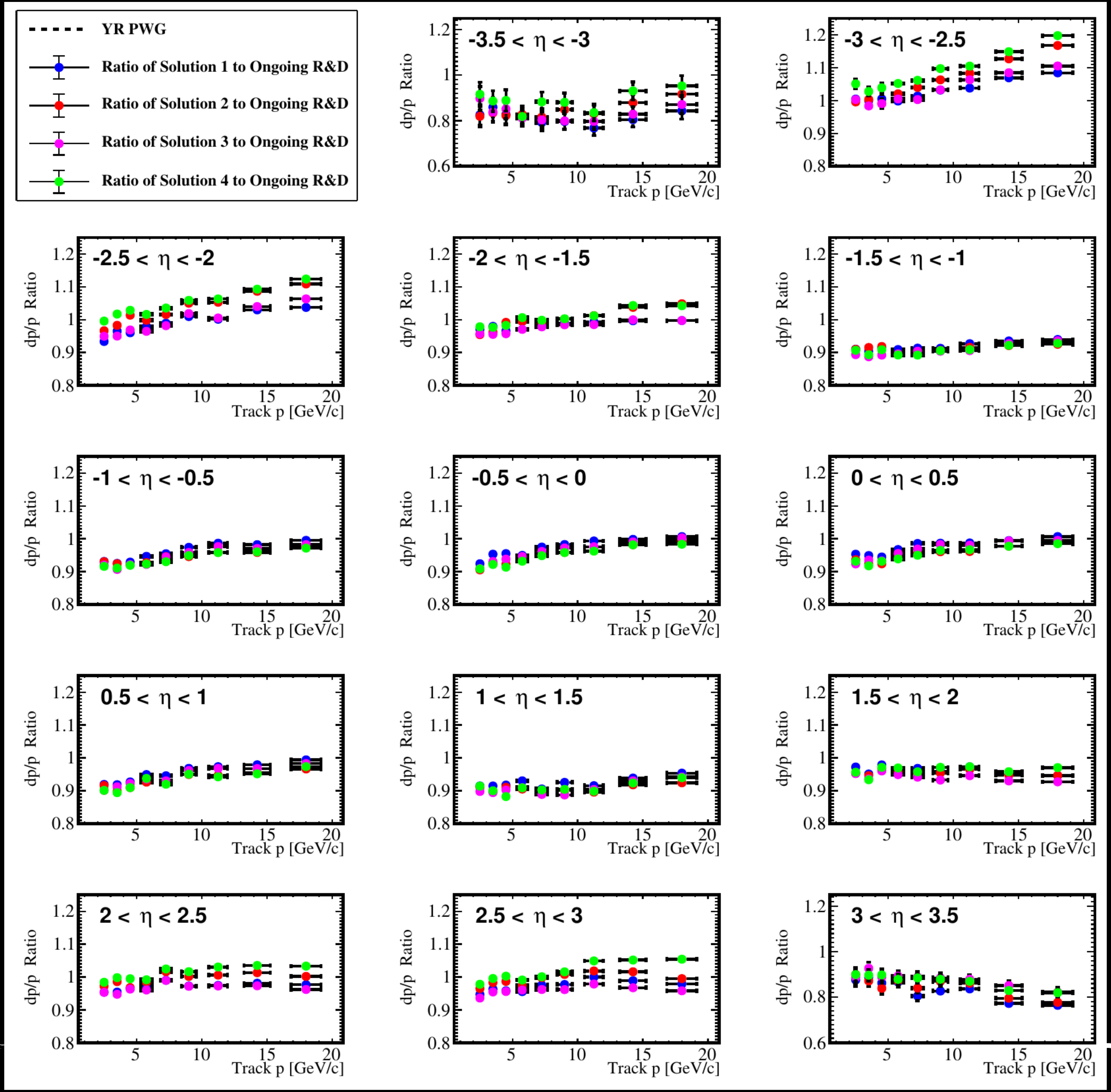


KF Efficiency

Polar Angular Reso

Second tier



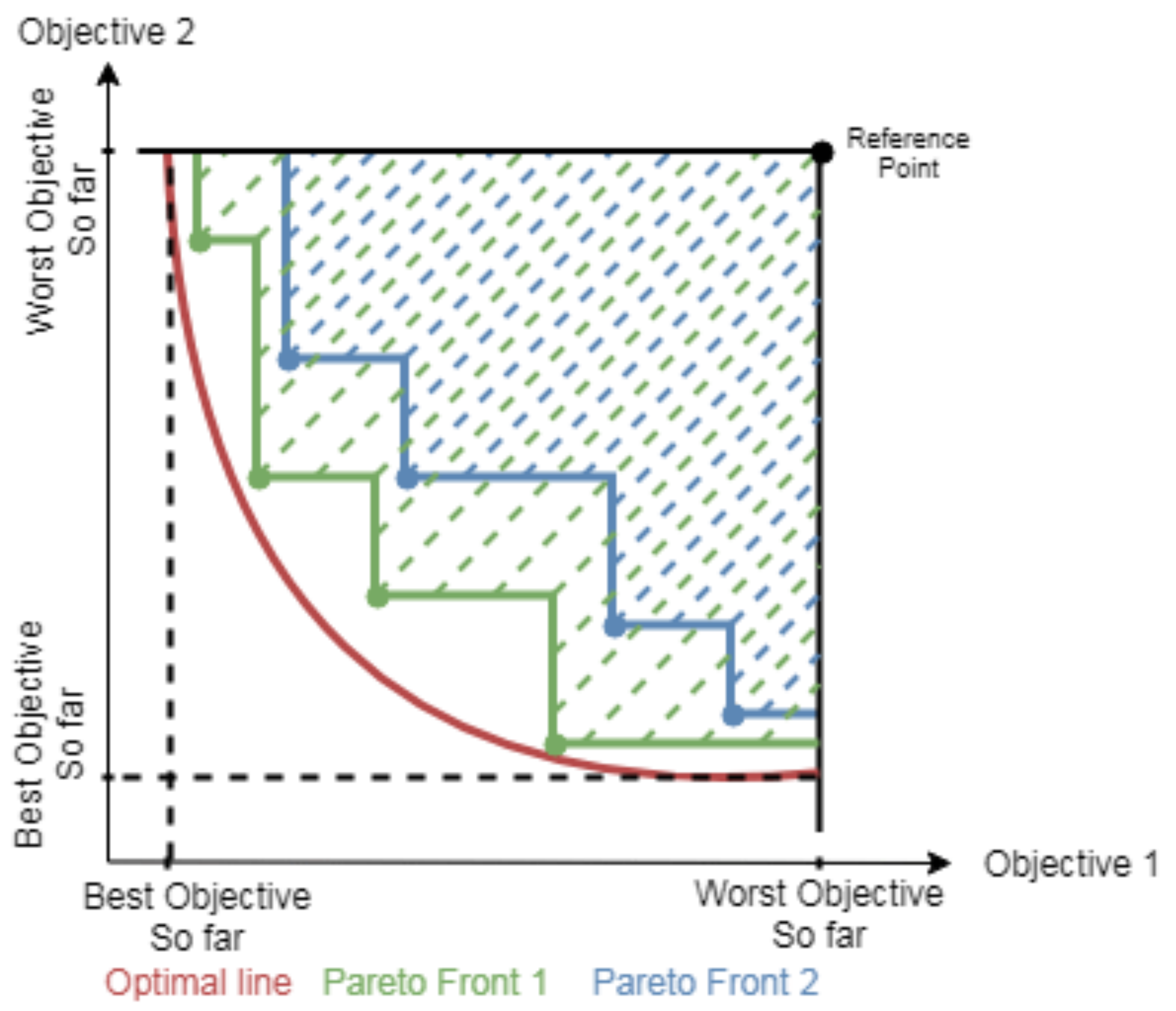


Highlights of this optimisation

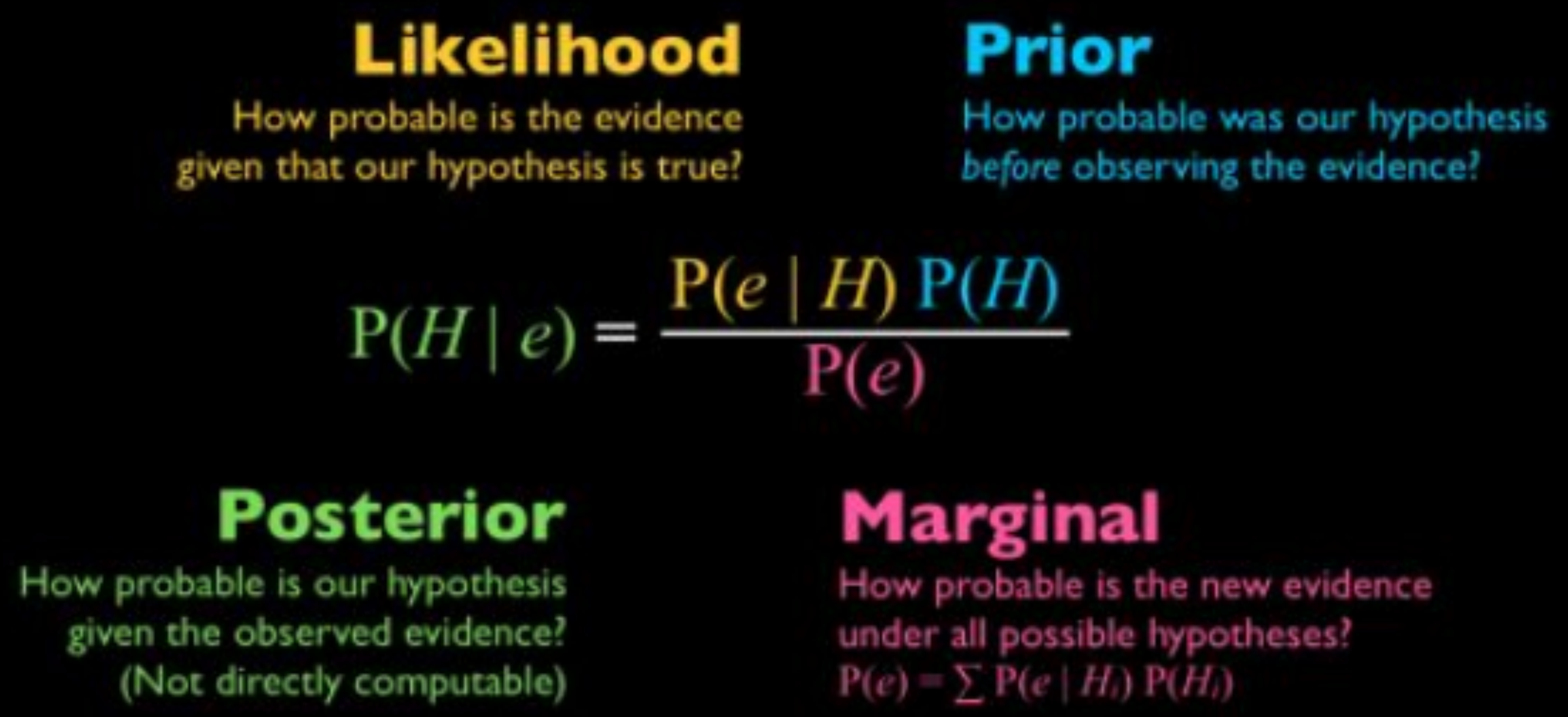
- Finer eta bins and momentum bins
- Includes almost all of the tracker subsystems for optimisation
- Includes optimisation of the support structures too
- Baseline detector setup corresponds to a projective design which itself is a result of previous phases of optimisation
- More optimisations with Bayesian based approaches are also carried out currently.

MOO details

- **Validating convergence.**
  - Look in the design space for improvements in the last few calls
  - Look into objective space. And perform cluster analysis on them
  - Make a custom metric to analyse convergence.
- **Hypervolume**
  - The volume of the First front w.r.t a reference point
- **Bayesian Optimization**
  - Used When the evaluation of each point is resource intensive.



Hyper volume definition



Likelihood
How probable is the evidence given that our hypothesis is true?

Prior
How probable was our hypothesis *before* observing the evidence?

$$P(H \mid e) = \frac{P(e \mid H)\, P(H)}{P(e)}$$

Posterior
How probable is our hypothesis given the observed evidence?
(Not directly computable)

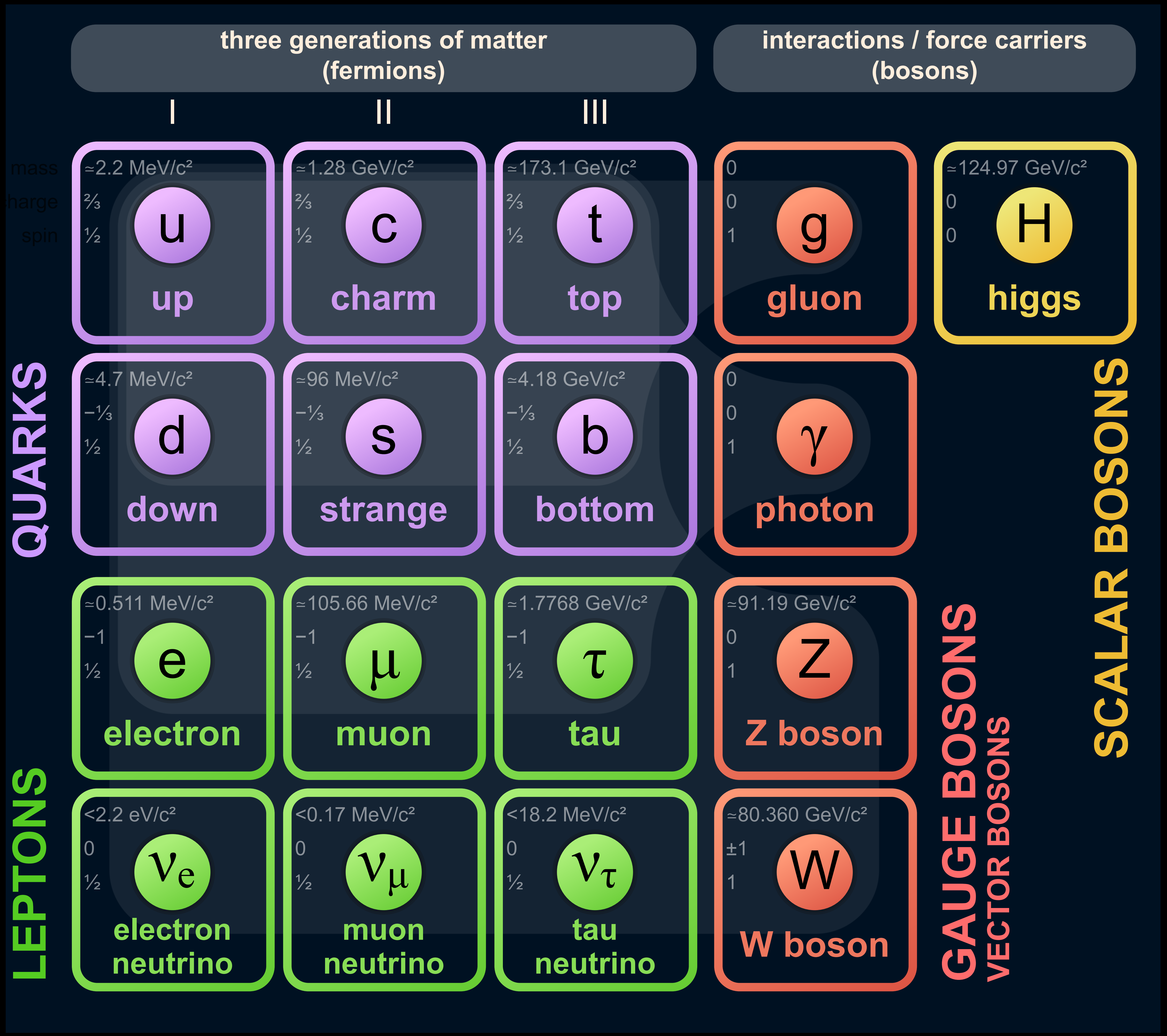
Marginal
How probable is the new evidence under all possible hypotheses?
$P(e) = \sum P(e \mid H_i)\, P(H_i)$

Backups level 2

The Standard Model of Physics

Describes the three forces in nature

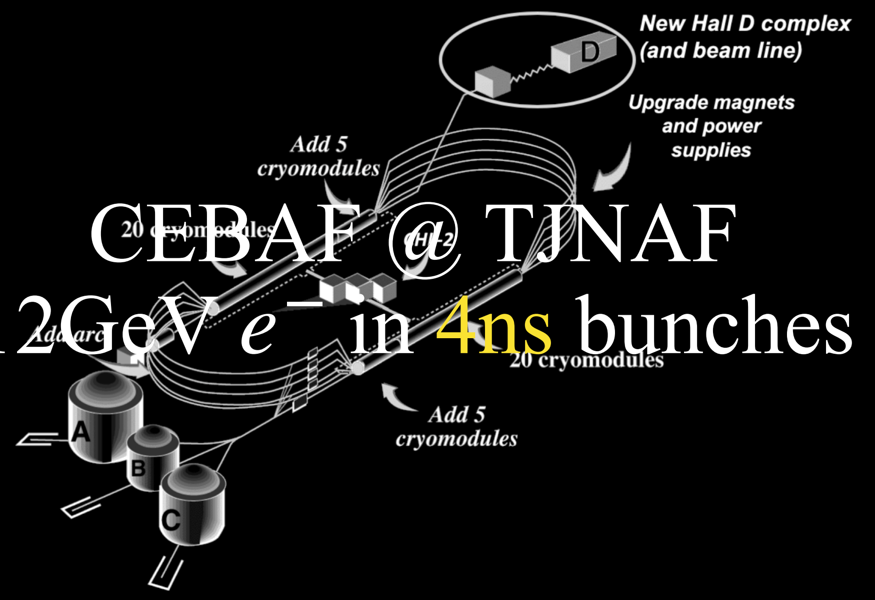
- Strong Nuclear Force
- Weak Nuclear Force
- Electromagnetic Force



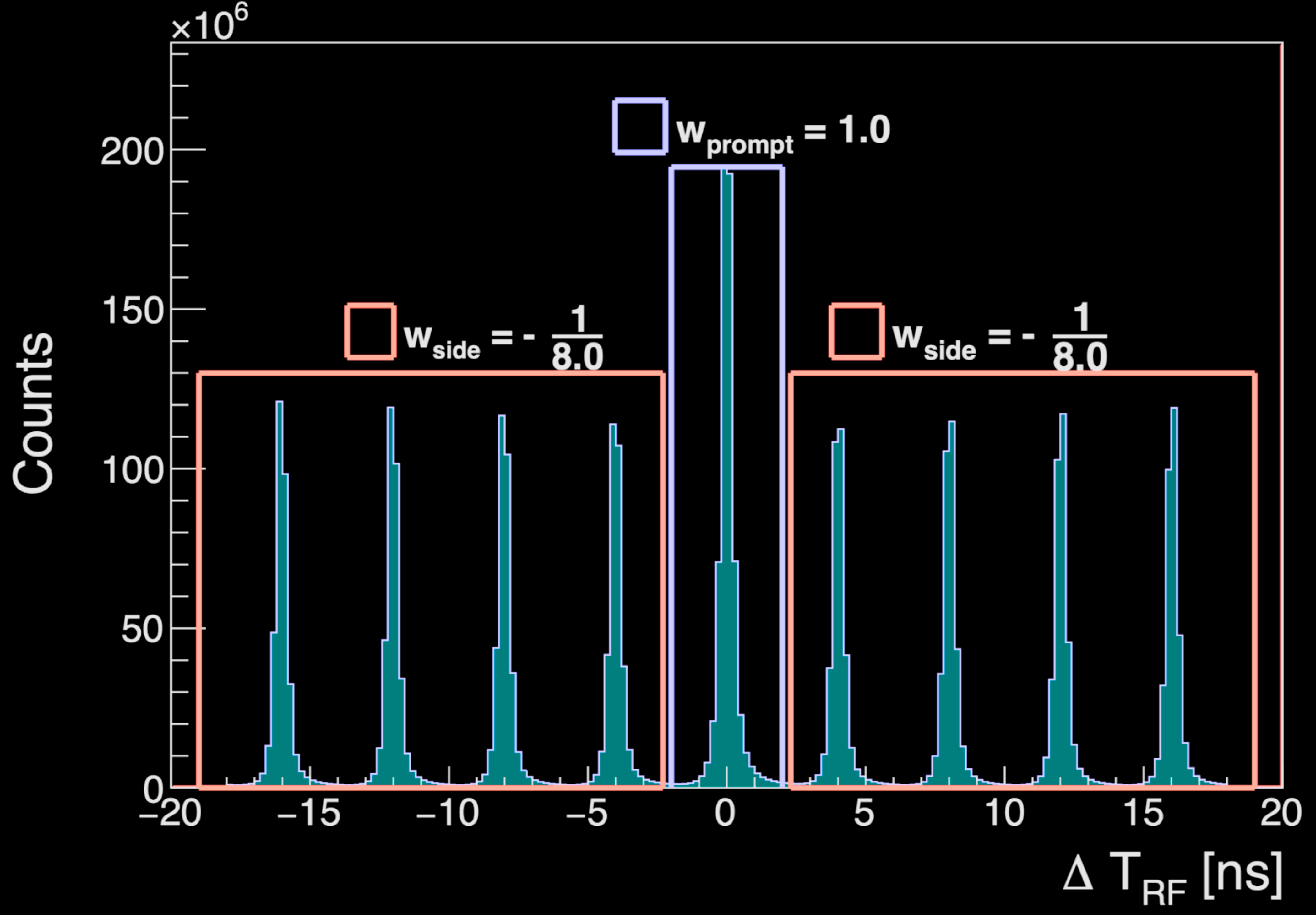
Successful theory by far in Physics

Photoproduction of $\omega\pi^0$ at GlueX

Weighing events in detail

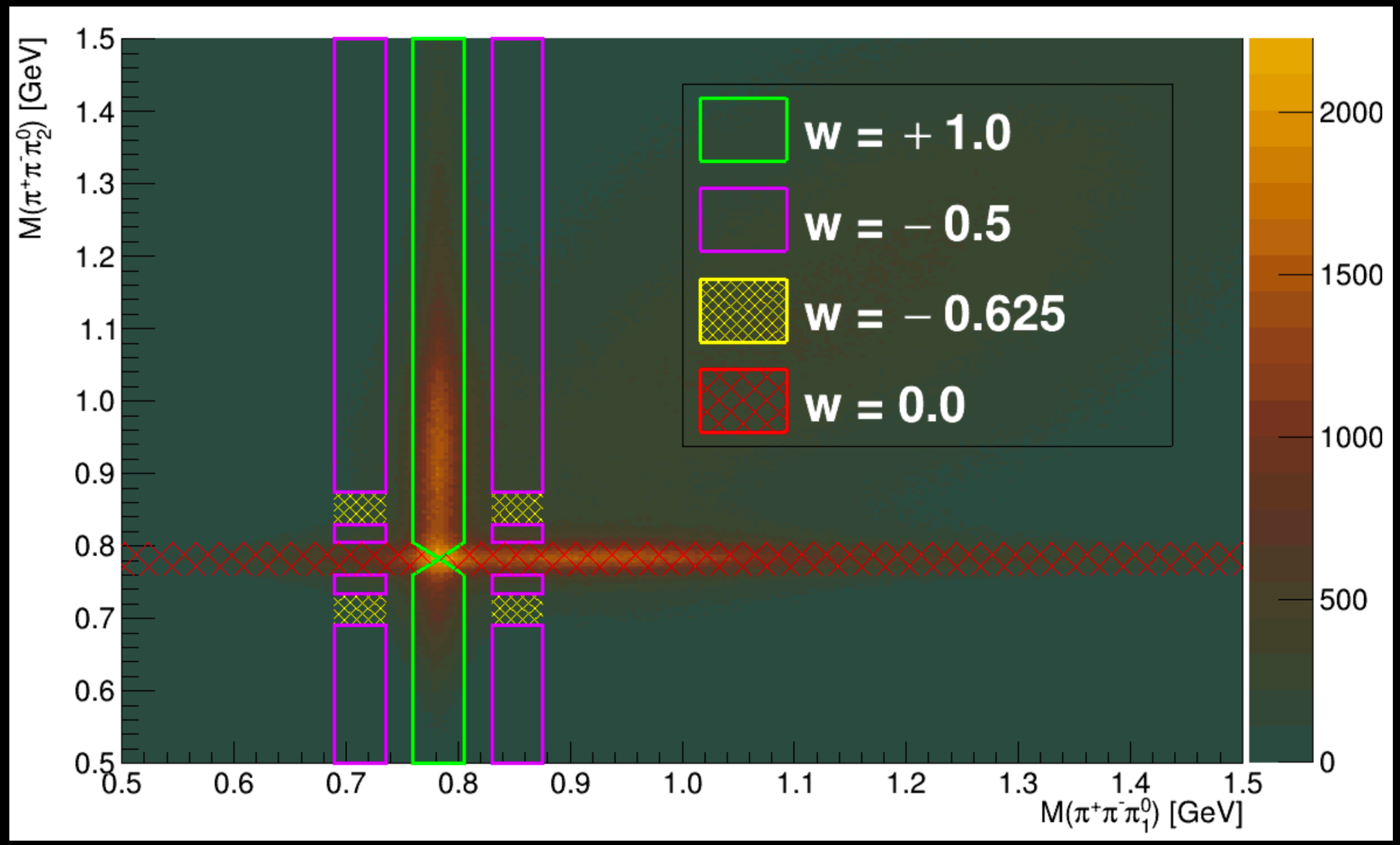


CEBAF @ TJNAF
12GeV e^- in 4ns bunches



×

$$\gamma p \rightarrow (\omega\pi^0)p \rightarrow (\pi^+\pi^-\pi^0_1)\pi^0_2 p$$

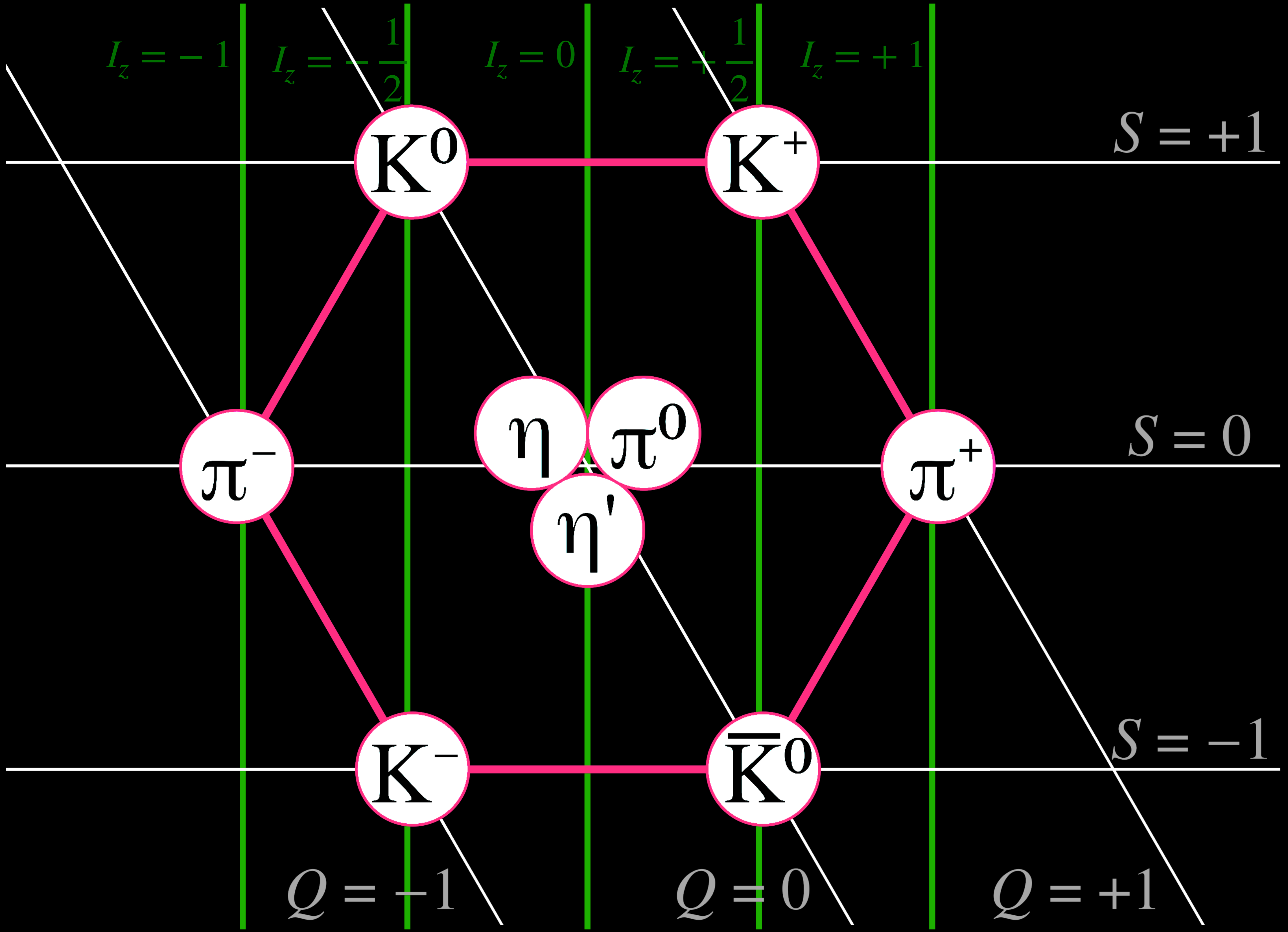


The Standard Model of Physics

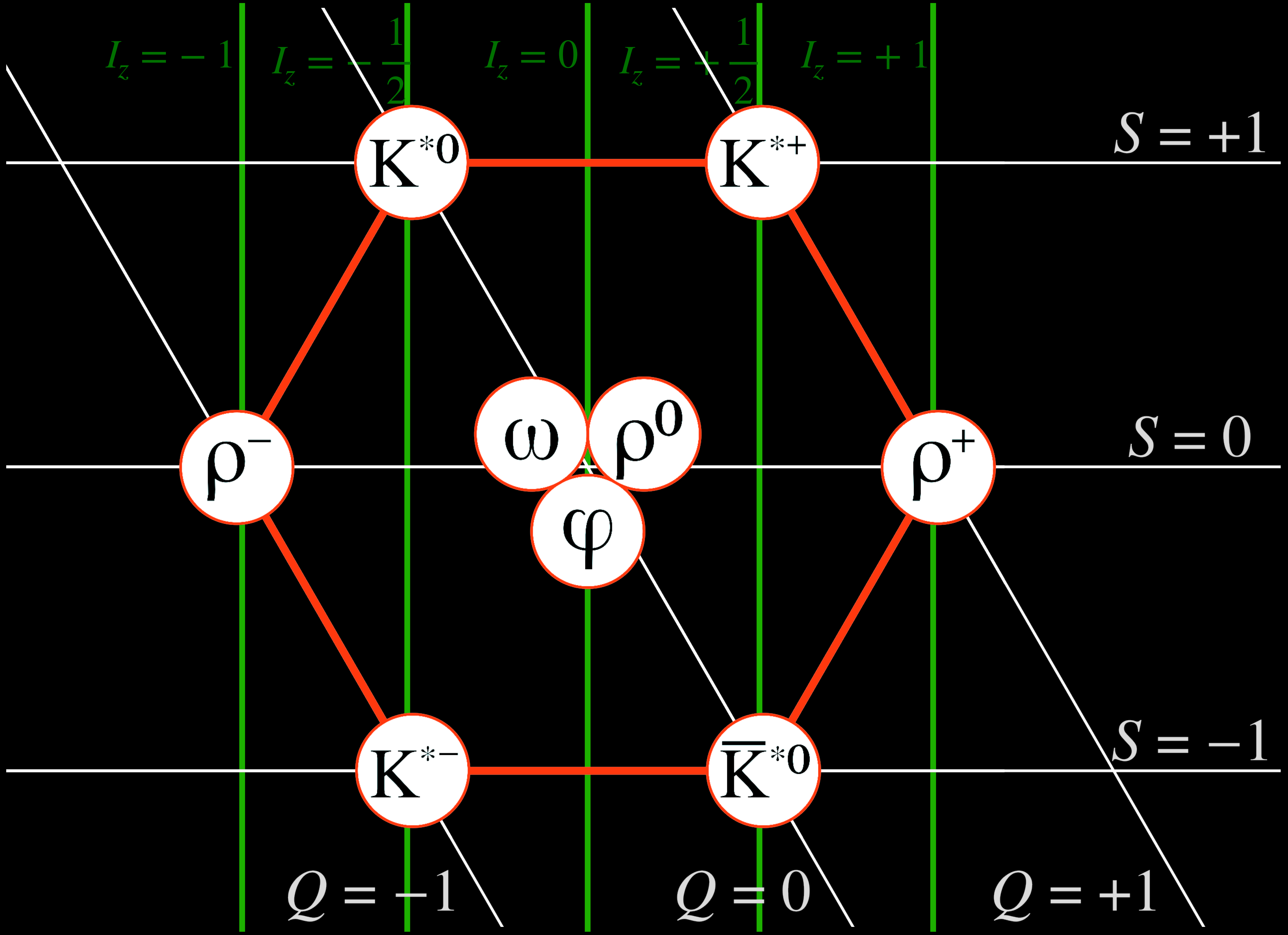
Theory of Strong interactions : Quark Model

Meson Nonets

Pseudo Scalar Meson (S = 0) Nonet

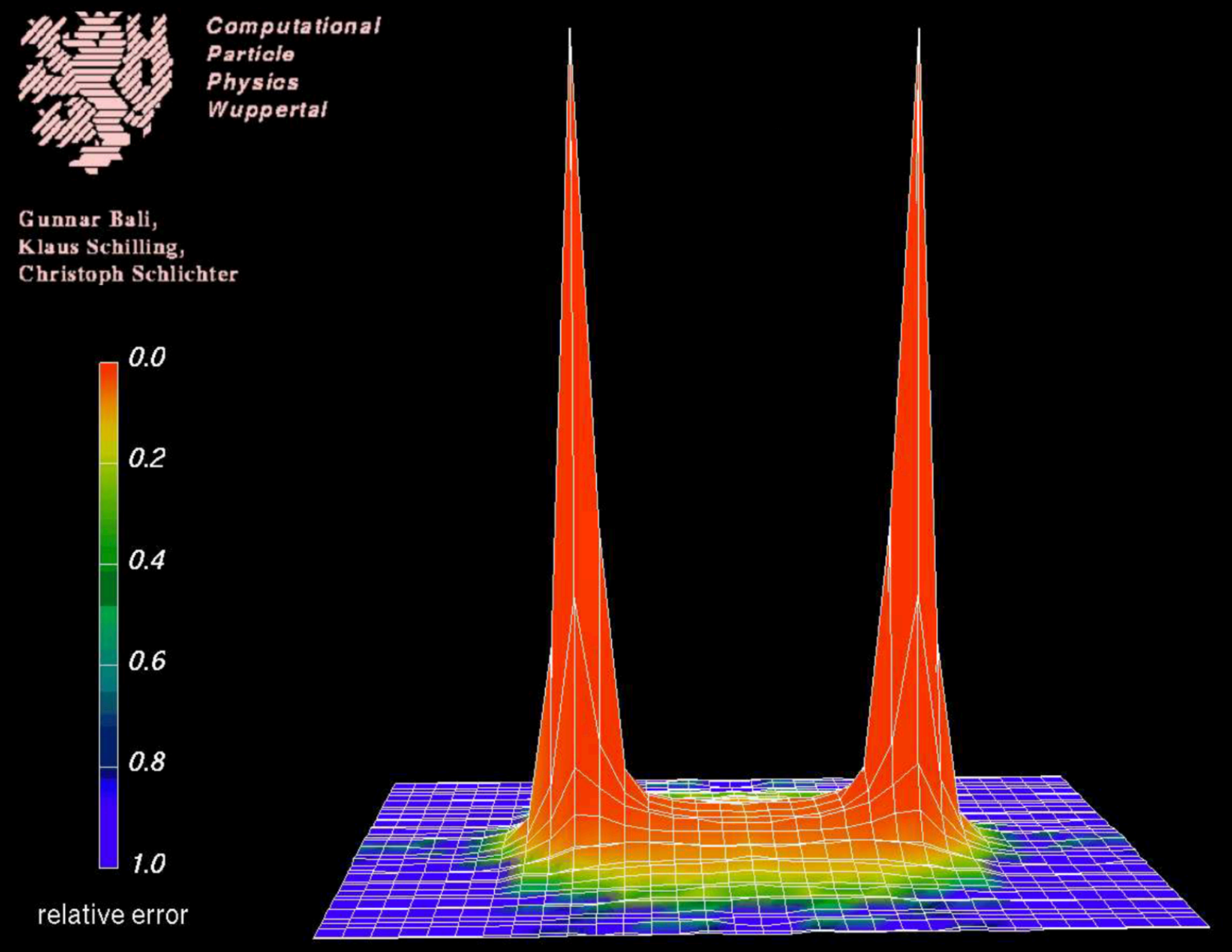


Vector Meson (S = 1) Nonet



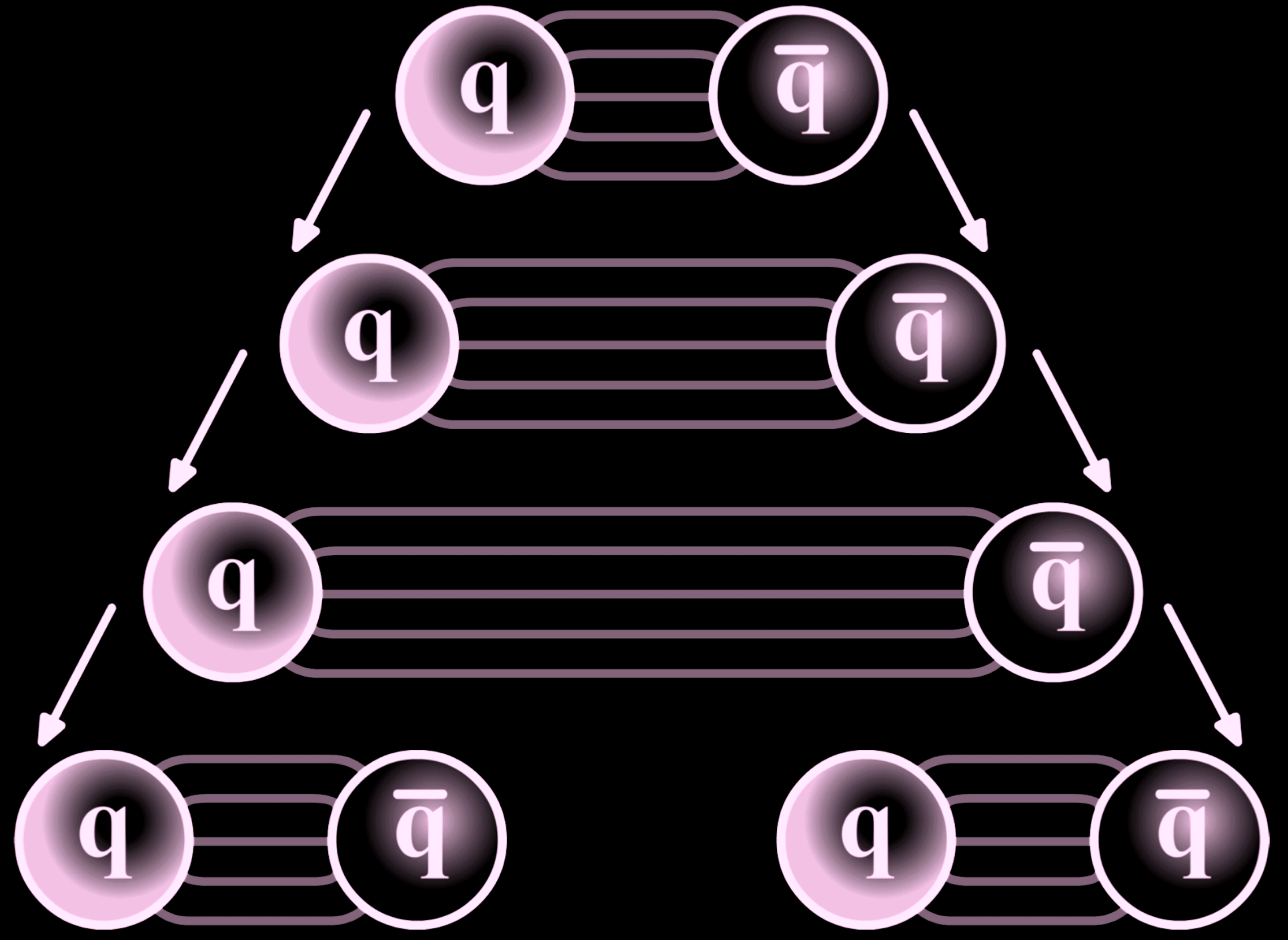
Summary of flux tube model

- Proposed by Nathan Isgur and Jack Paton by 1985[†]
- Analogy —
  - Two quarks connected by a elastic rubber band
  - When pulled apart, it gets stretched
  - The stretched region is called as flux tube
  - More stretched — more potential energy
- ||ly, the more farther the quarks the harder the flux tube pulls them back
- When broken new pair of $q\bar{q}$ gets formed and hence, no “free” quarks can be observed



Energy Density

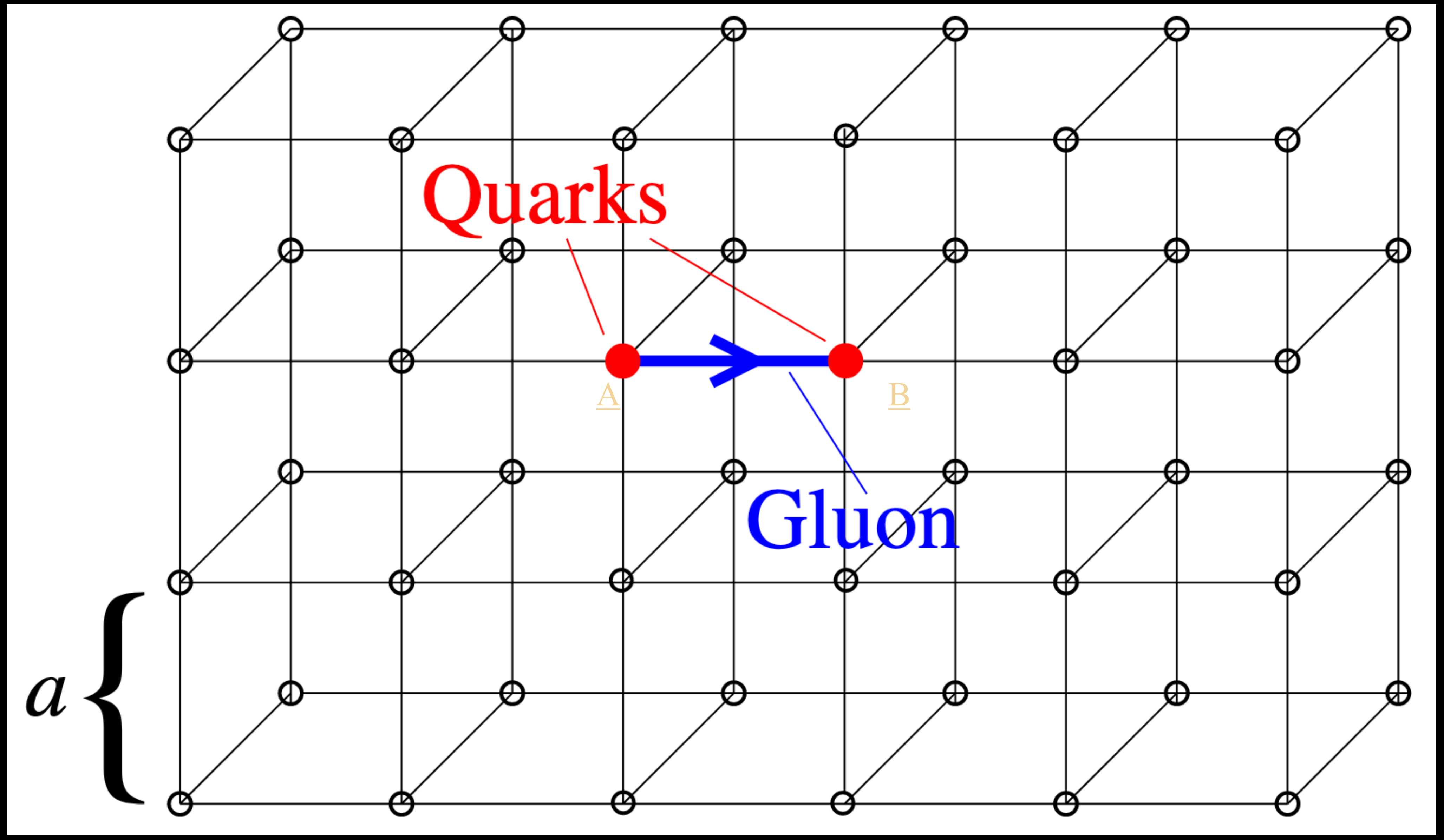
arXiv:hep-ph/9904330



[†] Phys. Rev. D **31**, 2910 – Published 1 Ju

Summary of Lattice QCD

- Develops from Path Integral formulation
  - Compute all possible "paths" btw 'A' & 'B'
  - Idea of MC Integration
- The Lattice is grid of space time
- Quarks are building blocks at each lattice point
- Gluons mediate between the lattice points
- Lattice spacing 'a' gets smaller, computation becomes exponentially costlier



NNPSS-2022 MIT

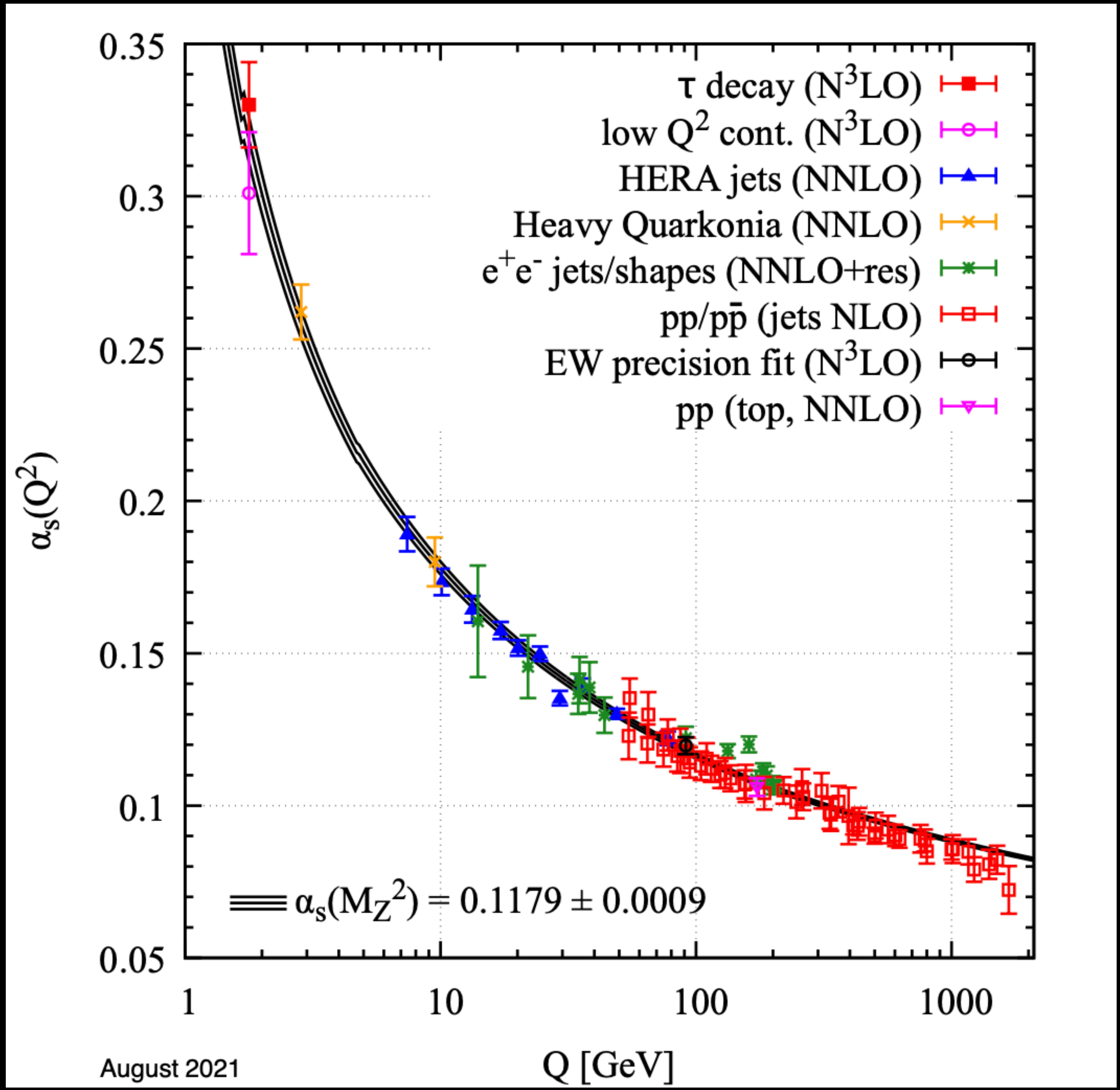
The Standard Model of Physics

Theory of Strong interactions : QCD

Key outcomes

- Color Confinement
  - No “free” quarks can be observed
  - All hadrons are color neutral.
- Asymptotic Freedom (Interaction Strength α_s)
  - Non-Perturbative - Large distance (Low Energy)
    - Lattice QCD - successful due to modern computing
  - Perturbative - Small distance (High Energy)

Interaction Strength as a function of Energy Scale

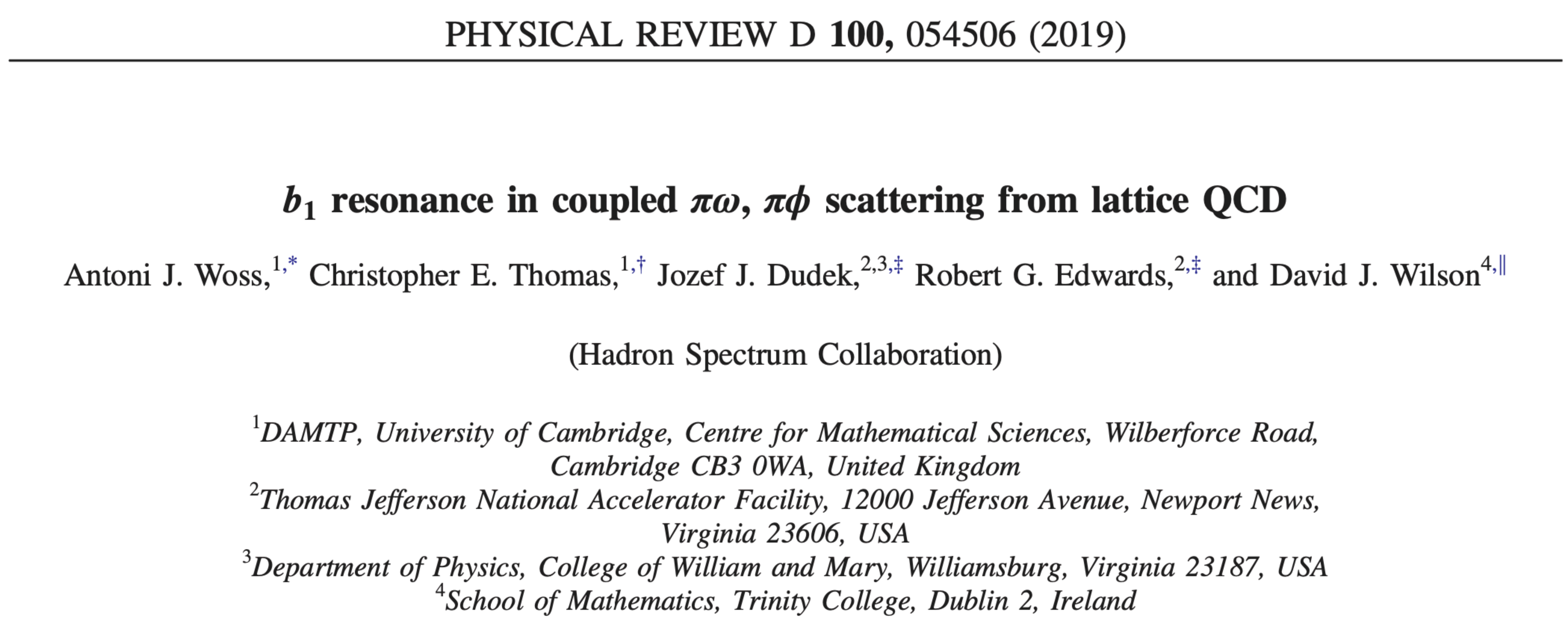


Particle Data Group Review of Parti

Volume 2022, Issue 8, August 2022,

Recent Lattice QCD work on $\omega\pi$

- Studies the decay of b_1 to $\omega\pi$
- With $m_\pi = 391\text{MeV}$ and $a_s = 0.12fm$
- Computed b_1 mass is 1380MeV
- DSRatio computed at the above mass



PHYSICAL REVIEW D **100,** 054506 (2019)

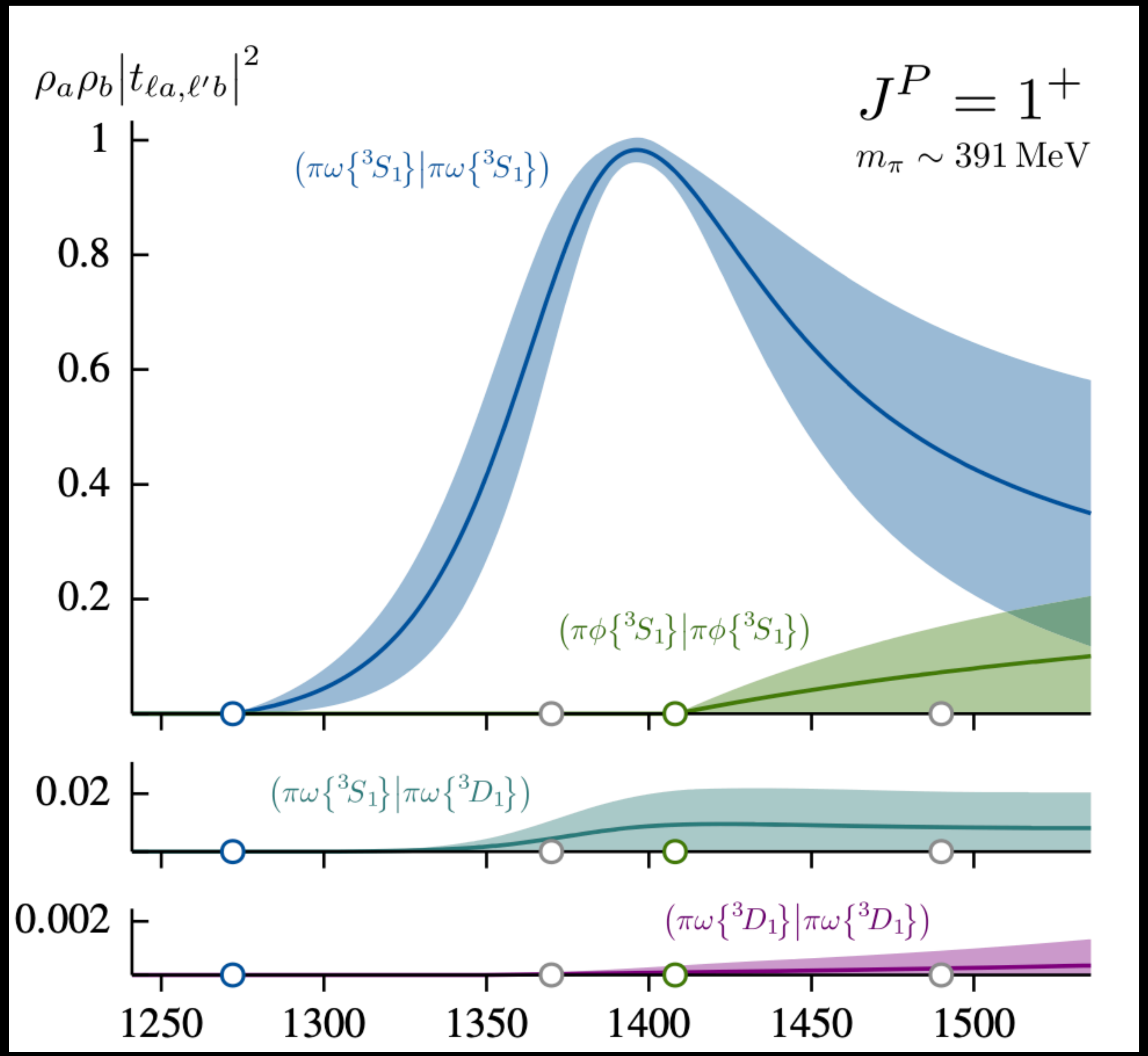
b_1 resonance in coupled $\pi\omega$, $\pi\phi$ scattering from lattice QCD

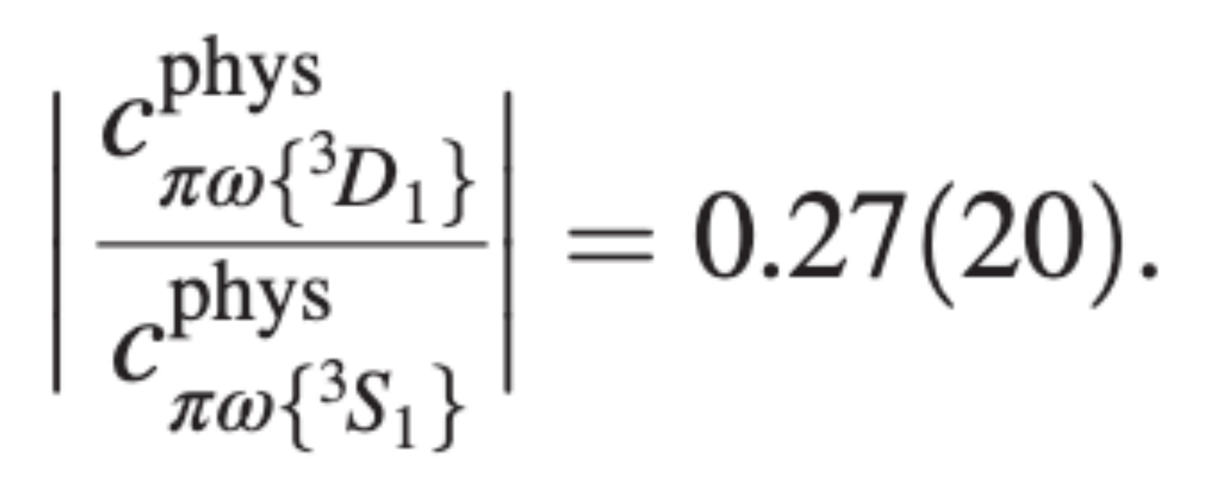
Antoni J. Woss,[1,*] Christopher E. Thomas,[1,†] Jozef J. Dudek,[2,3,‡] Robert G. Edwards,[2,‡] and David J. Wilson[4,∥]

(Hadron Spectrum Collaboration)

[1]*DAMTP, University of Cambridge, Centre for Mathematical Sciences, Wilberforce Road, Cambridge CB3 0WA, United Kingdom*
[2]*Thomas Jefferson National Accelerator Facility, 12000 Jefferson Avenue, Newport News, Virginia 23606, USA*
[3]*Department of Physics, College of William and Mary, Williamsburg, Virginia 23187, USA*
[4]*School of Mathematics, Trinity College, Dublin 2, Ireland*

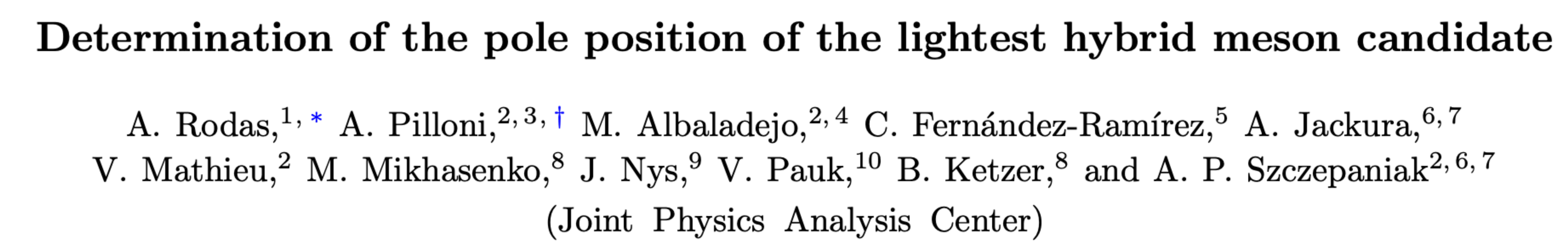
PHYSICAL REVIEW D 100, 054506 (2019)





$$\left|\frac{c^{\text{phys}}_{\pi\omega\{^3D_1\}}}{c^{\text{phys}}_{\pi\omega\{^3S_1\}}}\right| = 0.27(20).$$

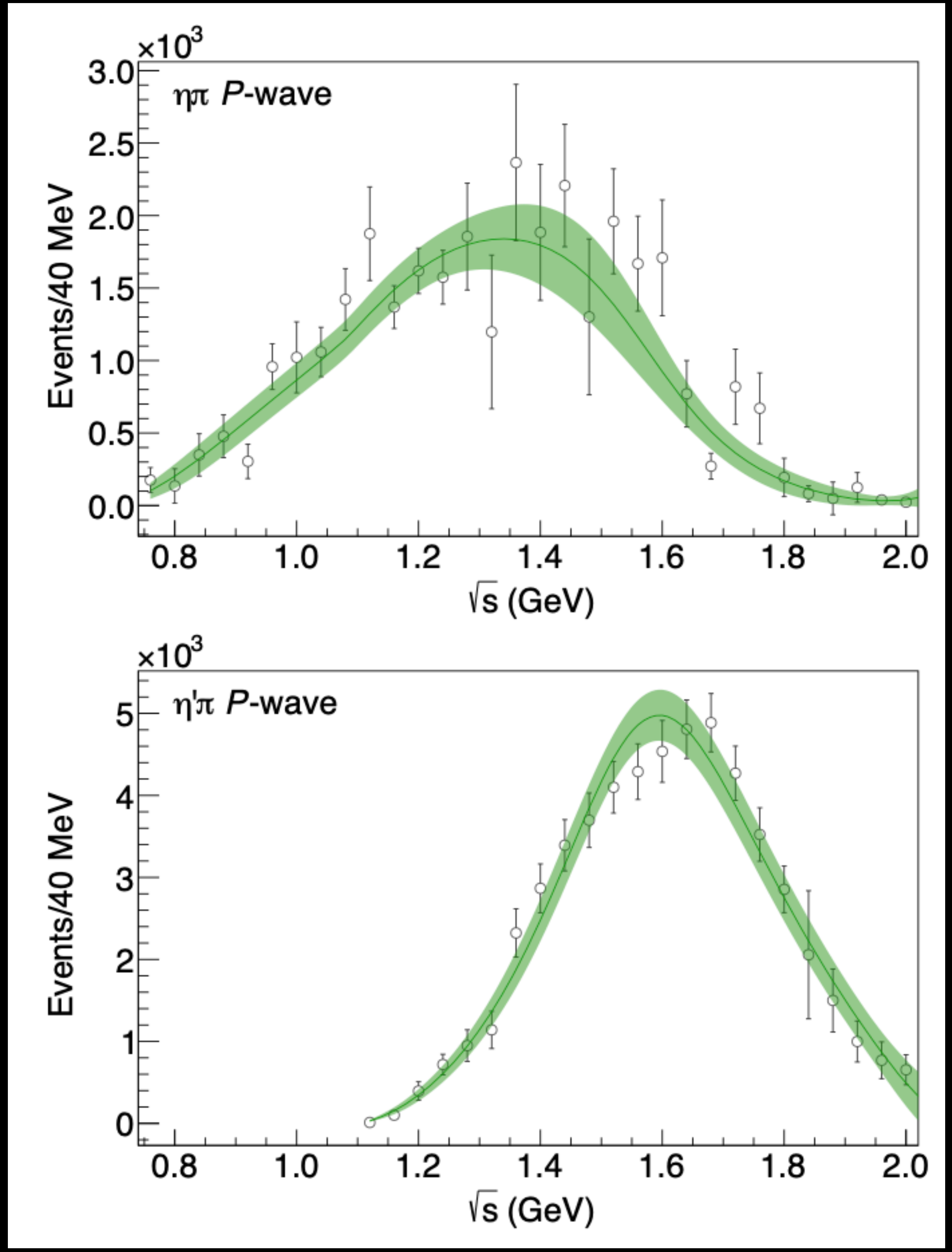
The lightest meson tension



Determination of the pole position of the lightest hybrid meson candidate

A. Rodas,[1,*] A. Pilloni,[2,3,†] M. Albaladejo,[2,4] C. Fernández-Ramírez,[5] A. Jackura,[6,7]
V. Mathieu,[2] M. Mikhasenko,[8] J. Nys,[9] V. Pauk,[10] B. Ketzer,[8] and A. P. Szczepaniak[2,6,7]
(Joint Physics Analysis Center)

- Experiments reported measuring Exotic $\pi_1(1400)$ through $\eta\pi$
  - E852 Collaboration
  - Crystal Barrel Collaboration
- Experiments also reported measuring Exotic $\pi_1(1600)$ through $\eta'\pi$
  - E852 Collaboration
  - VES Collaboration
  - COMPASS



$$M(\pi_1) = 1564 \pm 24 \pm 86 \quad \Gamma(\pi_1) = 492 \pm 54 \pm 102$$

Partial Wave Analysis

Lets get to Fitting: How to best choose a waveset ?

Waveset Name	Remarks	Wave sets			NPARS
		$[J^P]^\epsilon$	m	L	
1p	-	$[1^+]^\pm$	$-1, 0, 1$	S, D	14
0m1p	-	$[0^+]^\pm$	0	P	18
		$[1^+]^\pm$	$-1, 0, 1$	S, D	
1p1m	-	$[1^+]^\pm$	$-1, 0, 1$	S, D	26
		$[1^-]^\pm$	$-1, 0, 1$	P	
0m1p1m	-	$[0^+]^\pm$	0	P	30
		$[1^+]^\pm$	$-1, 0, 1$	S, D	
		$[1^-]^\pm$	$-1, 0, 1$	P	
0m1p1miso	-	Same as above + Isotropic Bkg			31
0mNeg1p1mPosIso	-	$[0^+]^-$	0	P	17
		$[1^+]^+$	$-1, 0, 1$	S, D	
		$[1^-]^+$	$-1, 0, 1$	P	
		Isotropic Bkg			
1p1mPos	-	$[1^+]^+$	$-1, 0, 1$	S, D	15
		$[1^-]^+$	$-1, 0, 1$	P	
0mNeg1pPos1mPosisoSepDS	Seperate dsratios for 3 m	Same as 0mNeg1pPos1mPosiso			19
1pPos1mPosSepDS	Seperate dsratios for 3 m	Same as 1p1mPos			17
1p1m2mPos		$[1^+]^\pm$	$-1, 0, 1$	S, D	46
		$[1^-]^\pm$	$-1, 0, 1$	P	
		$[2^-]^+$	$-2, -1, 0, 1, 2$	D, F	
1p1m2mPos2pPosiso		$[1^+]^\pm$	$-1, 0, 1$	S, D	45
		$[1^-]^\pm$	$-1, 0, 1$	P	
		$[2^-]^+$	$-1, 0, 1$	P, F	
		$[2^+]^+$	$-1, 0, 1$	D	
		Isotropic Bkg			

Model Metric:

- Likelihood Ratio Test (LRT) - impact of adding additional parameter

$$LRT = \frac{NLL_{\text{alternate}} - NLL_{\text{benchmark}}}{NPAR_{\text{alternate}} - NPAR_{\text{benchmark}}}$$

- Akaike Information Criterion (AIC) - favours a more complex model

$$AIC = \frac{2 \times NLL + 2 \times NPAR}{N}$$

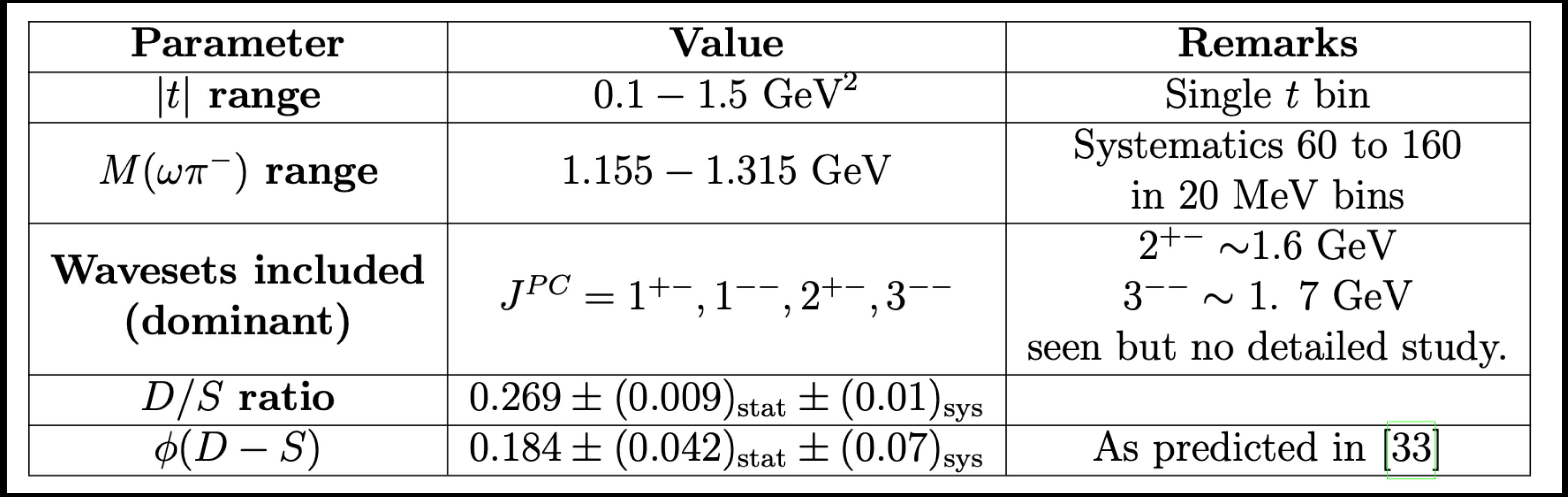
- Bayesian Information Criterion (BIC) - penalizes a complex model

$$BIC = \frac{2 \times NLL + 2 \times \ln(N) \times NPAR}{N}$$

Validate methodology using synthetic data (Signal MC)

Comparing previous experiments

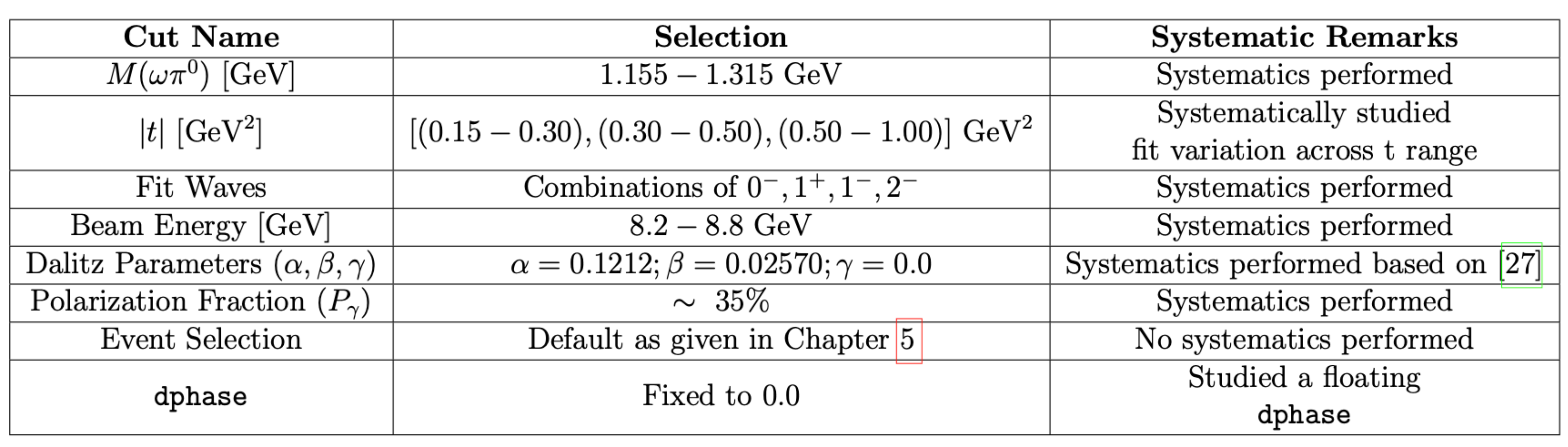
E852 Results



Parameter	**Value**	**Remarks**
$\lvert t\rvert$ **range**	0.1 – 1.5 GeV^2	Single t bin
$M(\omega\pi^-)$ **range**	1.155 – 1.315 GeV	Systematics 60 to 160 in 20 MeV bins
Wavesets included (dominant)	$J^{PC} = 1^{+-}, 1^{--}, 2^{+-}, 3^{--}$	2^{+-} ~1.6 GeV $3^{--} \sim 1.\ 7$ GeV seen but no detailed study.
D/S **ratio**	$0.269 \pm (0.009)_{\text{stat}} \pm (0.01)_{\text{sys}}$	
$\phi(D-S)$	$0.184 \pm (0.042)_{\text{stat}} \pm (0.07)_{\text{sys}}$	As predicted in [33]

- π beam so $S = 0$; Need to have spin flip for exotic production
- 4 dimensions, No Φ_{prod} in Intensity
- Cannot distinguish parity exchange Natural or UnNatural.

GlueX



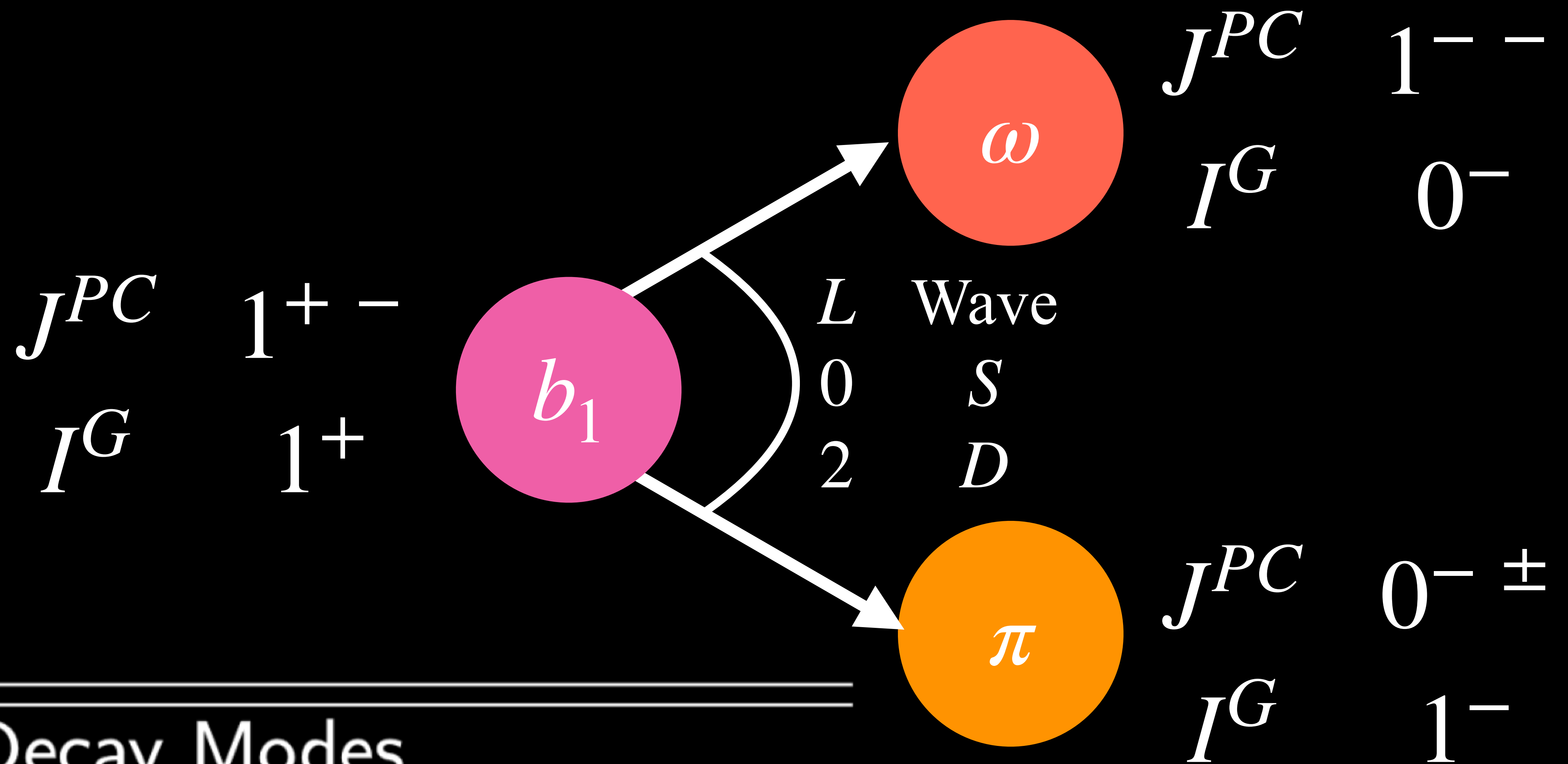
Cut Name	Selection	Systematic Remarks
$M(\omega\pi^0)$ [GeV]	1.155 – 1.315 GeV	Systematics performed
$\lvert t\rvert$ [GeV^2]	$[(0.15-0.30),(0.30-0.50),(0.50-1.00)]$ GeV^2	Systematically studied fit variation across t range
Fit Waves	Combinations of $0^-, 1^+, 1^-, 2^-$	Systematics performed
Beam Energy [GeV]	8.2 – 8.8 GeV	Systematics performed
Dalitz Parameters (α, β, γ)	$\alpha = 0.1212; \beta = 0.02570; \gamma = 0.0$	Systematics performed based on [27]
Polarization Fraction (P_γ)	$\sim$ 35%	Systematics performed
Event Selection	Default as given in Chapter 5	No systematics performed
`dphase`	Fixed to 0.0	Studied a floating `dphase`

- γ beam so $S = 1$, behaves like Vector meson; direct Exotic production
- 5 dimensions, Φ_{prod} in Intensity had to be encoded
- Can distinguish between Natural and Unnatural Exchange
  - Larger number of fit parameters to be included

Natural Partiy $P = (-1)^J$, UnNatural Parity $P = (-1)^{J+1}$

The b_1 Meson

Why study b_1 meson



J^{PC} 1^{+-}

I^G 1^+

b_1

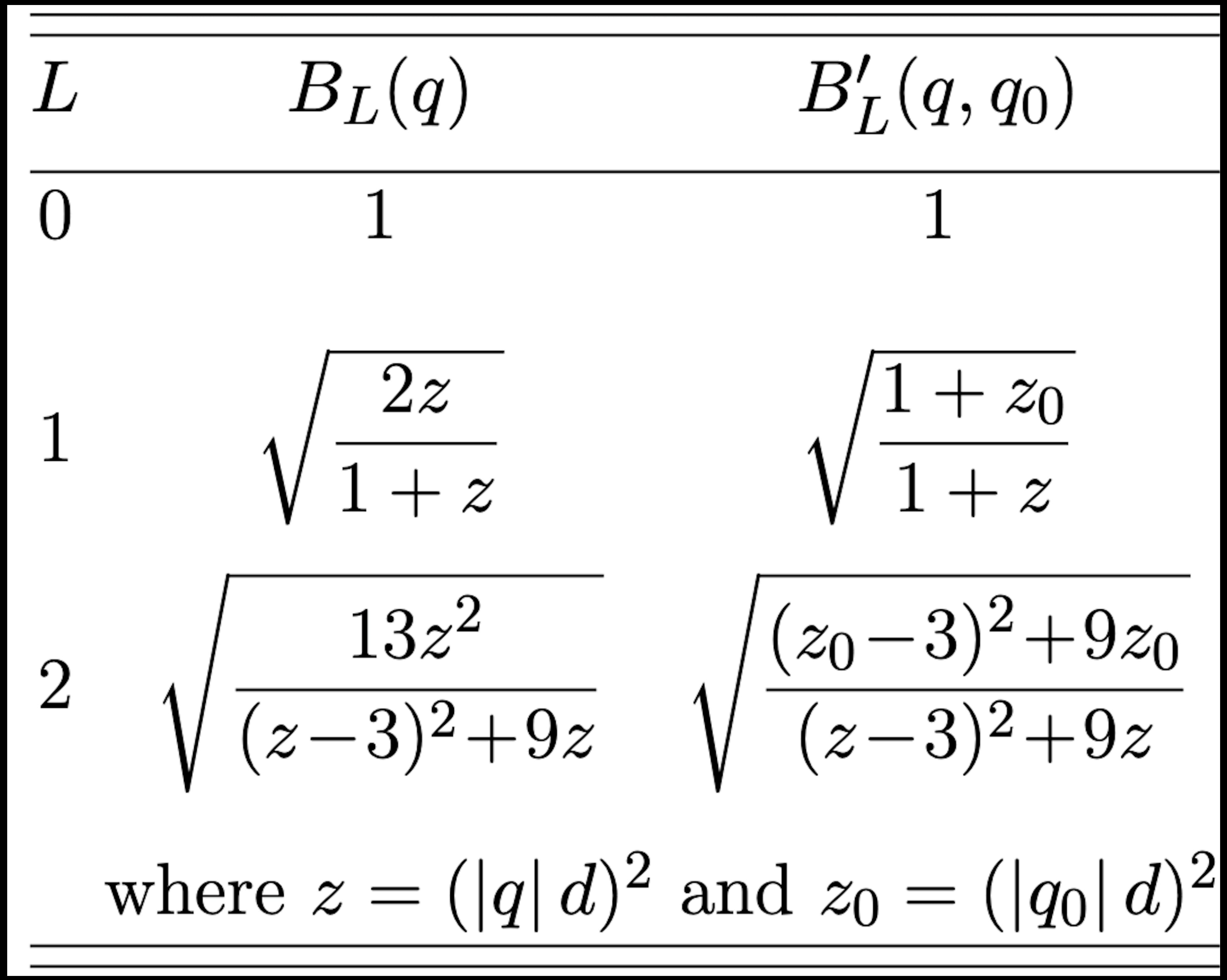
ω J^{PC} 1^{--} I^G 0^-

π J^{PC} $0^{-\pm}$ I^G 1^-

L	Wave
0	S
2	D

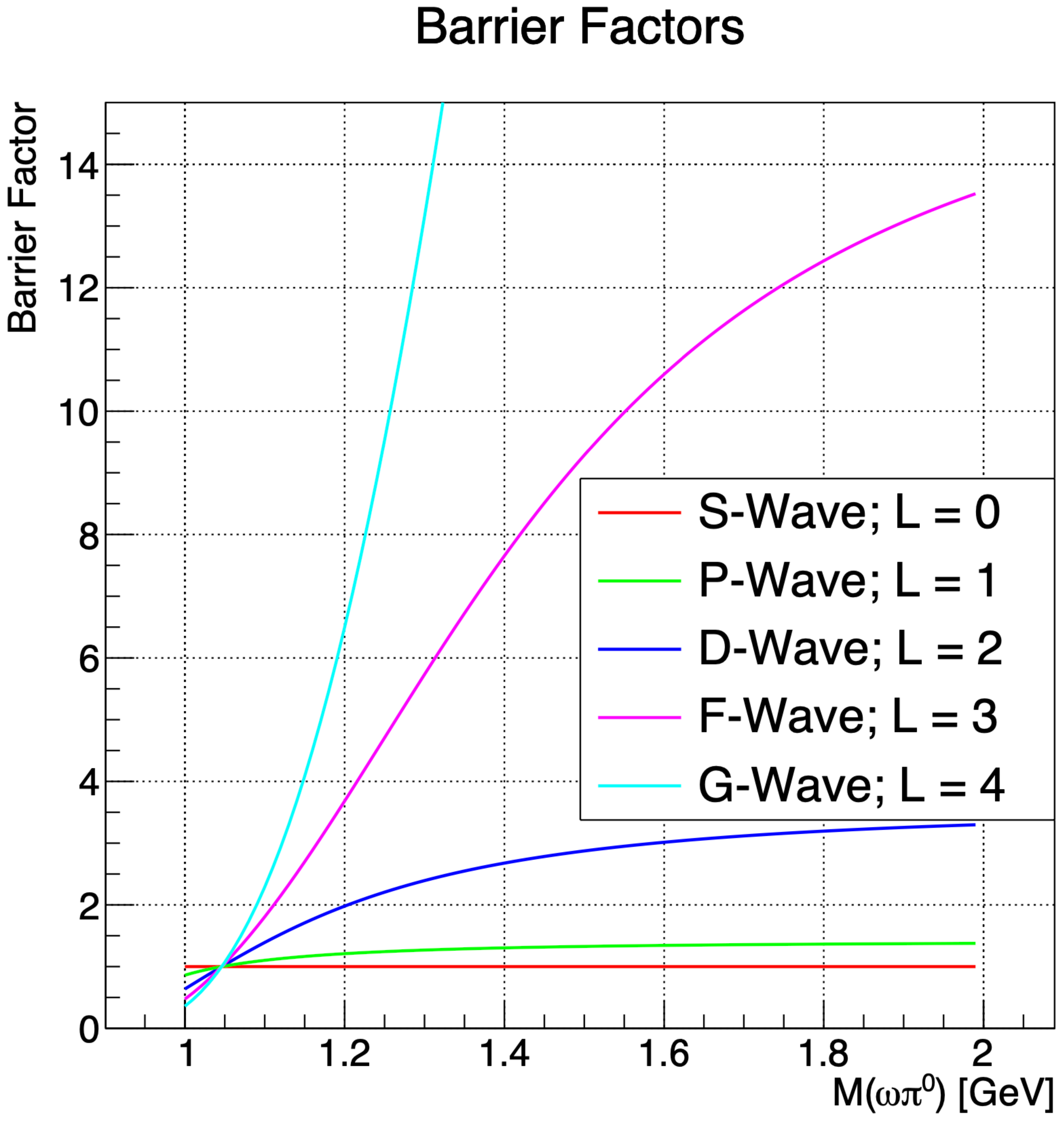
Name	J^{PC}	Total Width MeV		Allowed Decay Modes
π_1	1^{-+}	$81-168$	117	$\boxed{b_1\pi}$, $\pi\rho$, πf_1, $\pi\eta$, $\pi\eta'$, ηa_1, $\pi\eta(1295)$
η_1	1^{-+}	$59-158$	107	πa_1, πa_2, ηf_1, ηf_2, $\pi\pi(1300)$, $\eta\eta'$, KK_1^A, KK_1^B
η_1'	1^{-+}	$95-216$	172	KK_1^B, KK_1^A, KK^*, $\eta\eta'$
b_0	0^{+-}	$247-429$	665	$\pi\pi(1300)$, πh_1, ρf_1, $\boxed{\eta b_1}$
h_0	0^{+-}	$59-262$	94	$\boxed{\pi b_1}$, ηh_1, $KK(1460)$
h_0'	0^{+-}	$259-490$	426	$KK(1460)$, KK_1^A, ηh_1
b_2	2^{+-}	$5-11$	248	πa_1, πa_2, πh_1, $\eta\rho$, $\boxed{\eta b_1}$, ρf_1
h_2	2^{+-}	$4-12$	166	$\pi\rho$, $\boxed{\pi b_1}$, $\eta\omega$, $\boxed{\omega b_1}$
h_2'	2^{+-}	$5-18$	79	KK_1^B, KK_1^A, KK_2^*, ηh_1

Why include Barrier Factor

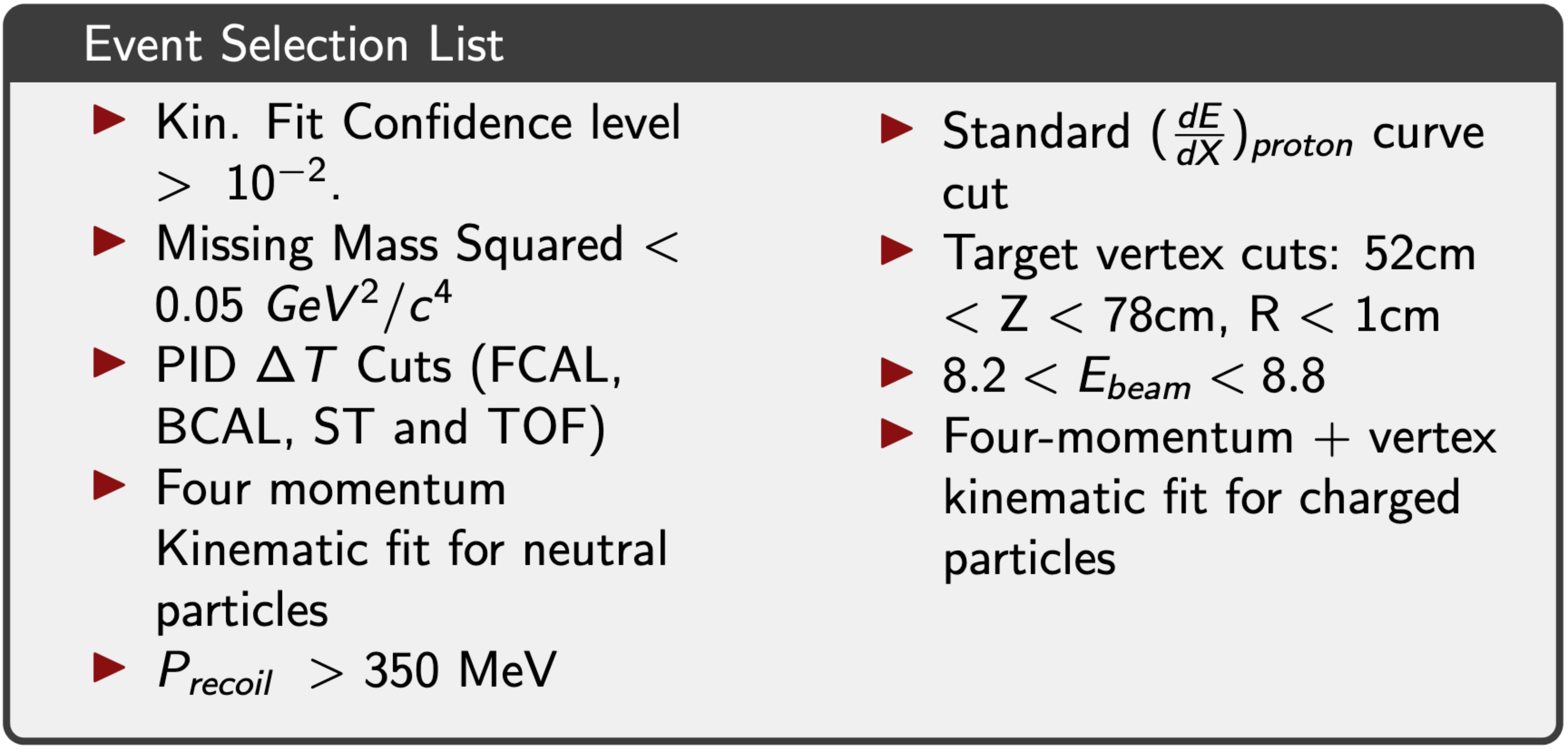


L	$B_L(q)$	$B'_L(q,q_0)$
0	1	1
1	$\sqrt{\frac{2z}{1+z}}$	$\sqrt{\frac{1+z_0}{1+z}}$
2	$\sqrt{\frac{13z^2}{(z-3)^2+9z}}$	$\sqrt{\frac{(z_0-3)^2+9z_0}{(z-3)^2+9z}}$

where $z=(\lvert q\rvert\, d)^2$ and $z_0=(\lvert q_0\rvert\, d)^2$



Data Selection Cuts

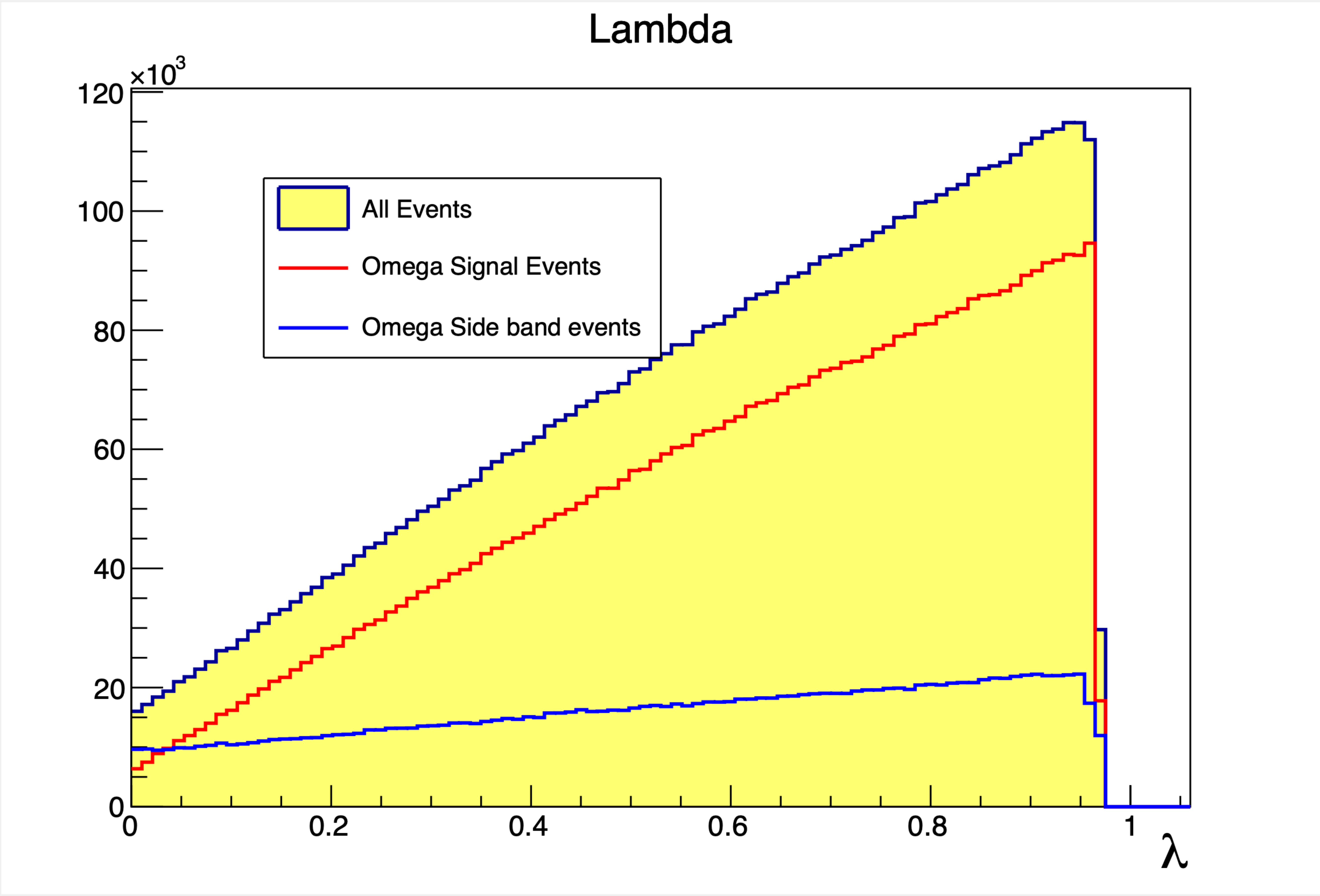


Event Selection List

- Kin. Fit Confidence level $> 10^{-2}$.
- Missing Mass Squared $< 0.05\ GeV^2/c^4$
- PID ΔT Cuts (FCAL, BCAL, ST and TOF)
- Four momentum Kinematic fit for neutral particles
- $P_{recoil} > 350$ MeV
- Standard $(\frac{dE}{dX})_{proton}$ curve cut
- Target vertex cuts: 52cm $< Z <$ 78cm, R $<$ 1cm
- $8.2 < E_{beam} < 8.8$
- Four-momentum + vertex kinematic fit for charged particles

More on Chapter 5 Thesis.

Lambda cut



λ definition

- In the COM of $\omega(\pi^+\pi^-\pi^0)$, the quantity λ is calculated.
- The quantity represents the true ω events in the sample.
- $\lambda = \frac{4|\vec{p}_{\pi^+} x \vec{p}_{\pi^-}|}{(M(\omega)-M(\pi^0))^2}$

Signal MC

- Generated Signal MC with 2 resonances
  - 1^+ b_1 wave ($M = 1.235\text{GeV}, \Gamma = 0.14\text{GeV}$)
  - 1^- ρ wave ($M = 1.465\text{GeV}, \Gamma = 0.4\text{GeV}$)
- After Fitting, check for fit fractions and relative phases between different waves
- Compare to what was generated to validate
- More on Chapter 6 in Thesis

AmpTools

Working schematic

N Randomized Fit

Make $|t|$, $M(\omega\pi^0)$, E_γ cut

Randomly initialize params

Compute Intensity using params

Estimate the likelihood

$$-2\ln(\mathfrak{L}(\theta)) = -2(\sum_{i}^{N} \ln I(x;\theta) - \int I(x;\theta)\eta(x)dx)$$

Use MINUIT to choose next step

Use MC Integration technique

Embed efficiency $\eta(x)$

Estimate min Distance

If Stopping criteria Return

PWA-Why not mass dependence

Greater Model dependence — So additional systematics

Already will make an assumption about the domination of b_1 in the region

Solution — Piecewise hybrid solution

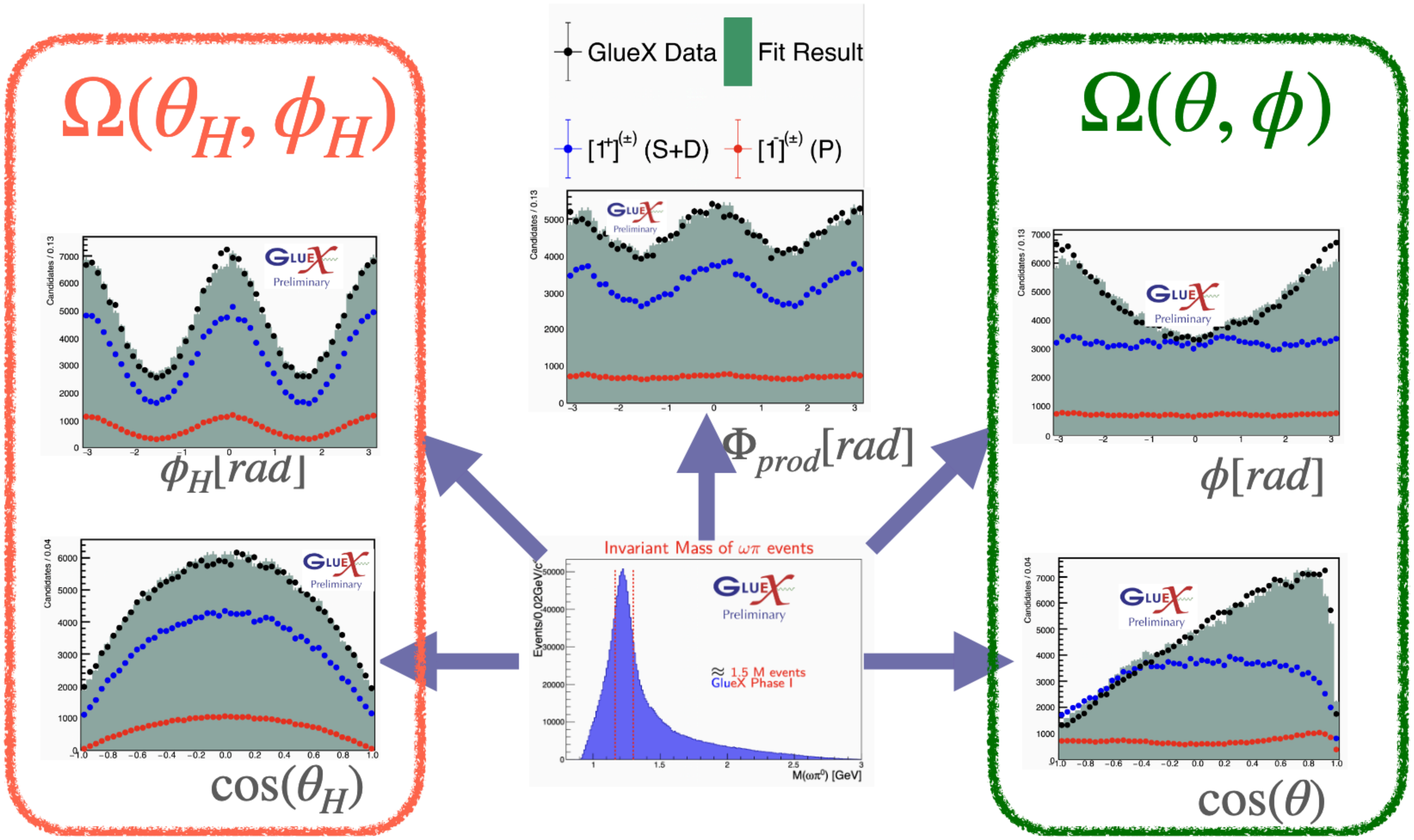
But stick with independent as much as possible.

Mass has smaller systematics compared to Fit waves

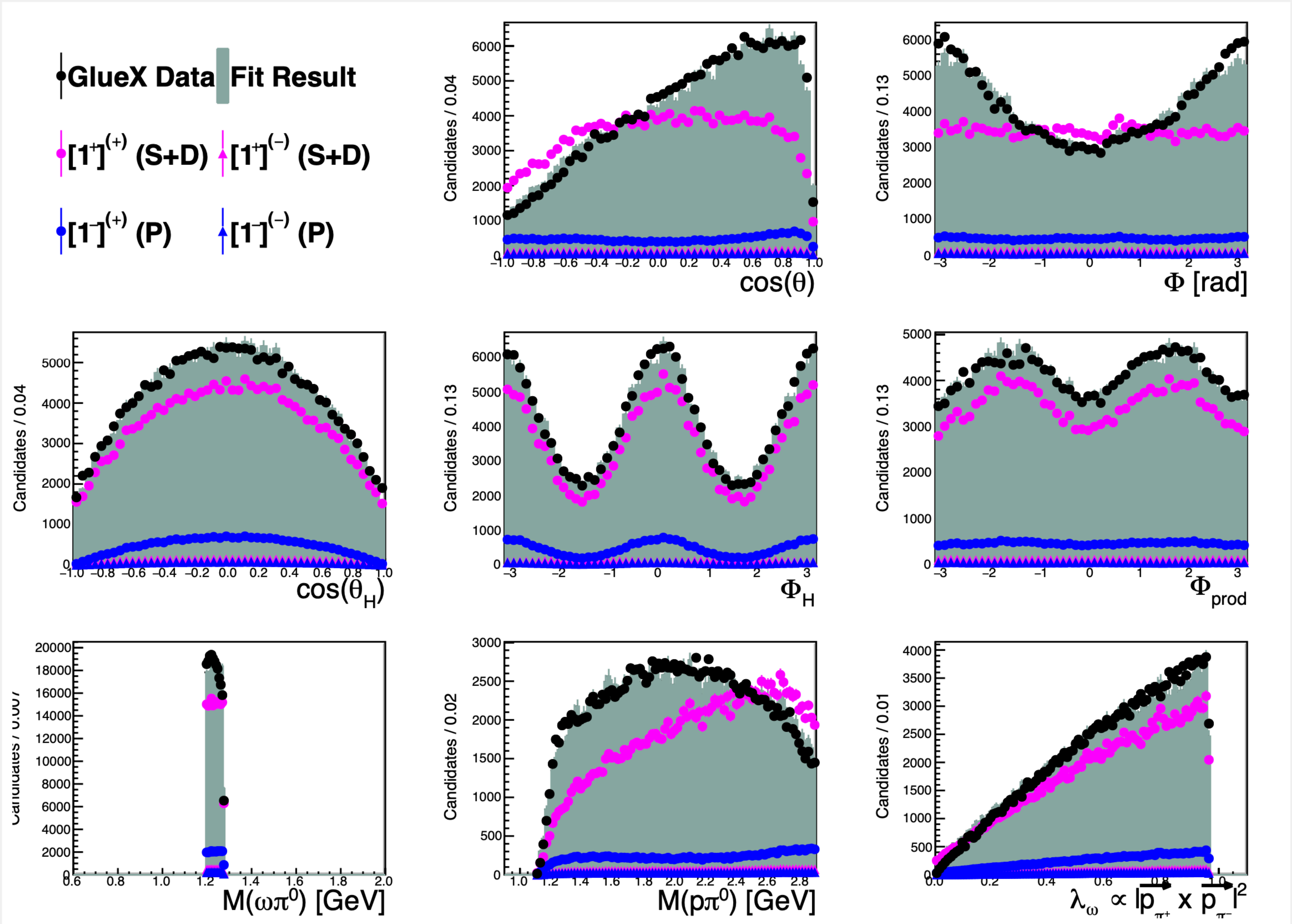
$$
\begin{aligned}
I(\Phi, \Omega, \Omega_H) &= 2\kappa \\
&\left\{(1-P_\gamma)\left[\left|\sum_{i,m}[J_i]_m^{(-)}F_i^{(-)}(M,\vec{x})\mathfrak{Im}(Z)\right|^2 + \sum_{i,m}[J_i]_m^{(+)}F_i^{(+)}(M,\vec{x})\mathfrak{Re}(Z)\right|^2\right] \\
&+(1+P_\gamma)\left[\left|\sum_{i,m}[J_i]_m^{(+)}F_i^{(+)}(M,\vec{x})\mathfrak{Im}(Z)\right|^2 + \sum_{i,m}[J_i]_m^{(-)}F_i^{(-)}(M,\vec{x})\mathfrak{Re}(Z)\right|^2\right]\right\}
\end{aligned}
$$

Fit Projections in decay angles

In a given Mass $M(\omega\pi^0)$ and t bin.



Fit Projections in decay angles



For each fit in each bin

$1.195 < M(\omega\pi^0) < 1.275$ GeV

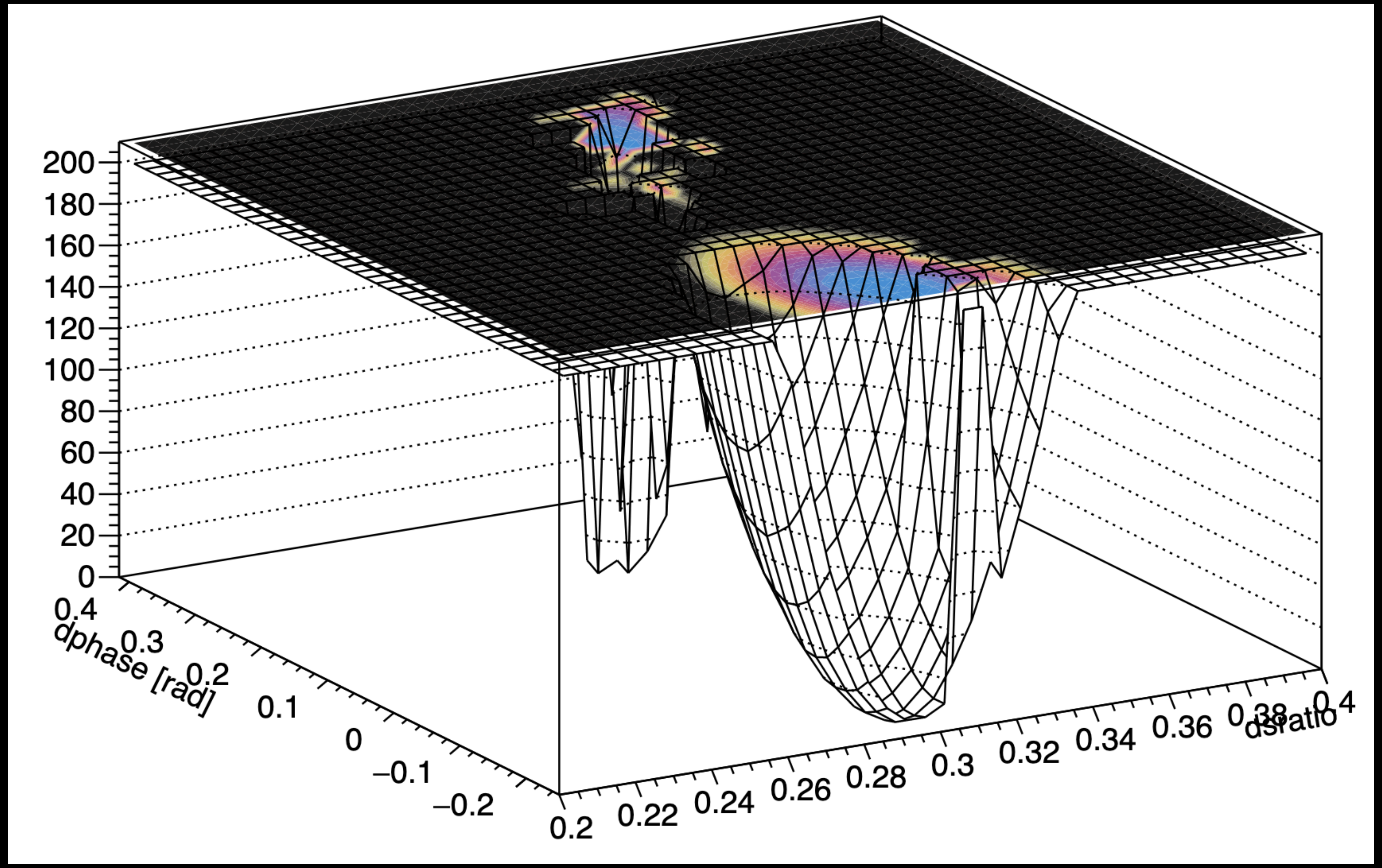
$0.15 < |t| < 0.30$ GeV^2

Systematics analysis

Chapter 7 in thesis

Systematics analysis - changing phase

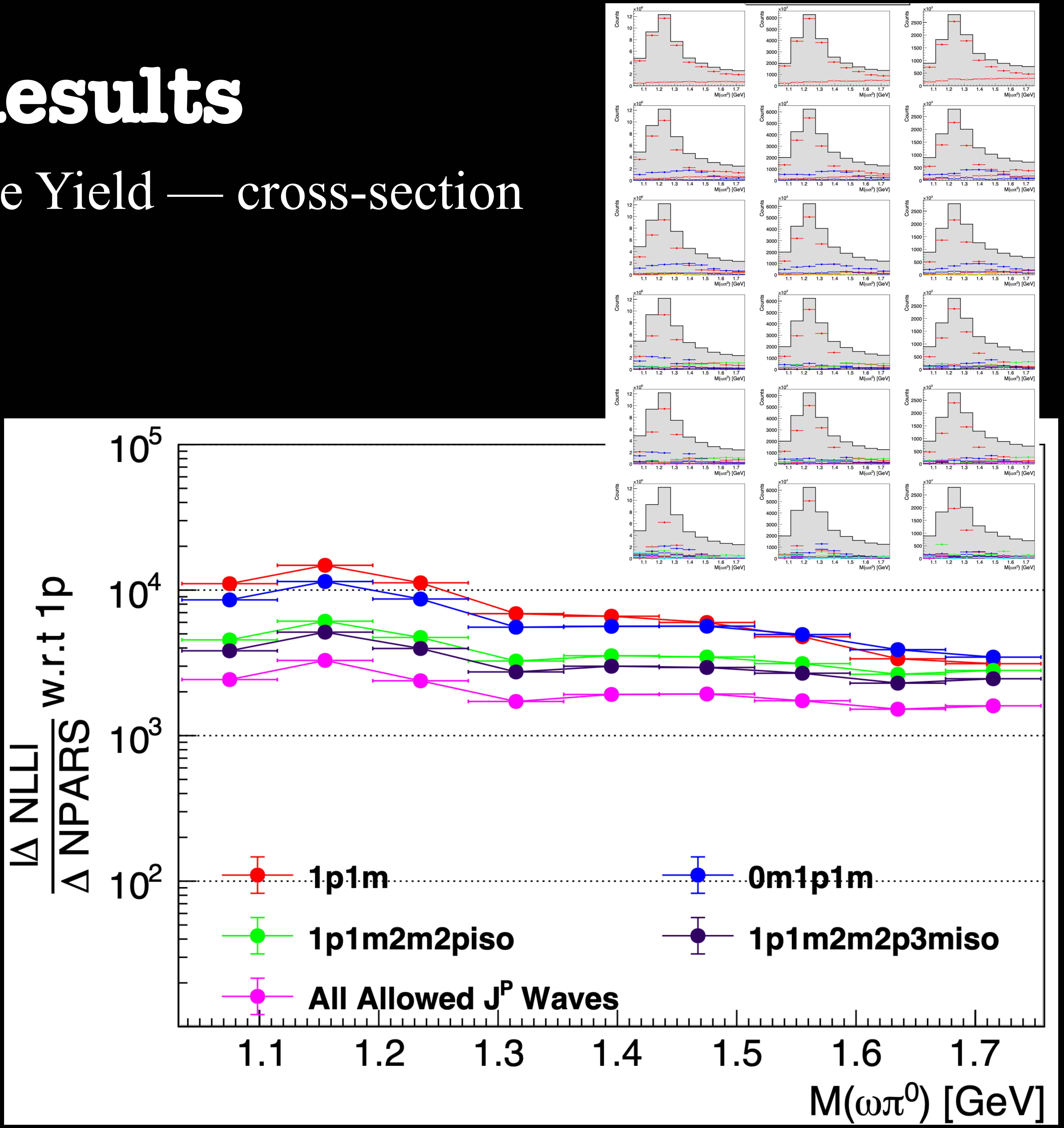
$$\begin{aligned}\mathcal{I}(\Phi,\Omega,\Omega_H) = 2\kappa\Bigg\{ &(1-P_\gamma)\Bigg[\Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(-)}_m\Bigg(\mathfrak{Im}(Z^{(S)}) + D/S\ e^{i\phi_{D-S}}\,\mathfrak{Im}(Z^{(D)})\Bigg)\Bigg|^2\\ &+\Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(+)}_m\Bigg(\mathfrak{Re}(Z^{(S)}) + D/S\ e^{i\phi_{D-S}}\,\mathfrak{Re}(Z^{(D)})\Bigg)\Bigg|^2\Bigg]\\ &+(1+P_\gamma)\Bigg[\Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(+)}_m\Bigg(\mathfrak{Im}(Z^{(S)}) + D/S\ e^{i\phi_{D-S}}\,\mathfrak{Im}(Z^{(D)})\Bigg)\Bigg|^2\\ &+\Bigg|\sum_{m=-1,0,1}[1^+(S)]^{(-)}_m\Bigg(\mathfrak{Re}(Z^{(S)}) + D/S\ e^{i\phi_{D-S}}\,\mathfrak{Re}(Z^{(D)})\Bigg)\Bigg|^2\Bigg]\Bigg\}\end{aligned}$$



Partial Wave Analysis : Results

Extending beyond b_1 mass : Recipe to compute Yield — cross-section

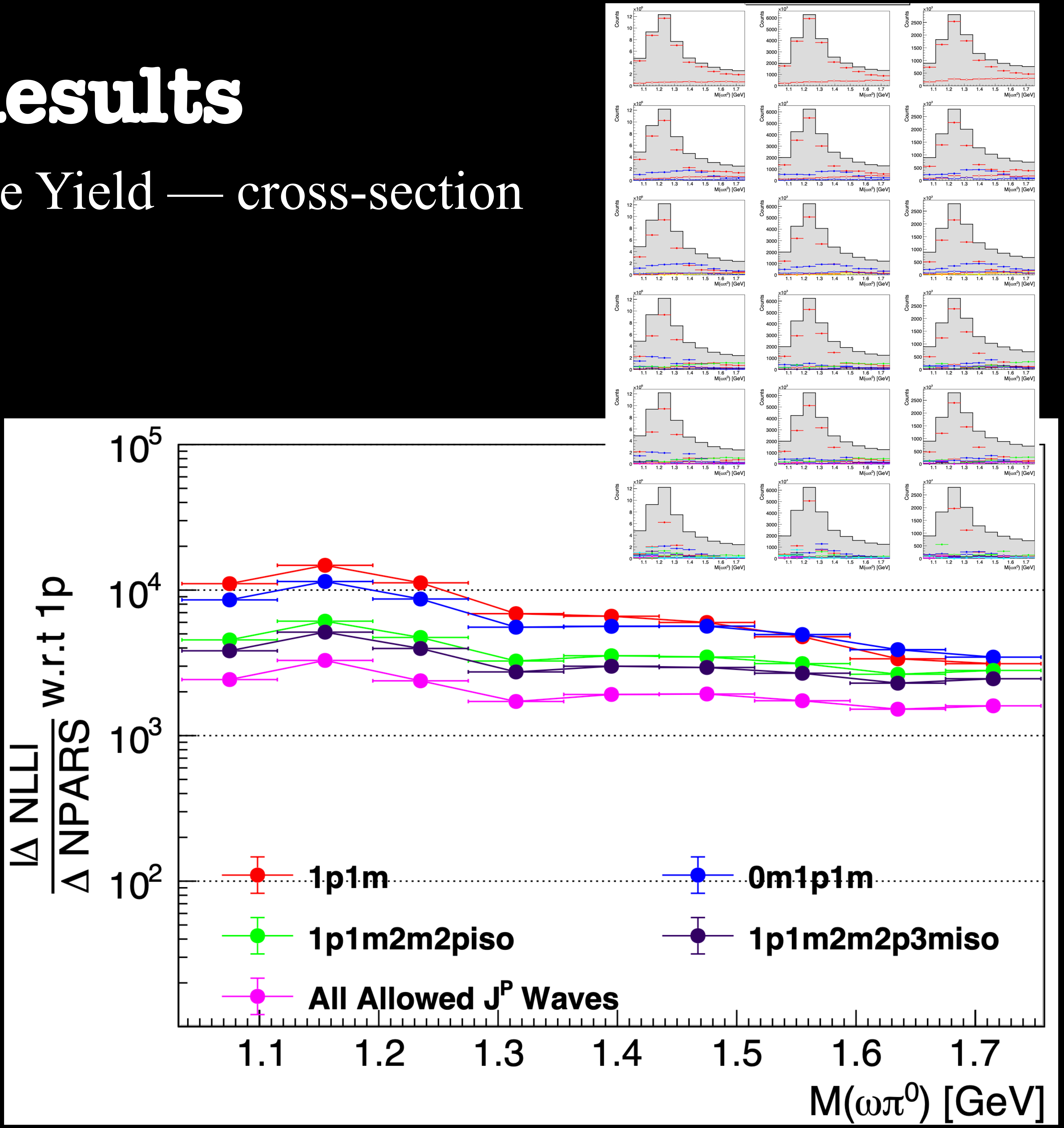
- Repeat with Data selection
- Fits made 80 MeV bins in $M(\omega\pi^0)$
- Combination of waves upto $J = 3$
- Model Selection criterion applied
- Data prefers a larger waveset higher mass region



Partial Wave Analysis : Results

Extending beyond b_1 mass : Recipe to compute Yield — cross-section

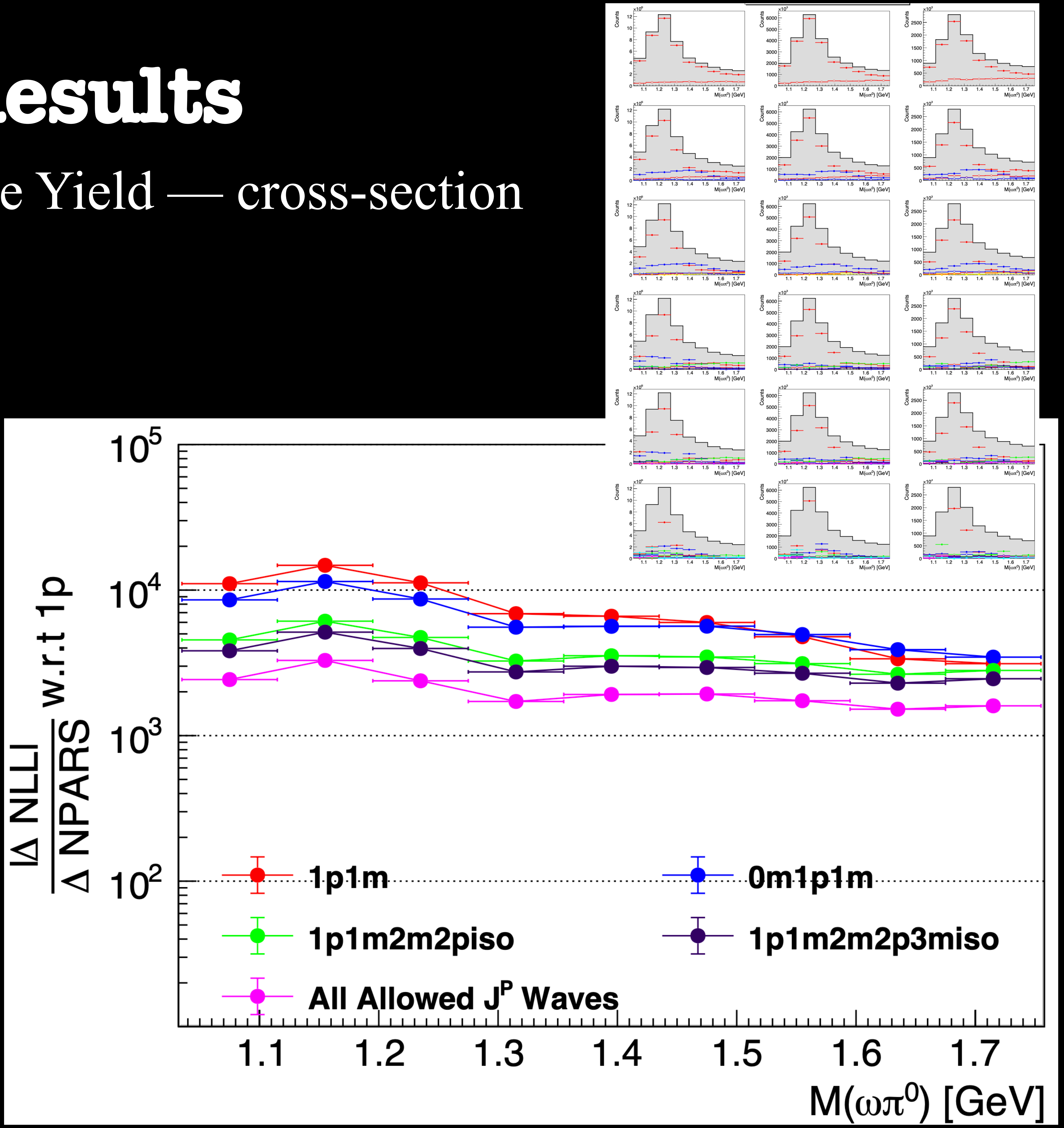
- Have fig reference to continuous fits.



Partial Wave Analysis : Results

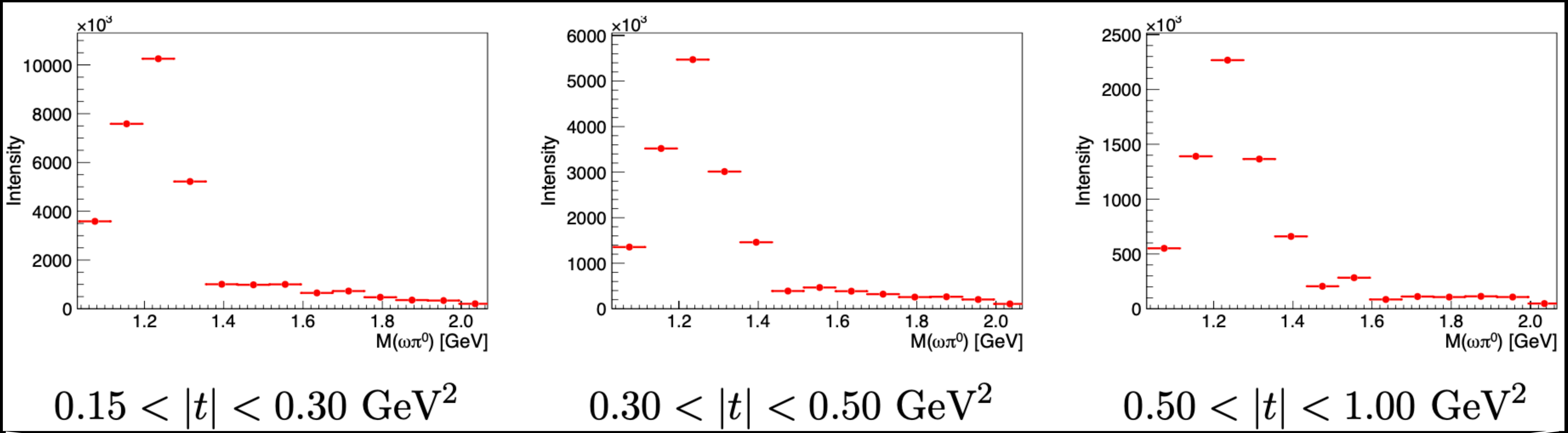
Extending beyond b_1 mass : Recipe to compute Yield — cross-section

- Beyond thesis. Have the extended version.



Partial Wave Analysis : Results

Extending beyond b_1 mass : Recipe to compute Yield — cross-section

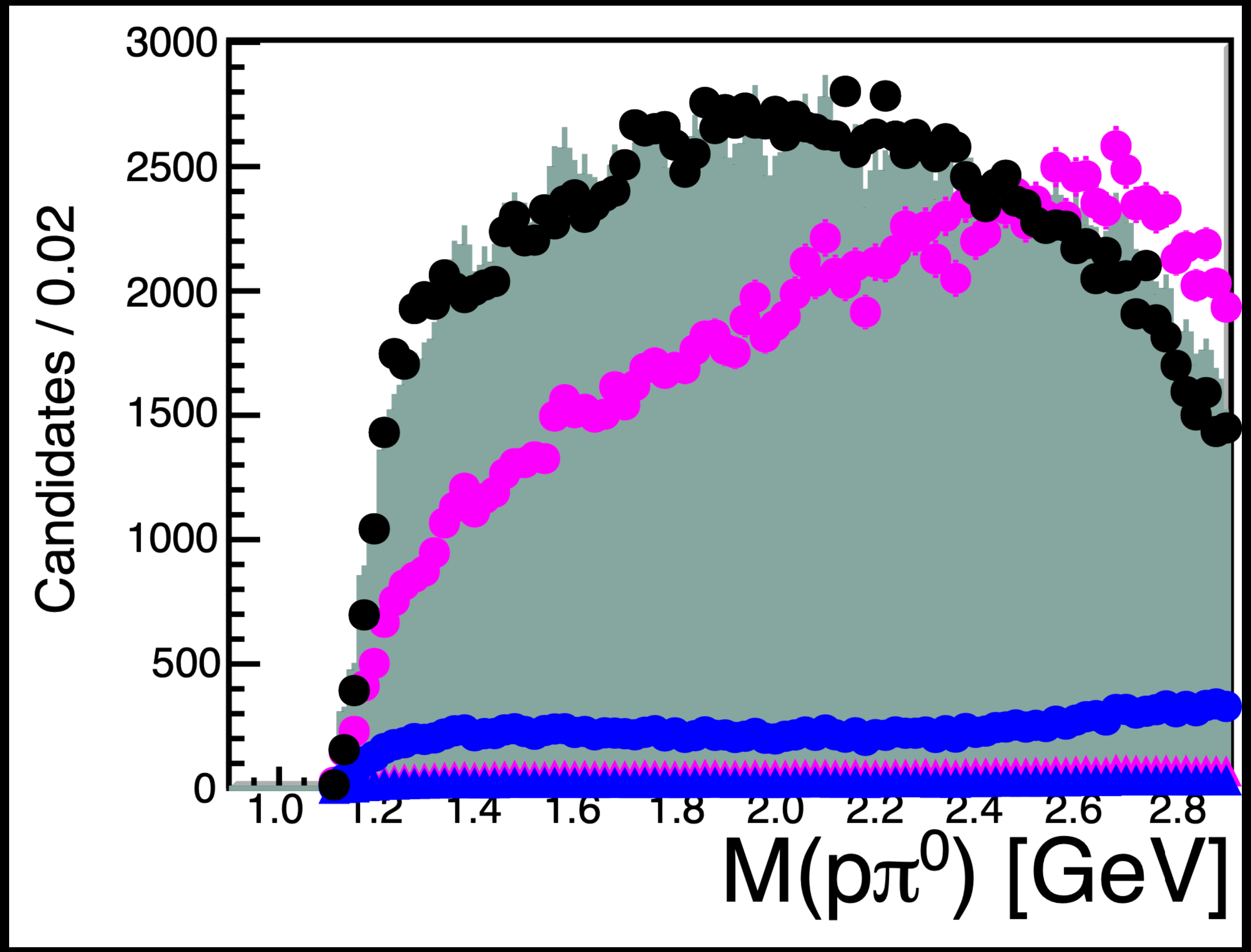


$0.15 < |t| < 0.30\ \mathrm{GeV}^2$ $0.30 < |t| < 0.50\ \mathrm{GeV}^2$ $0.50 < |t| < 1.00\ \mathrm{GeV}^2$

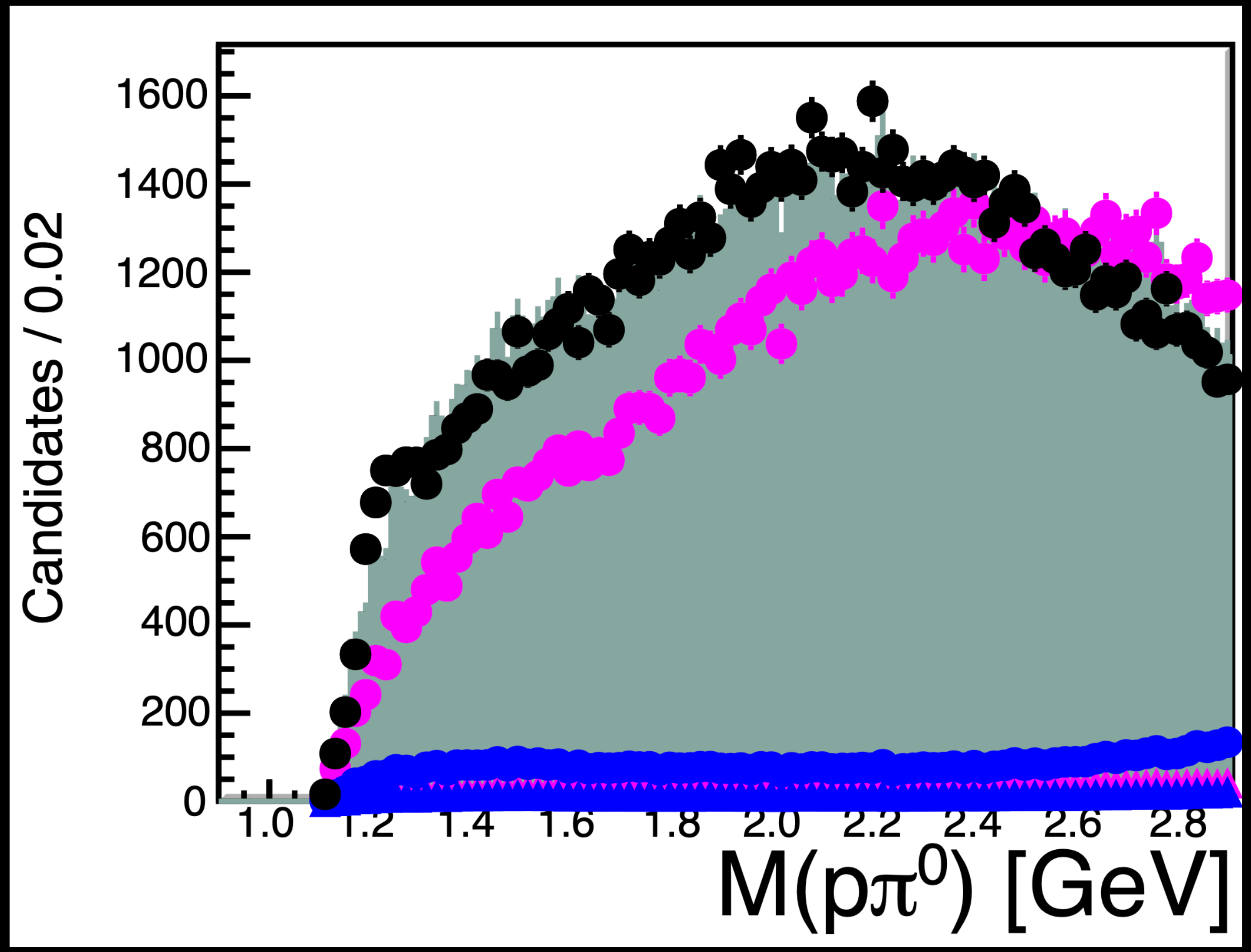
$$\sigma = \frac{\boxed{N}}{\epsilon \times \text{Flux} \times \text{Target} \times \mathcal{B}(b_1(1235) \to \omega\pi^0) \times \mathcal{B}(\omega \to \pi^+\pi^-\pi^0) \times \mathcal{B}(\pi^0 \to 2\gamma)}$$

Partial Wave Analysis : Ongoing and Future work

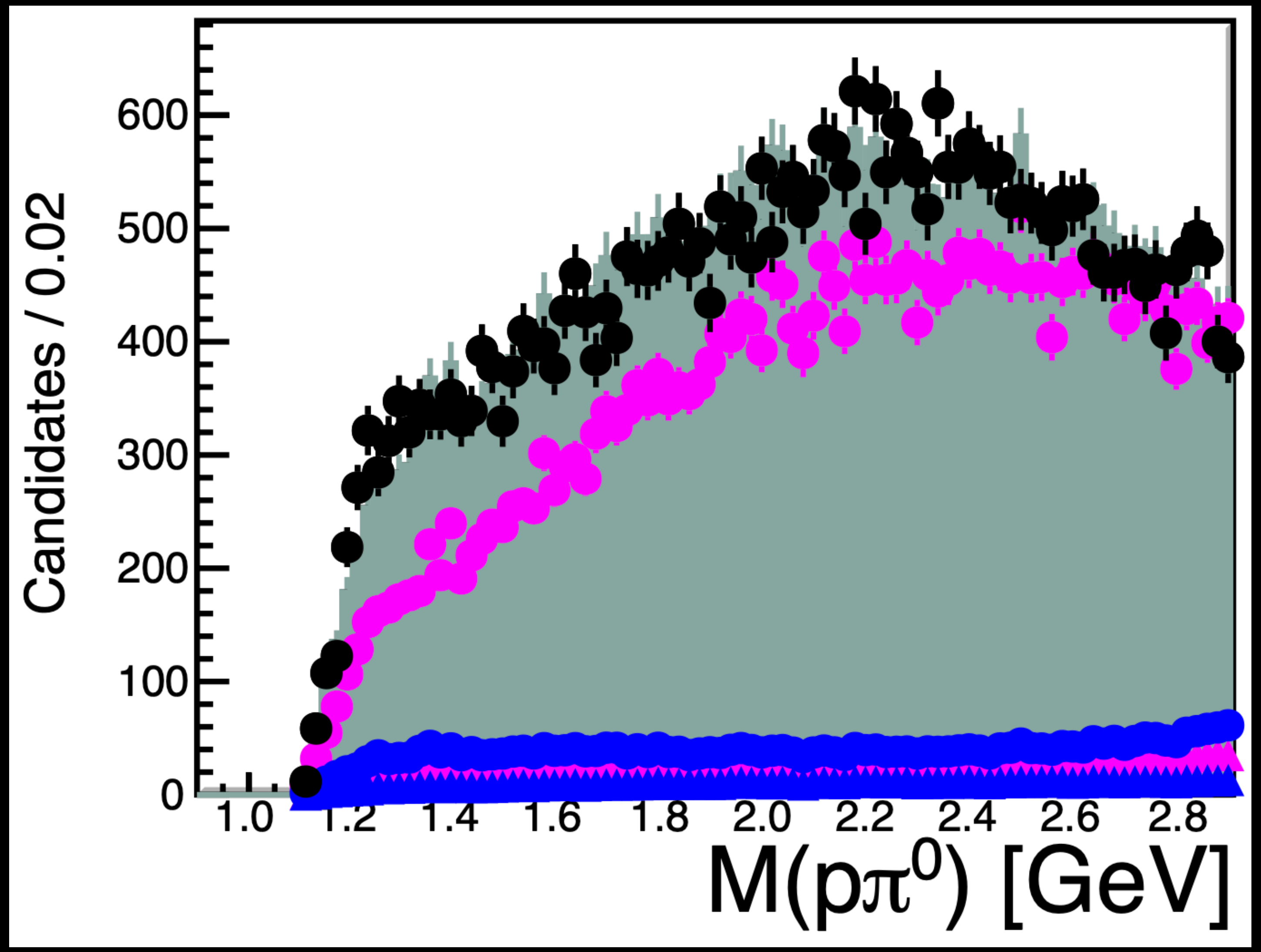
low |t|



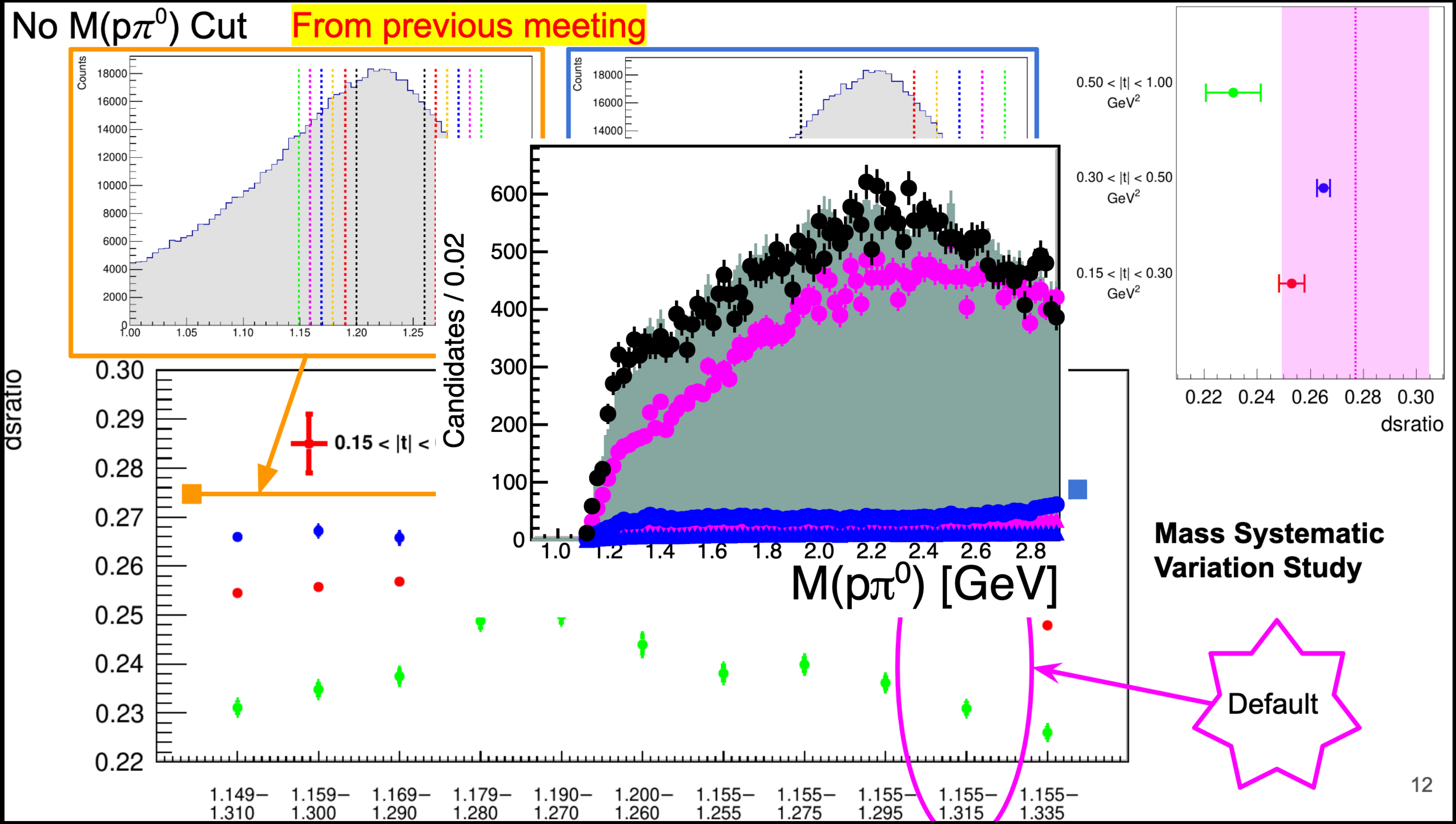
mid |t|



high |t|



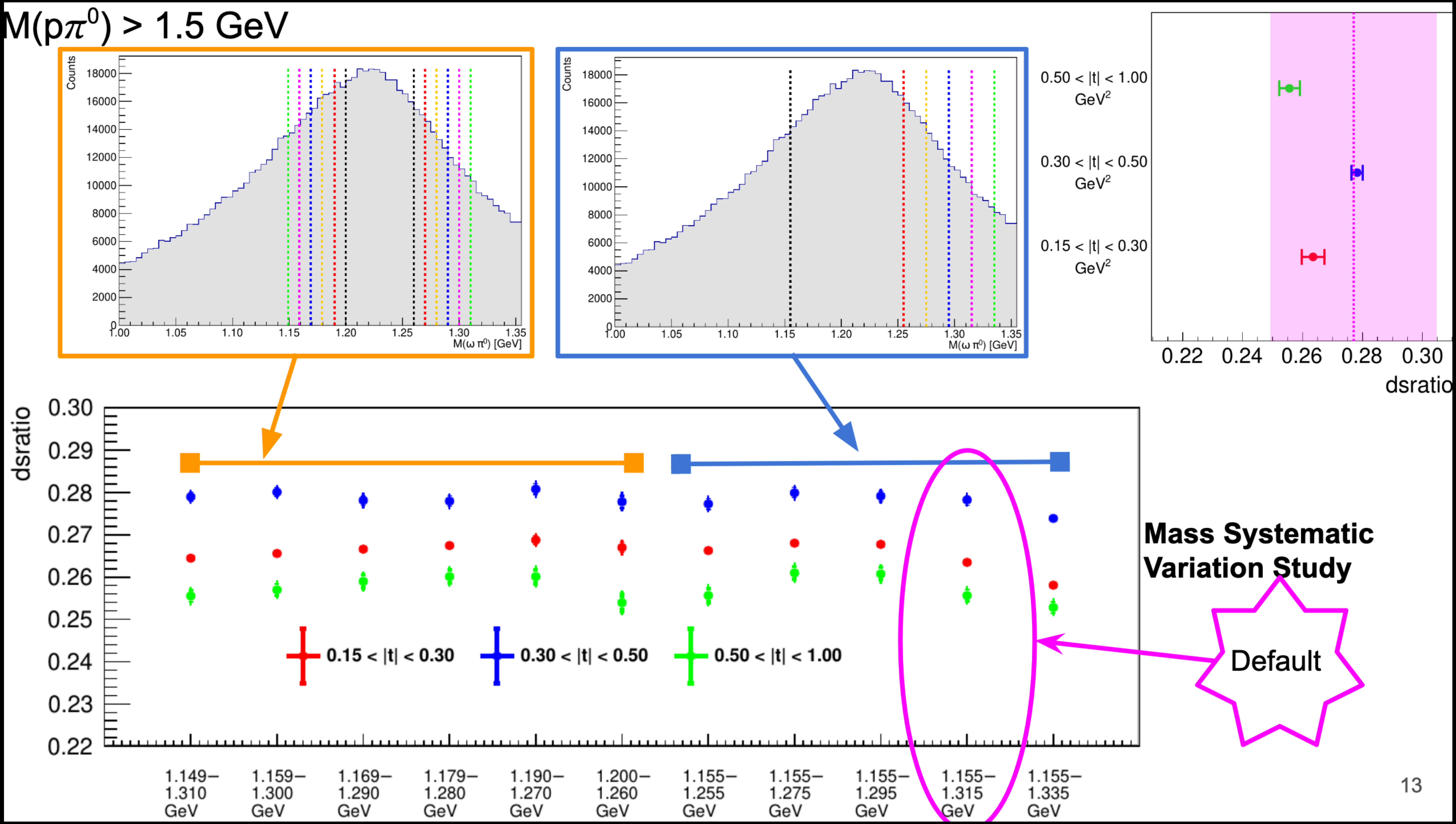
Partial Wave Analysis : Ongoing and Future work



Mass Systematic Variation Study

Default

Partial Wave Analysis : Ongoing and Future work



M($p\pi^0$) > 1.5 GeV

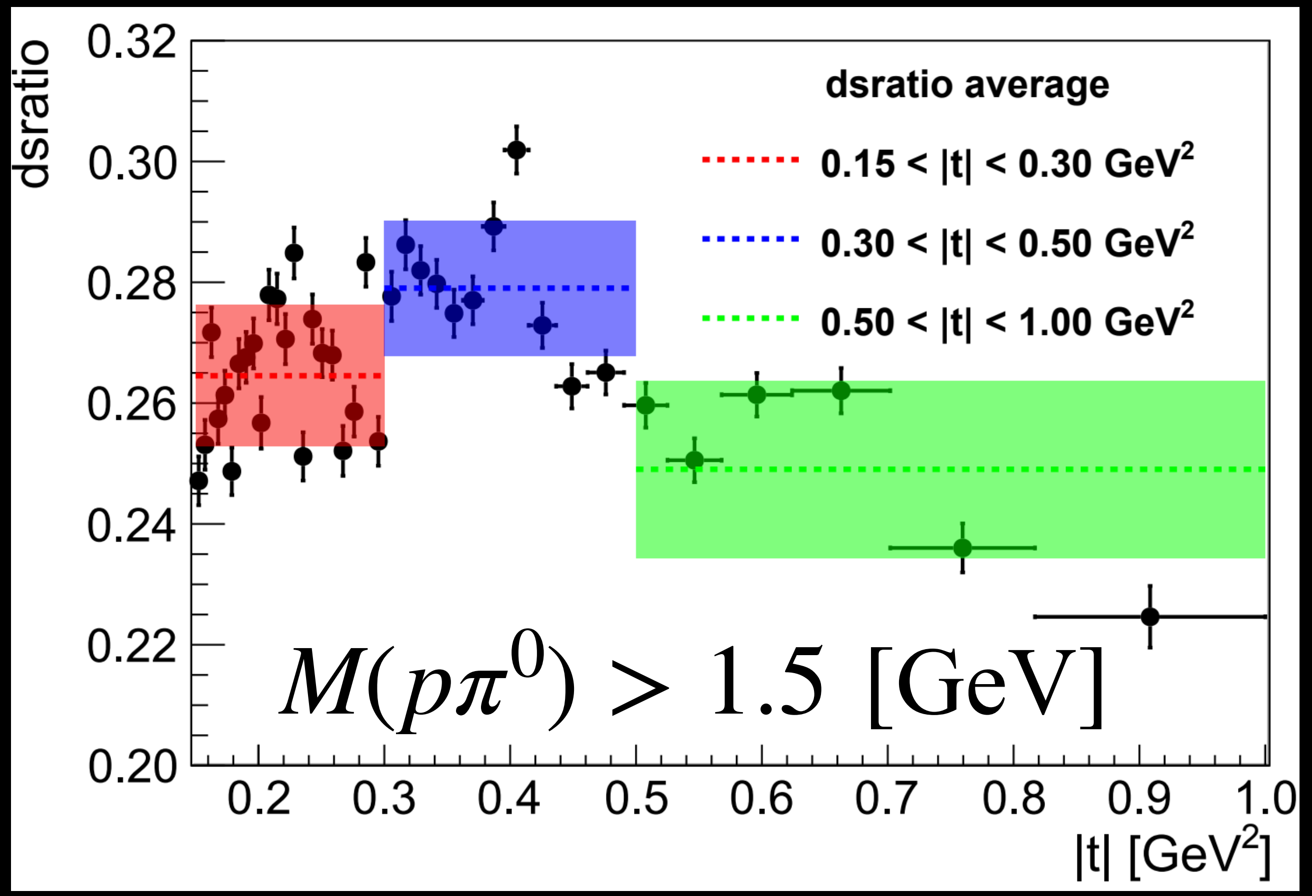
Mass Systematic Variation Study

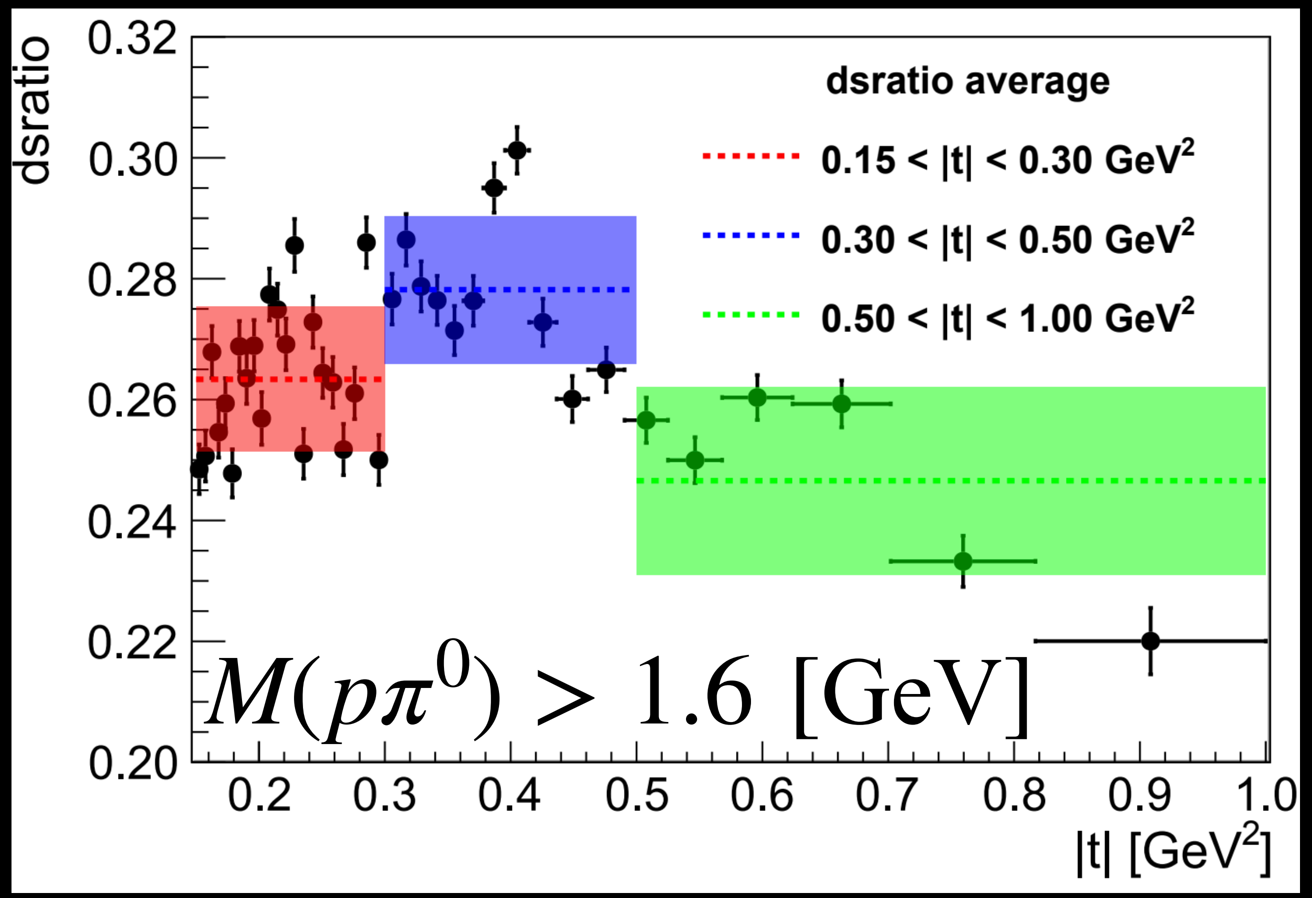
Default

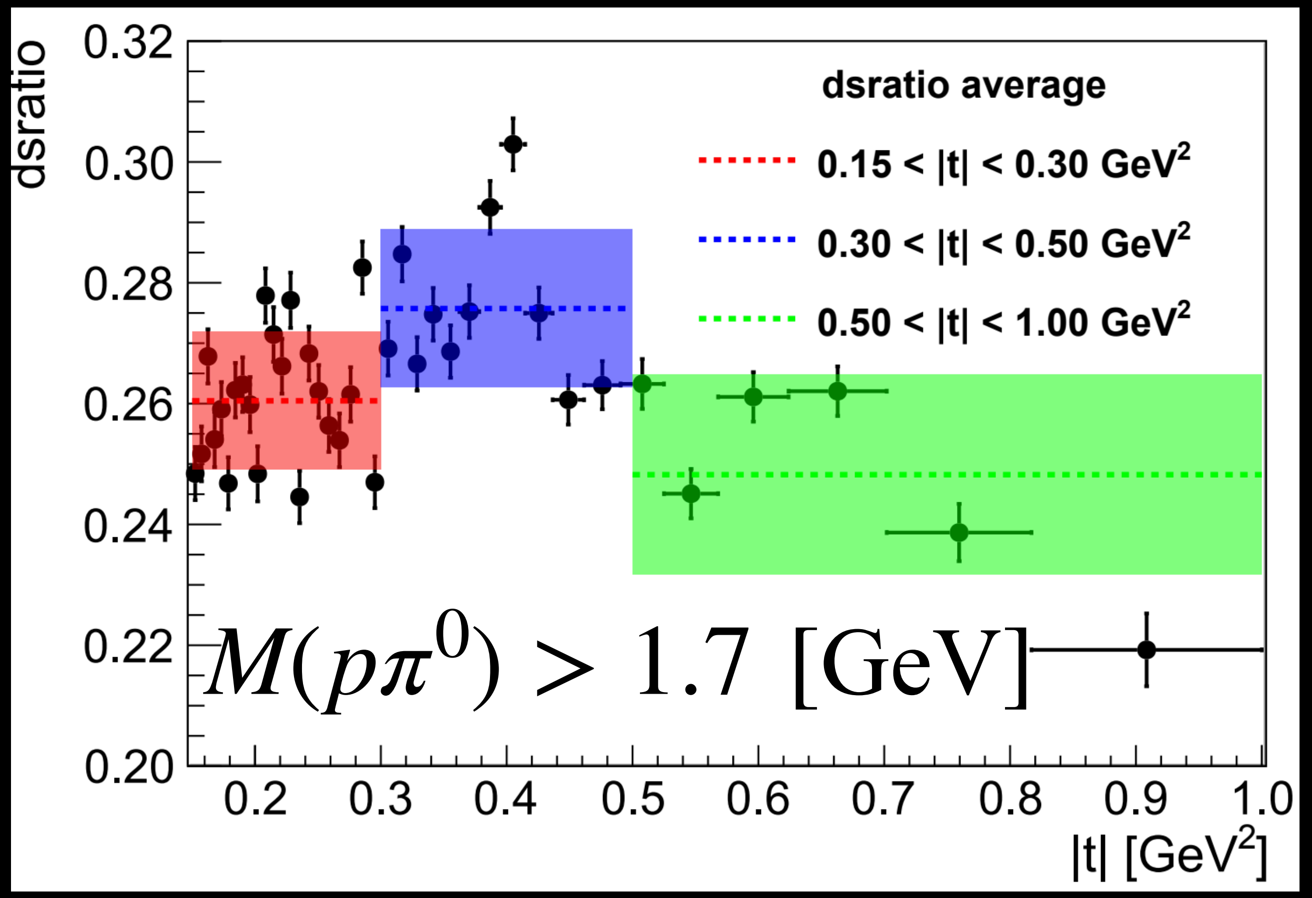
Partial Wave Analysis : Ongoing and Future work

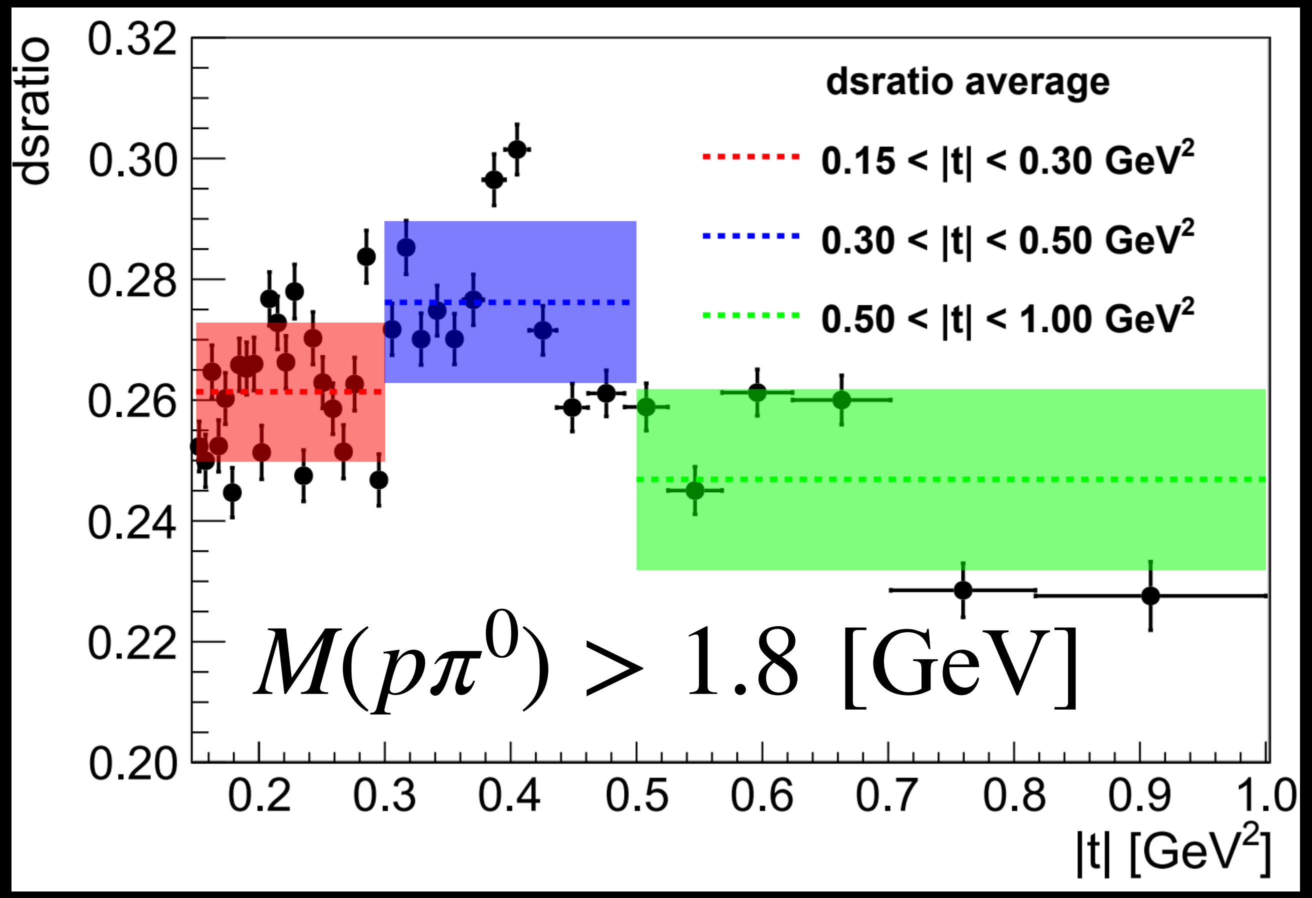
Roadmap for publication

- Analyze the effect of $M(p\pi^0)$ contribution
  - Analyzed various $M(p\pi^0)$ cut
  - Vanhove analysis based cut? — Statistics ↓
- Systematics on Data Selection cuts
  - KinFit CL cut
  - Accidental subtraction
  - 2D-ω side band subtraction
- More rigours model selection
  - Lasso based regularization in cost term
  - Feature importance metric — DataScience
- Independent fits in wide $M(\omega\pi^0)$ range
  - Extract Yield
  - More systematics — Extract cross-section
  - Extract cross section





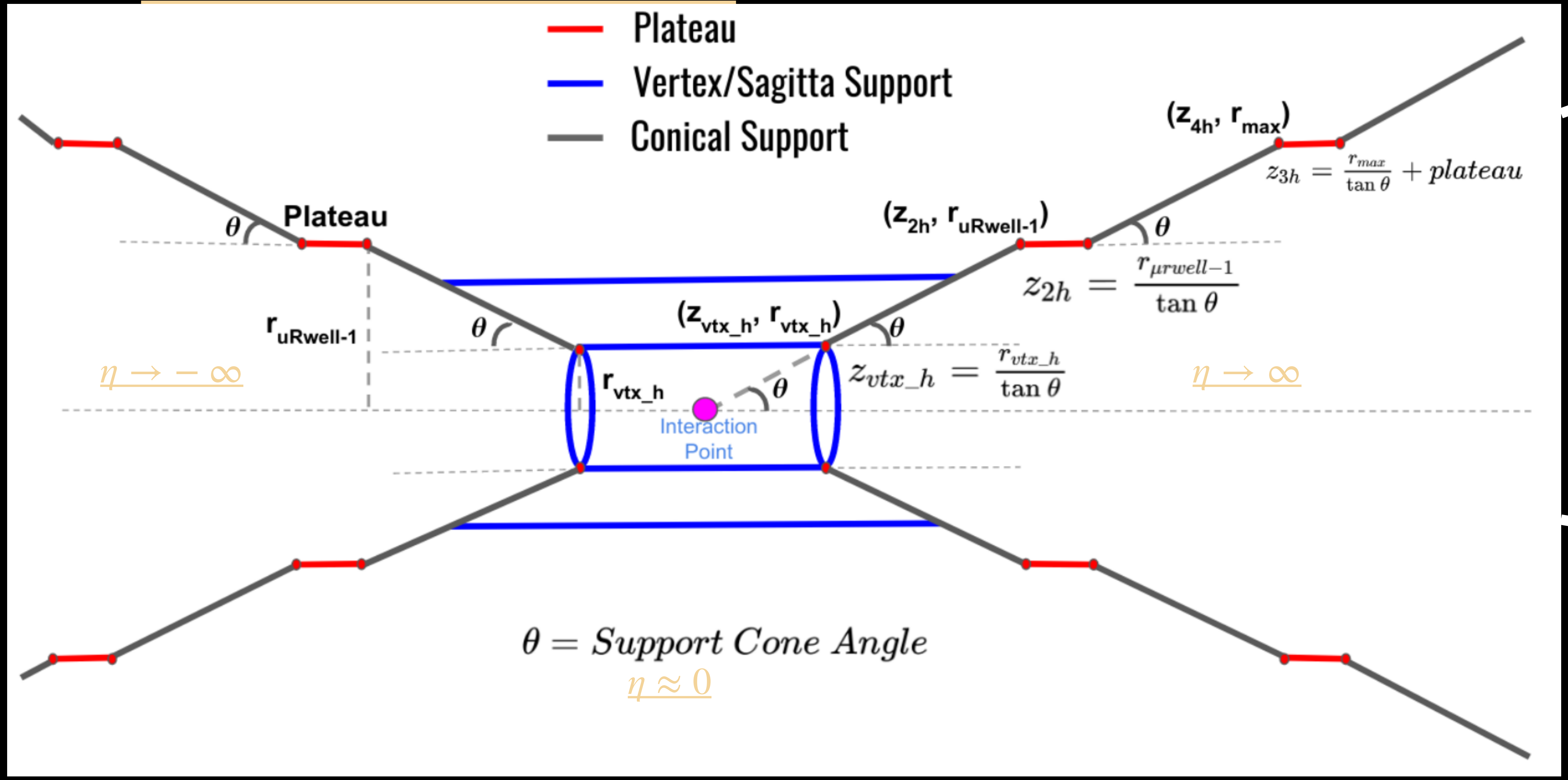




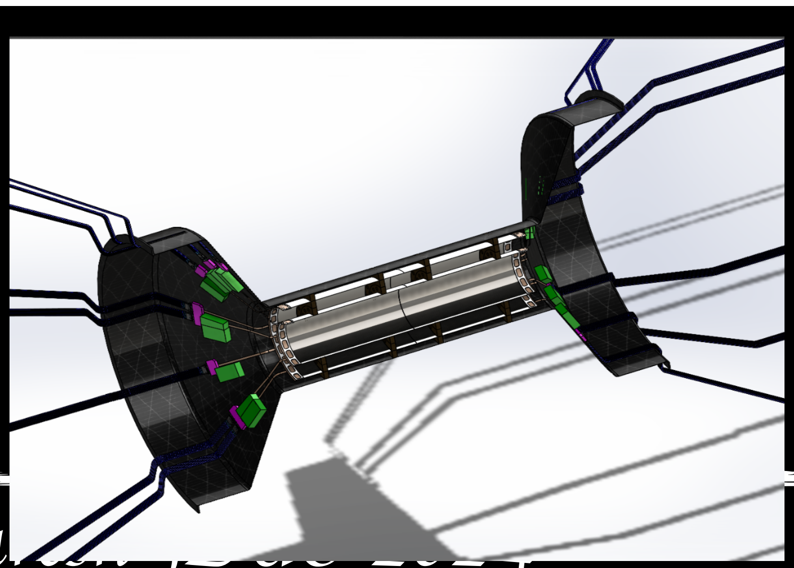
Parametrization

Parametrization is an essential part of an automated optimization:

- explores different designs
- avoids overlaps of volumes
- encodes constraints

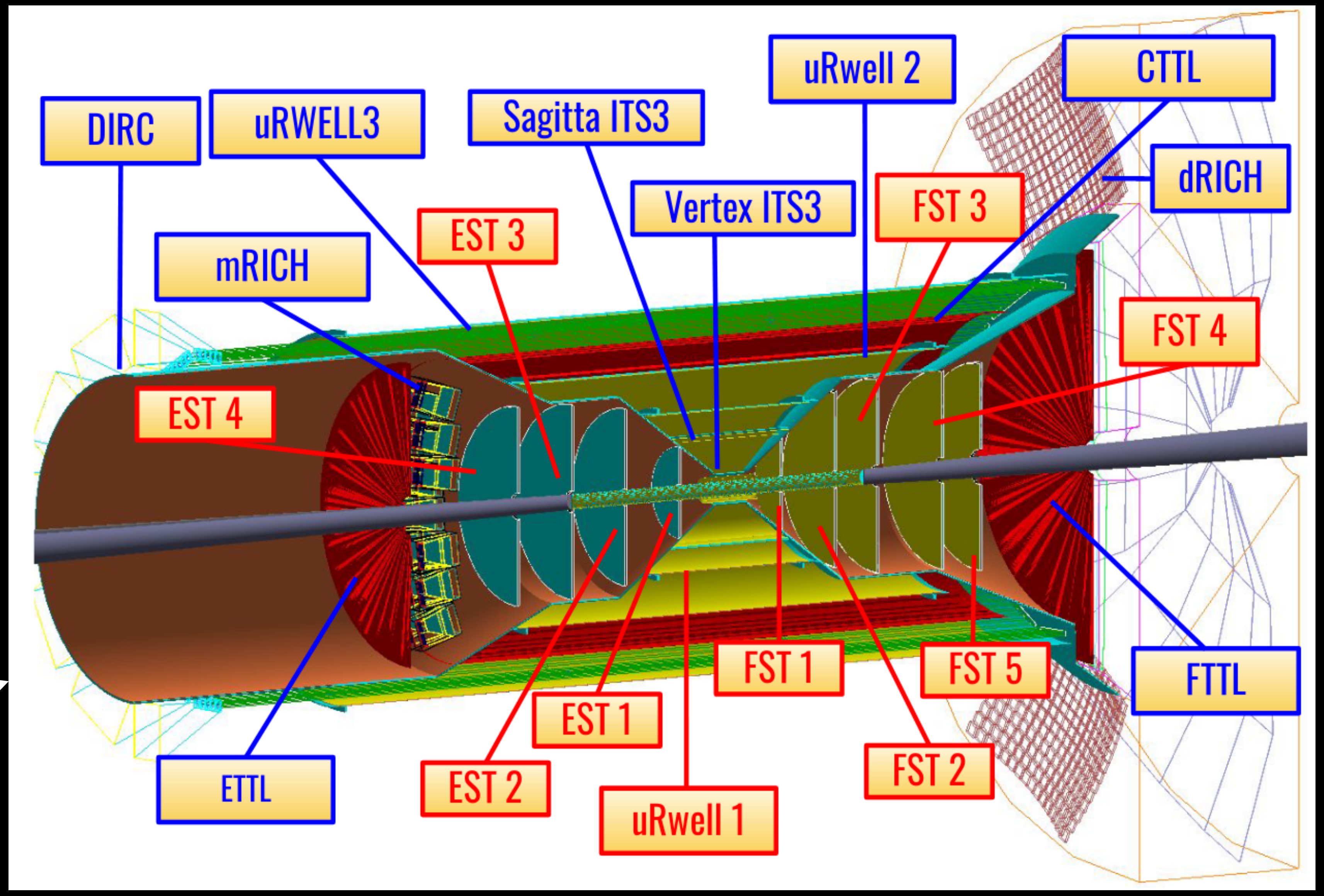


$$\eta \equiv -\ln\left[\tan\left(\frac{\theta}{2}\right)\right]$$

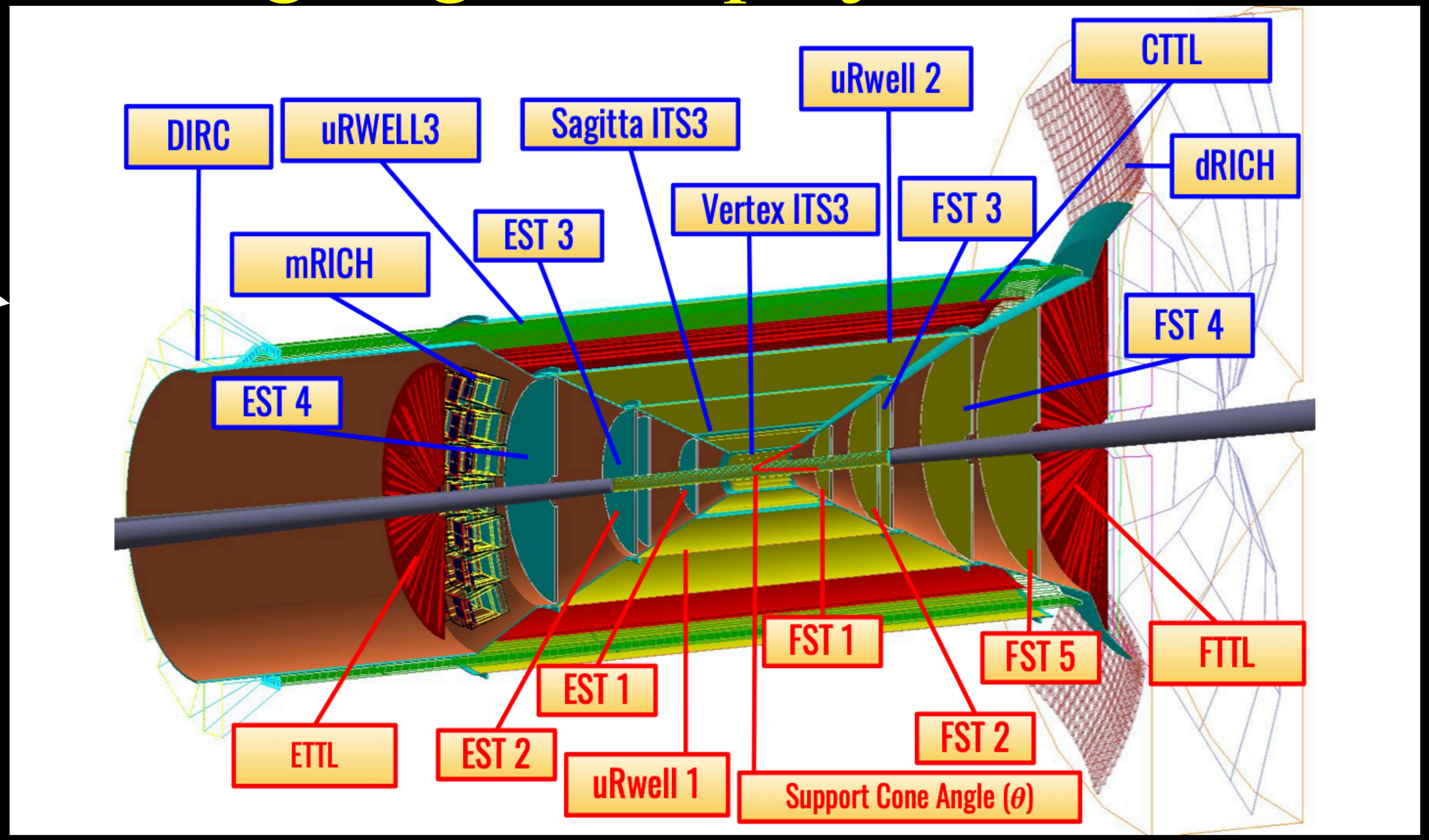


Implementation of support structures with realistic material budgets

Reference design

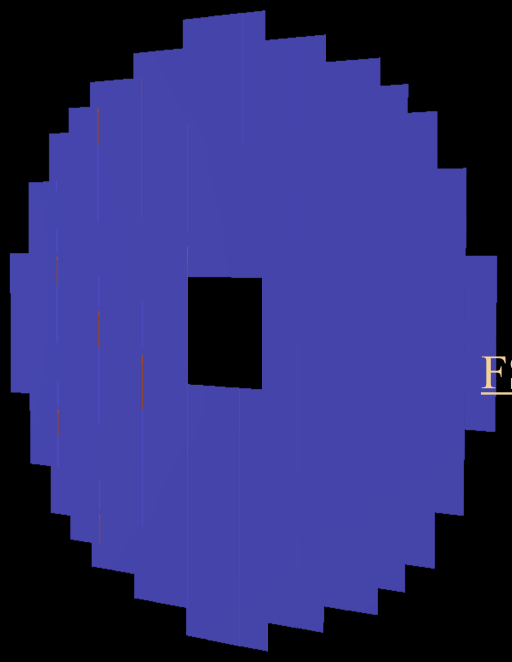


Ongoing R&D projective

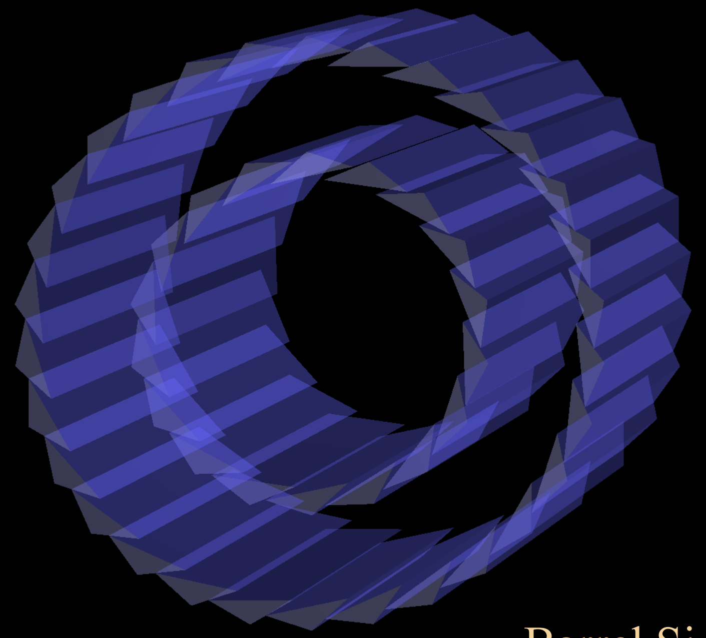


Variable pars; Fixed pars

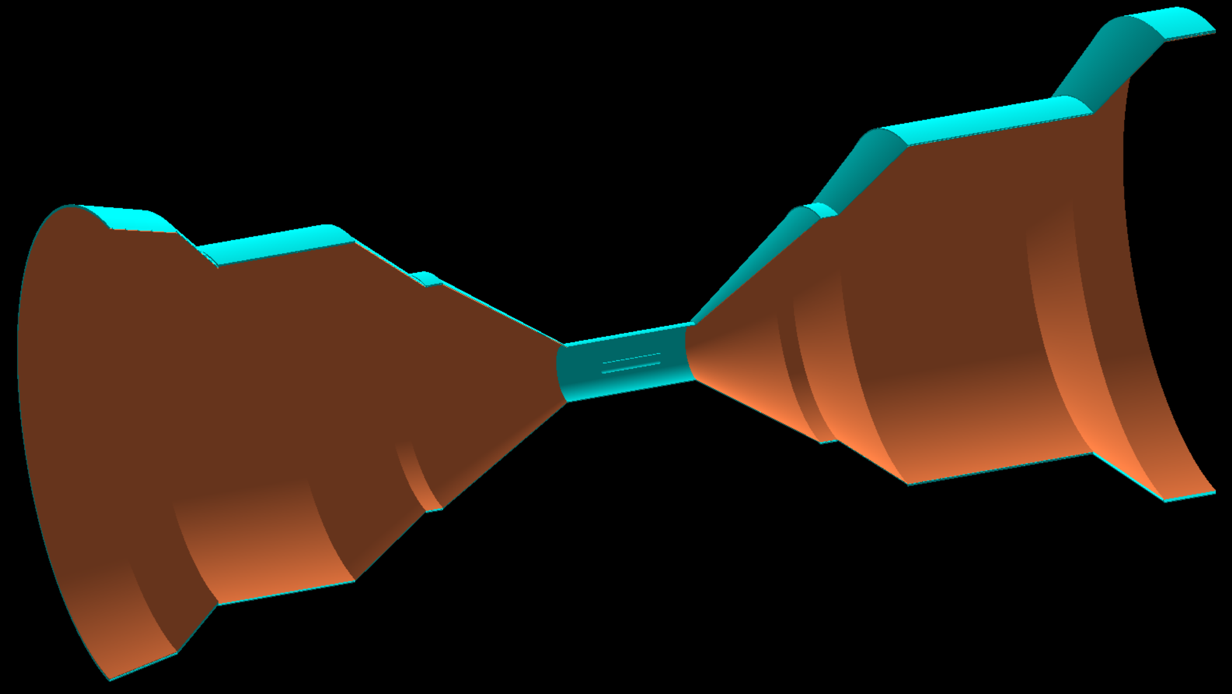
Constraints



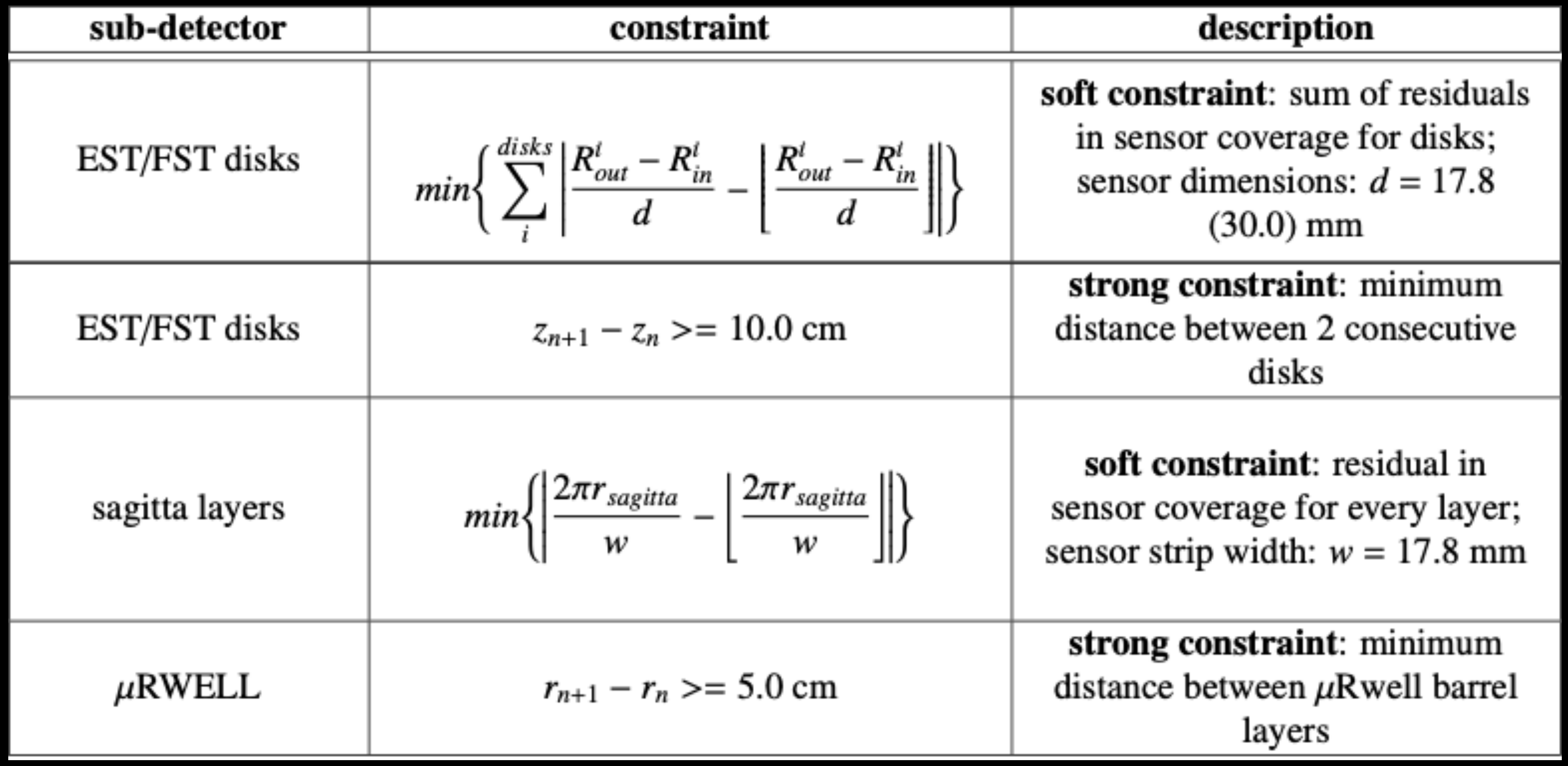
FST/EST Disks



Barrel Si Layer



- **Design Parameters** (O(N) ≈ 10)
  - Based on an extensive parameterization.
- **Constraints** being used (n_const ≥ 3)
  - HARD The minimum distance between 2 disks should be >= 10 cm (giving room for services)
  - SOFT The Rmax-Rmin for the disks have to be multiple of 3.00 cms and 1.8 cms (Tiling of pixels)
- **Overlaps checks**
  - GEANT4 unstable when overlaps are detected in volumes.
  - Overlaps are checked for every design explored and penalized.



sub-detector	constraint	description
EST/FST disks	$min\left\{\sum_{i}^{disks}\left\|\frac{R^{i}_{out}-R^{i}_{in}}{d}-\left\lfloor\frac{R^{i}_{out}-R^{i}_{in}}{d}\right\rfloor\right\|\right\}$	**soft constraint**: sum of residuals in sensor coverage for disks; sensor dimensions: d = 17.8 (30.0) mm
EST/FST disks	$z_{n+1}-z_n$ >= 10.0 cm	**strong constraint**: minimum distance between 2 consecutive disks
sagitta layers	$min\left\{\left\|\frac{2\pi r_{sagitta}}{w}-\left\lfloor\frac{2\pi r_{sagitta}}{w}\right\rfloor\right\|\right\}$	**soft constraint**: residual in sensor coverage for every layer; sensor strip width: w = 17.8 mm
μRWELL	$r_{n+1}-r_n$ >= 5.0 cm	**strong constraint**: minimum distance between μRwell barrel layers

Extensive details at arXiv:2205.09185

Implementing Objectives

- Objective functions Average of Weighted Averages (n_obj ≥ 2)
    - Momentum resolution dp/p
    - Theta resolution dθ/θ
    - Projected dθ/θ at PID location.
    - Kalman Filtering inefficiency (improving the tracking reconstruction ability of the algorithm)

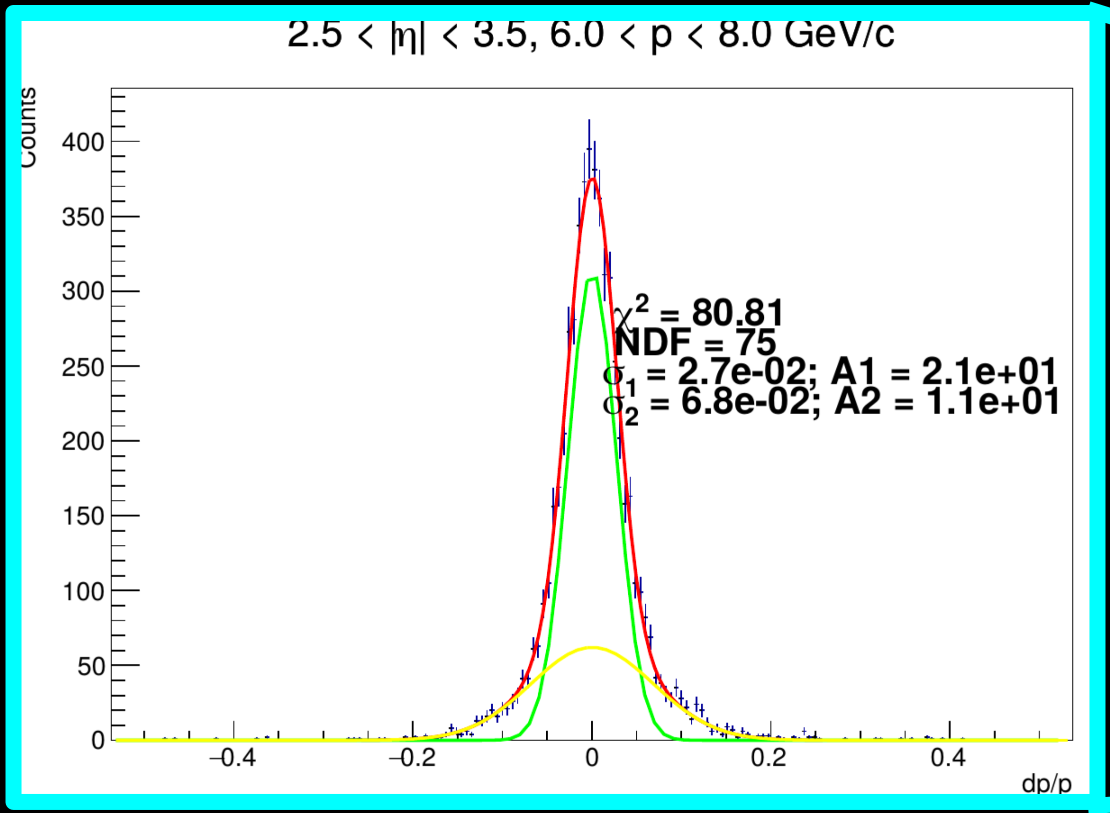
- Validation of the solutions
    - Validate by comparing optimal vs baseline dφ resolution, vertex resolution and reconstruction efficiency

Implementing Objectives

Weighted sum with errors along η

Robust fitting procedure in fine-grained phase-space

Propagate uncertainties in fits throughout

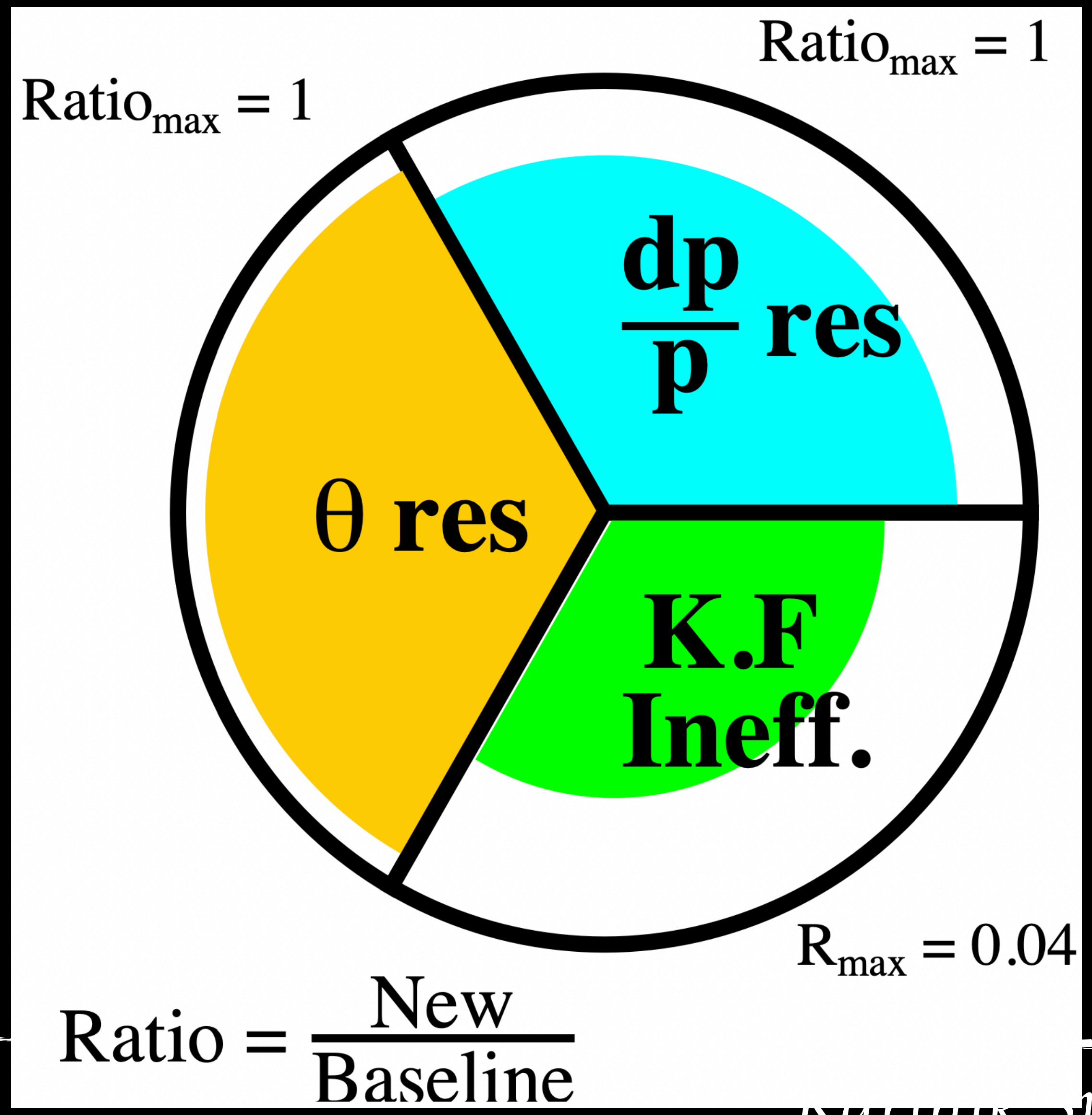


Weighted sum with errors along η

$$\bar{x}_\eta = \frac{\Sigma_p x_p w_p}{\Sigma_p w_p}$$

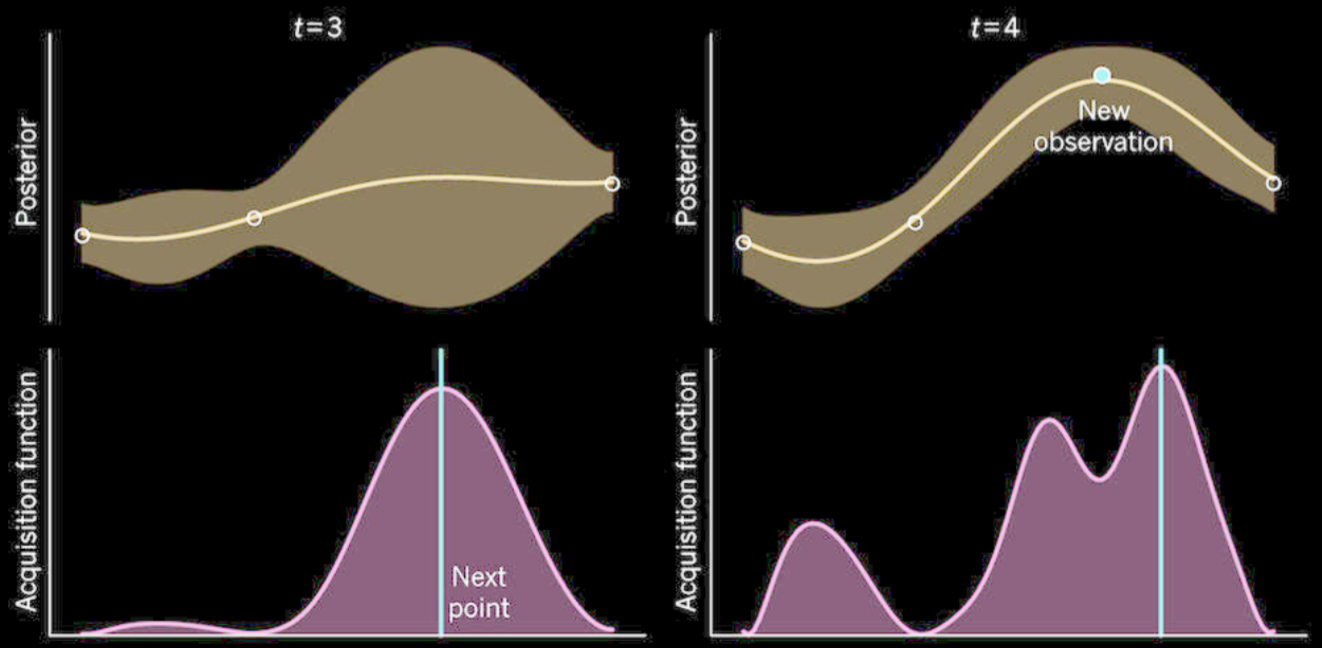
Avg in a η bin

$$\bar{x} = \frac{\Sigma_\eta^{N_\eta} \bar{x}_\eta}{N_\eta}$$



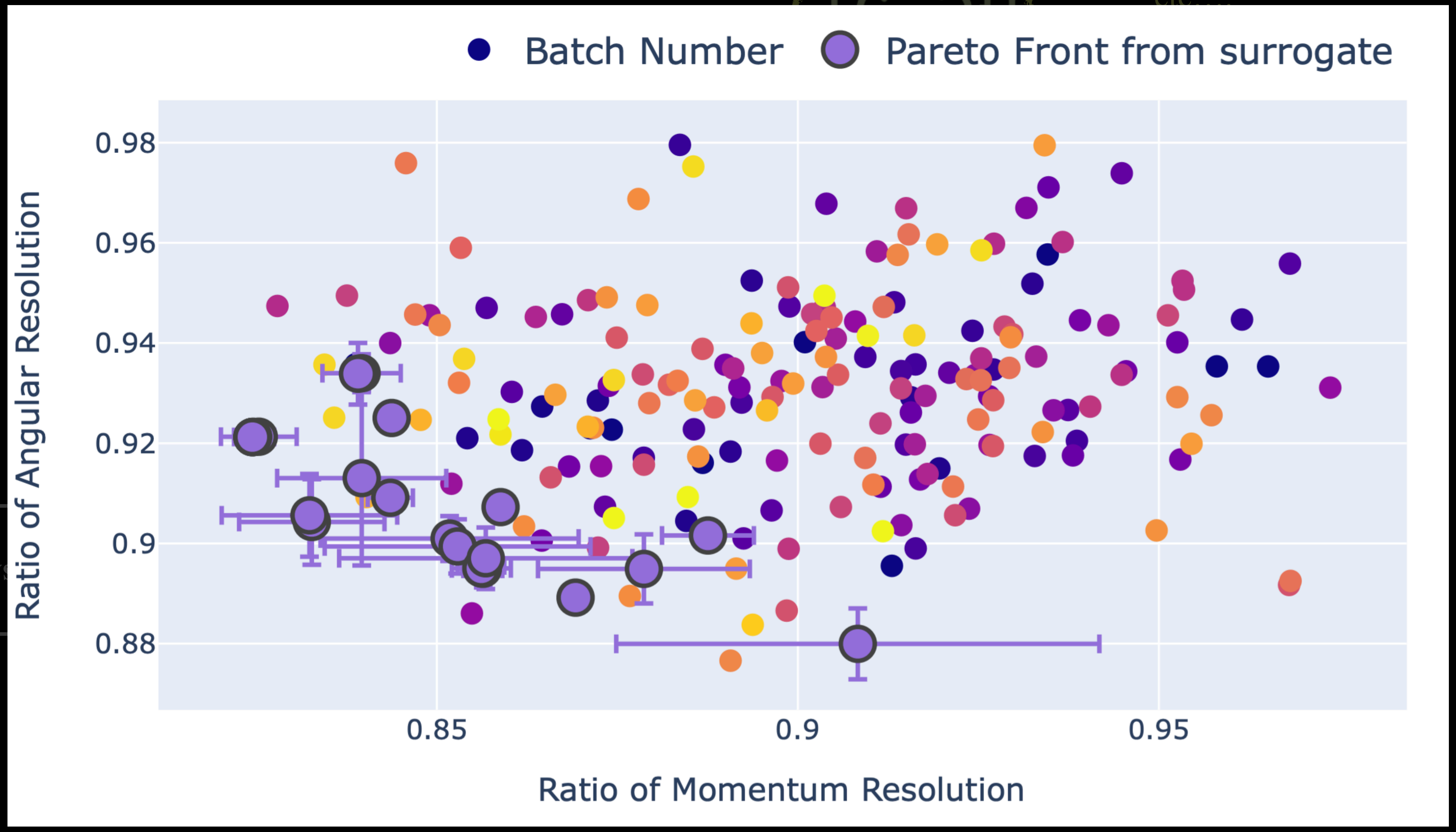
$$\text{Ratio} = \frac{\text{New}}{\text{Baseline}}$$

AI assisted Detector design



- **Ax - BoTorch**
  - Apt when evaluations of objectives are costly. Typical for the problem in hand.
  - Builds surrogate models that maps objective space to design parameter space.
  - Uses novel qNEHVI acq. function with reduced computational complexity arxiv:2105.08195.

- **Implementation**
  - 1 Level Parallelization (≈ 120cores)
  - N_objectives = 2
  - BATCH_SIZE - 3 (q)
  - N_BATCH - 50
  - $^{\eta \approx 0}$ qNEHVI + SAASBO



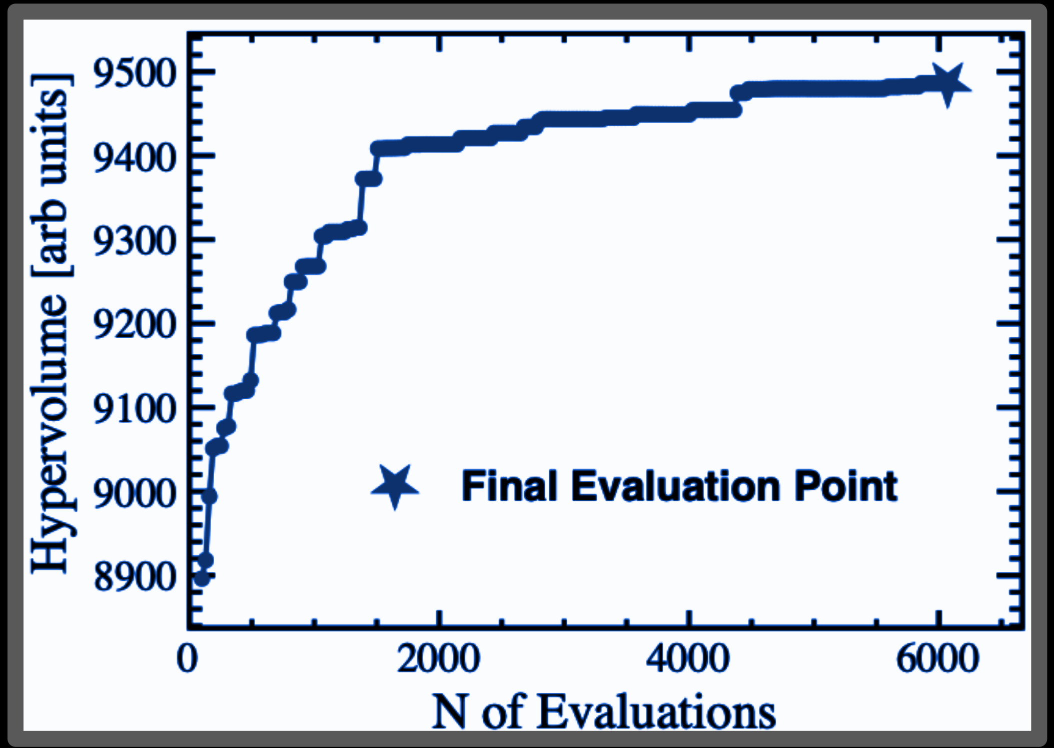
Interactive Visualization of the result

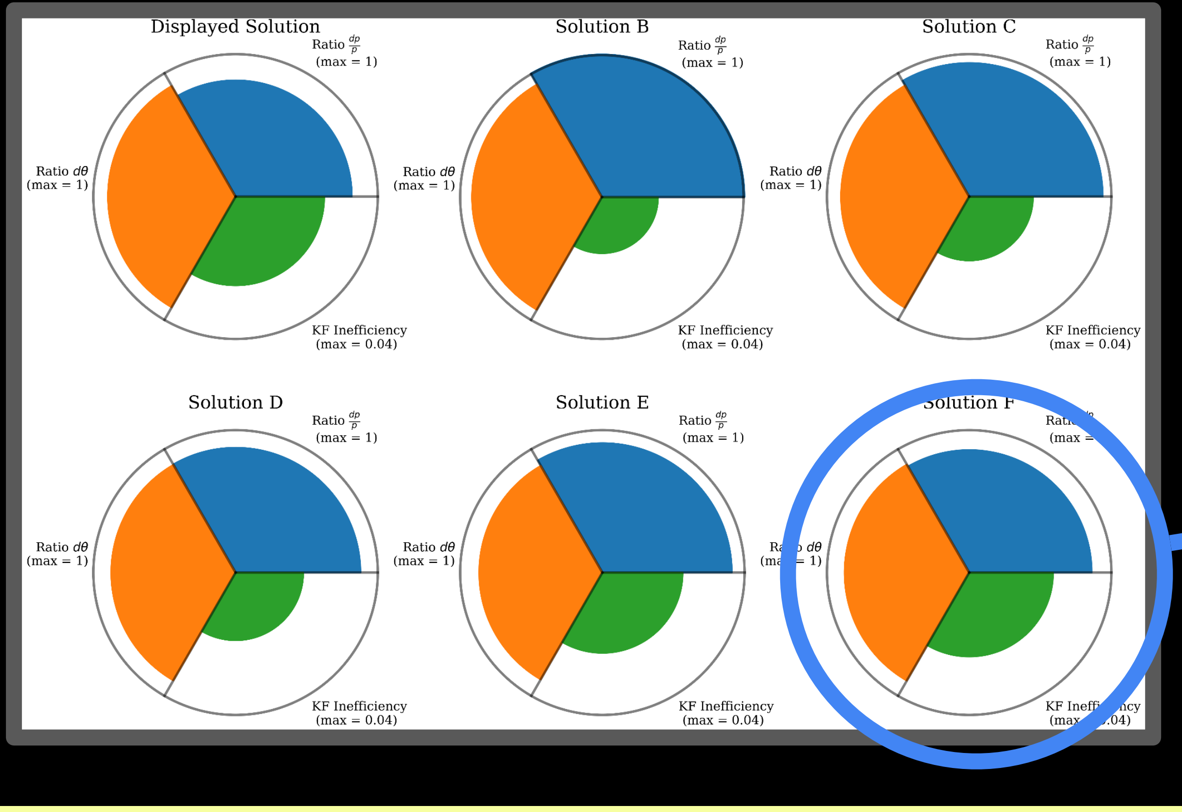
Analyzing results

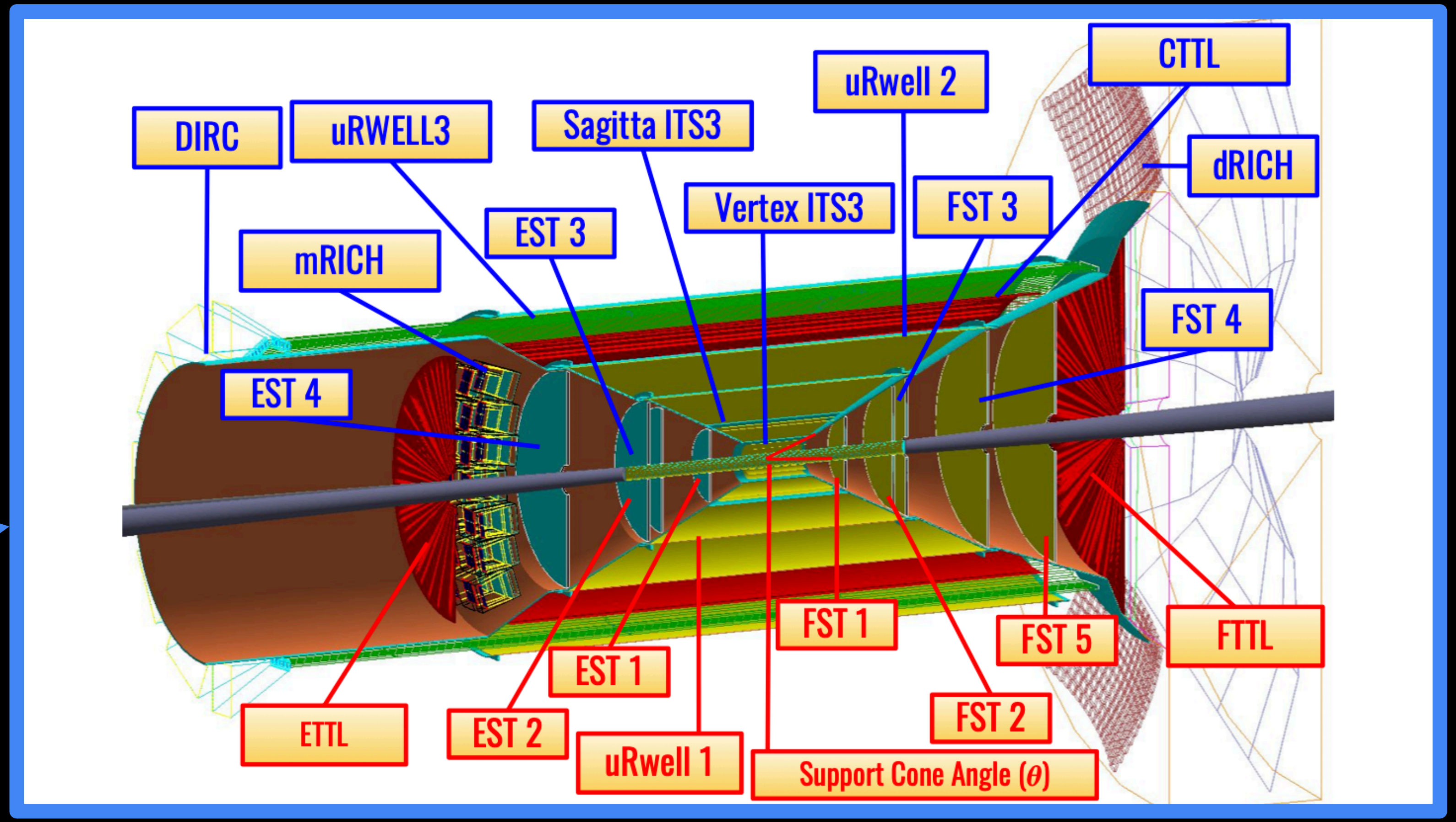
1 Can take a snapshot any time during evaluation

2 Updated Pareto Front at time t

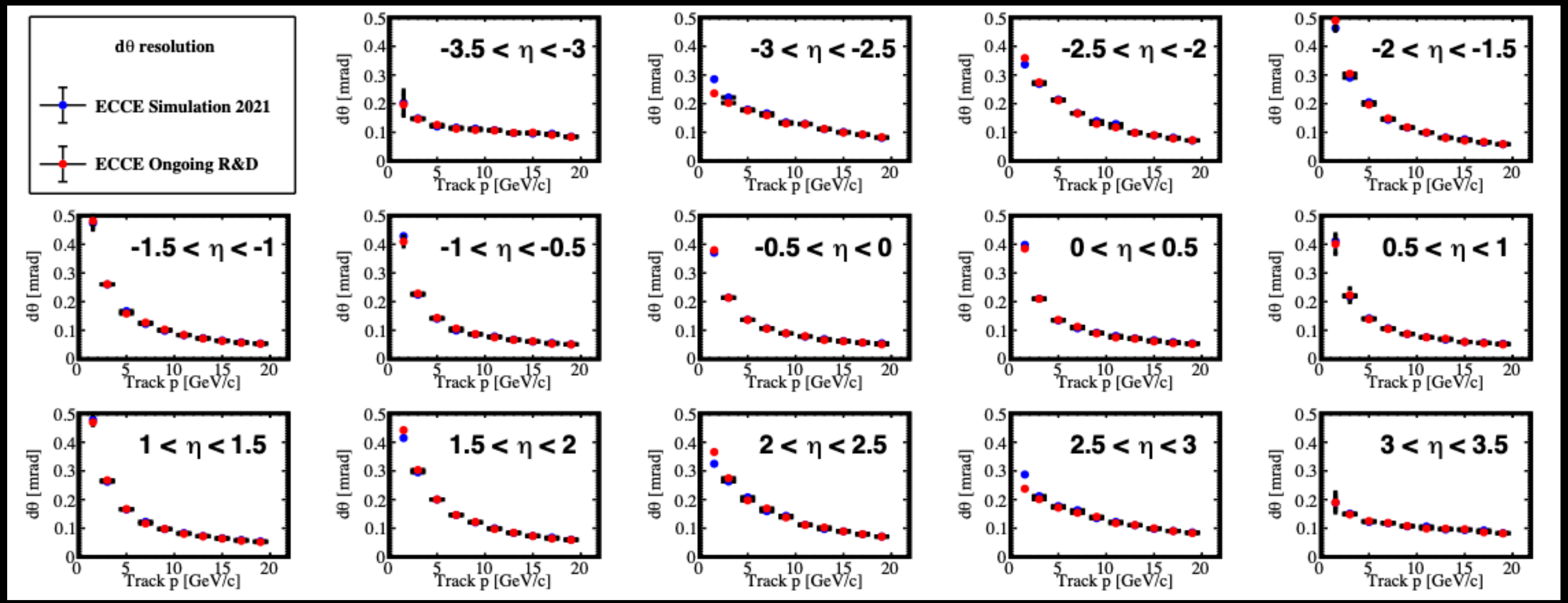
3 Each point is a design

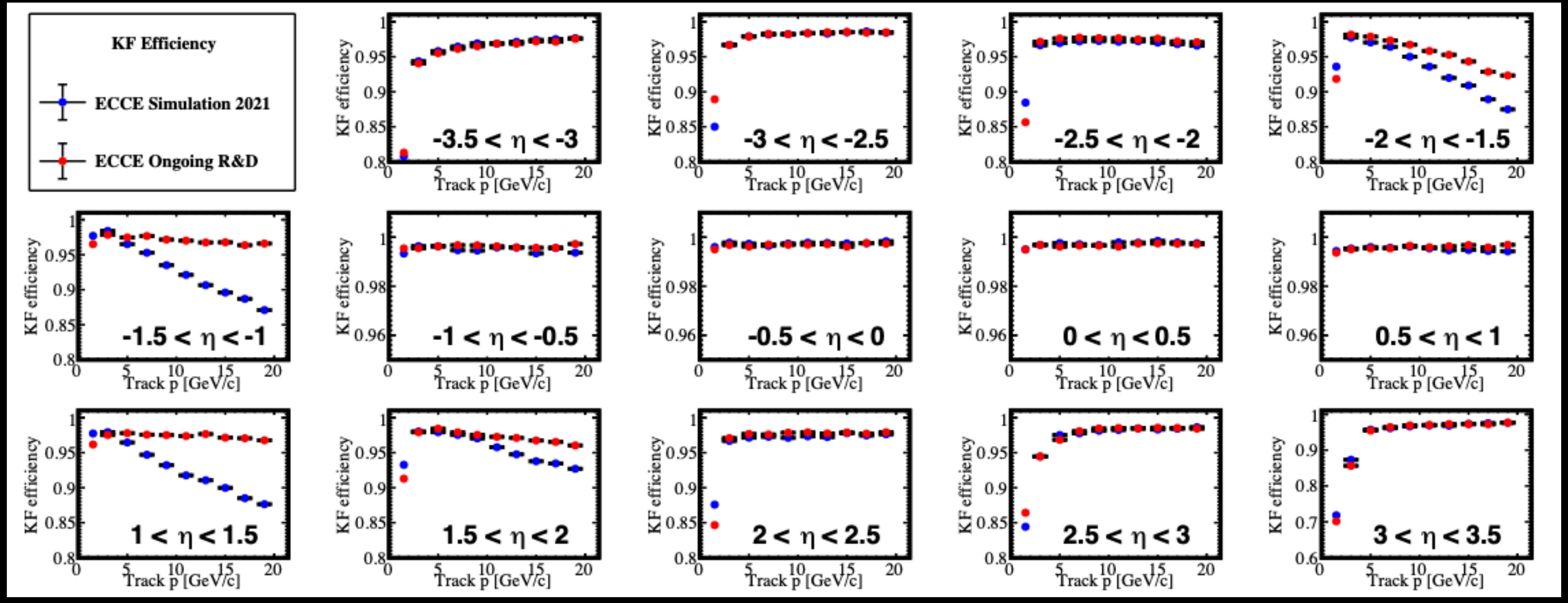






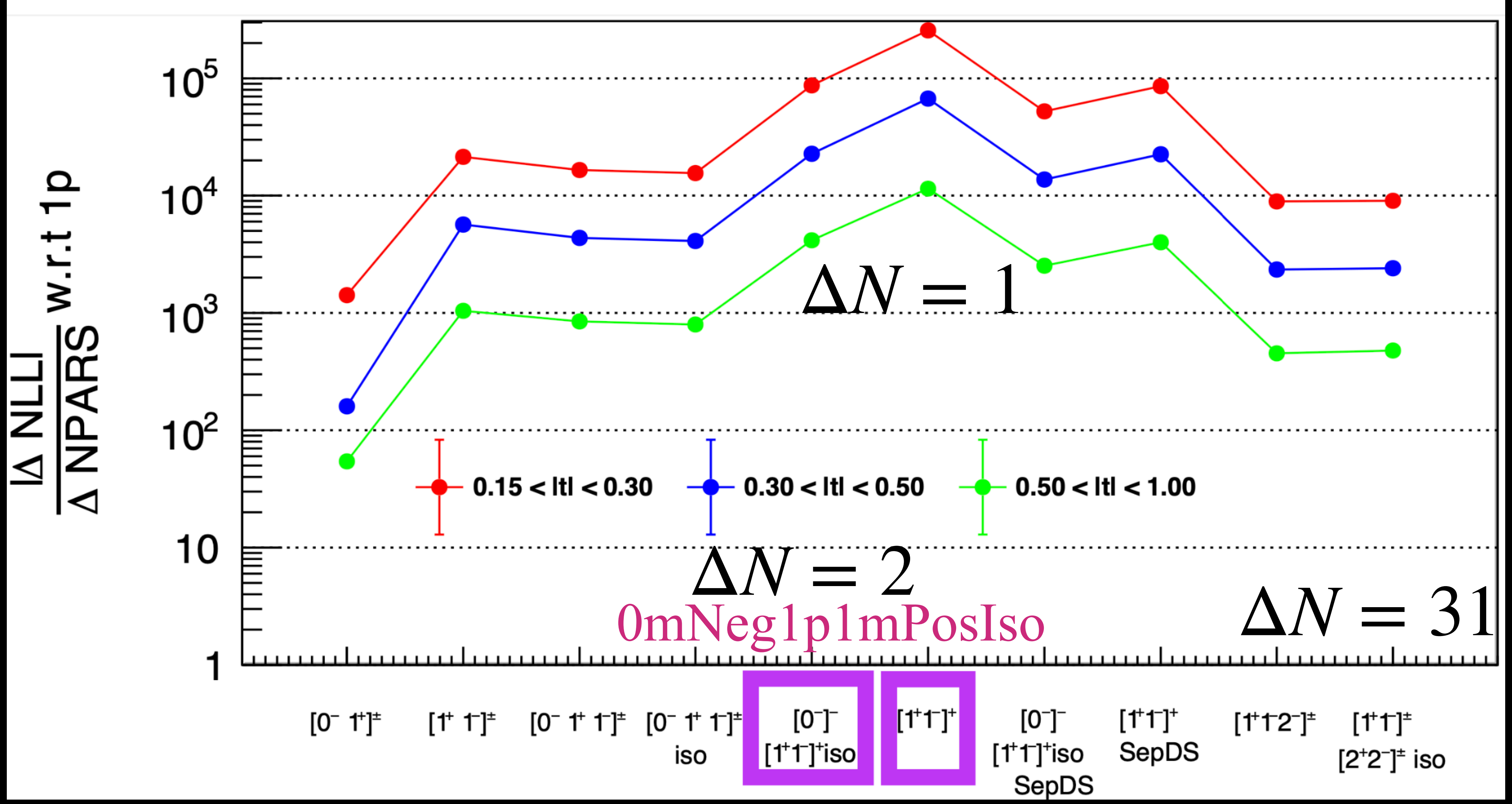
4 Analysis of Objectives (momentum resolution, angular resolution, KF Efficiency)





Partial Wave Analysis

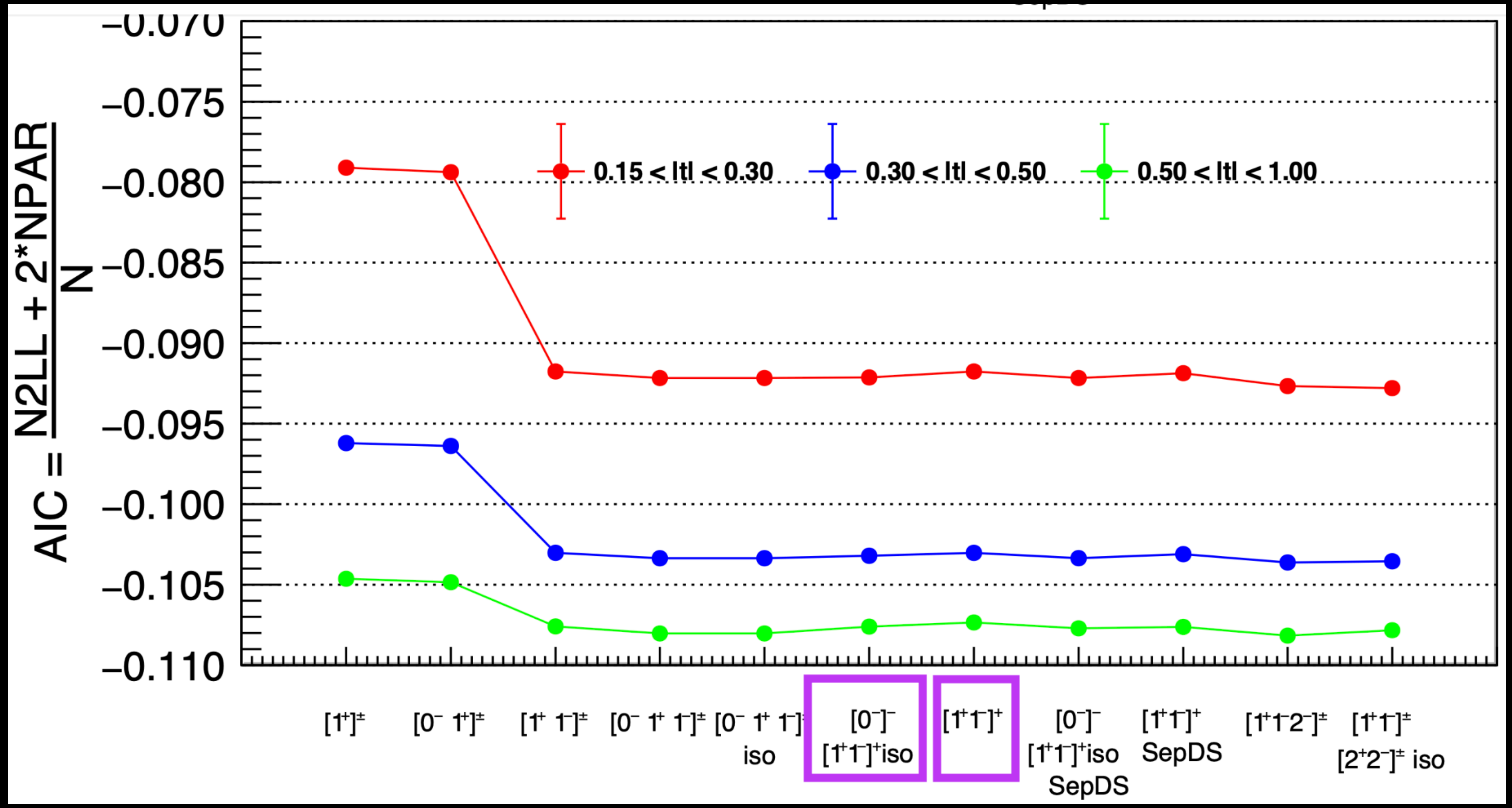
Lets get to Fitting: How to best choose a waveset ?

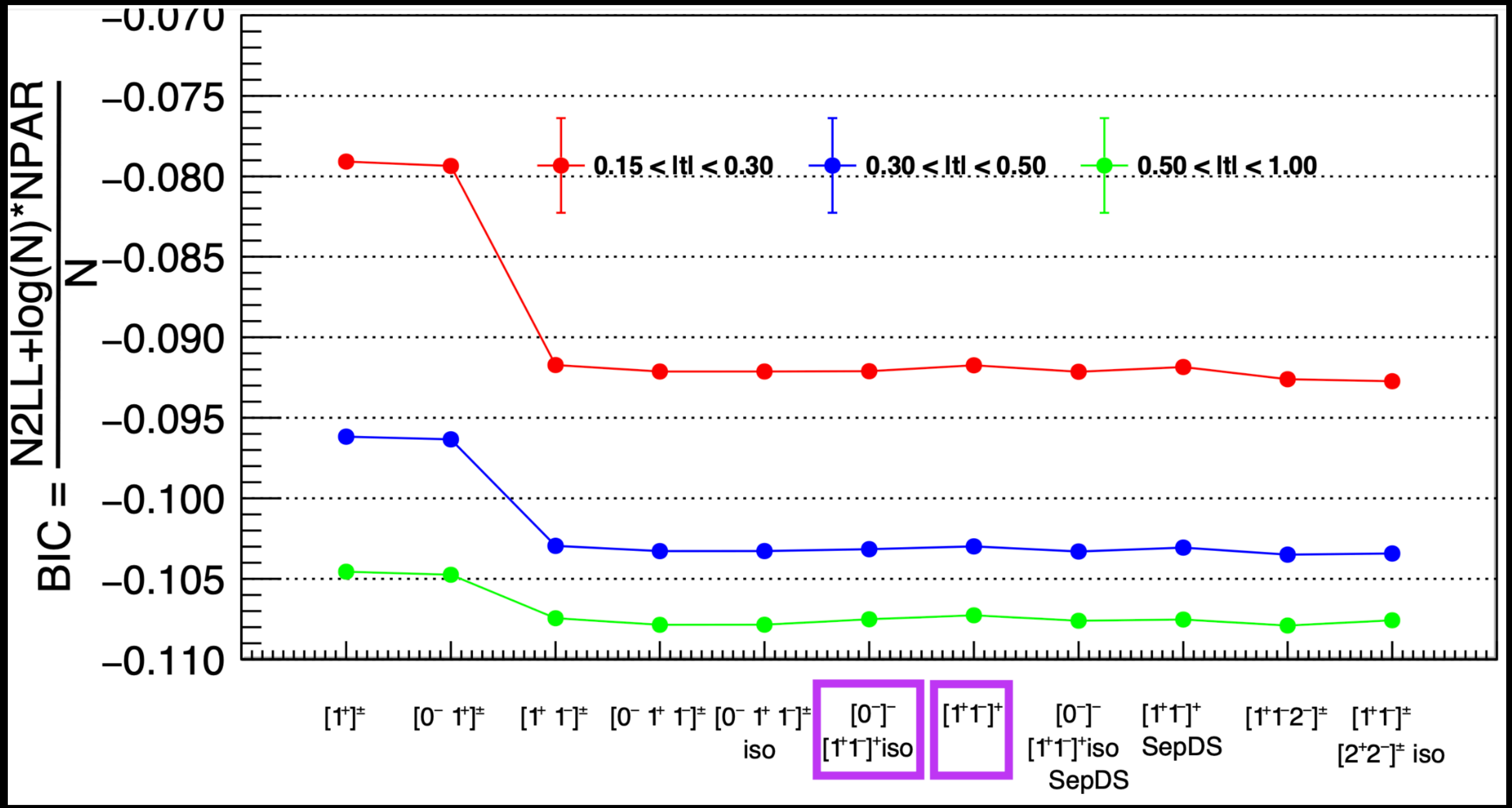


1p1mPos

Best Model for GlueX Phase-I Data :

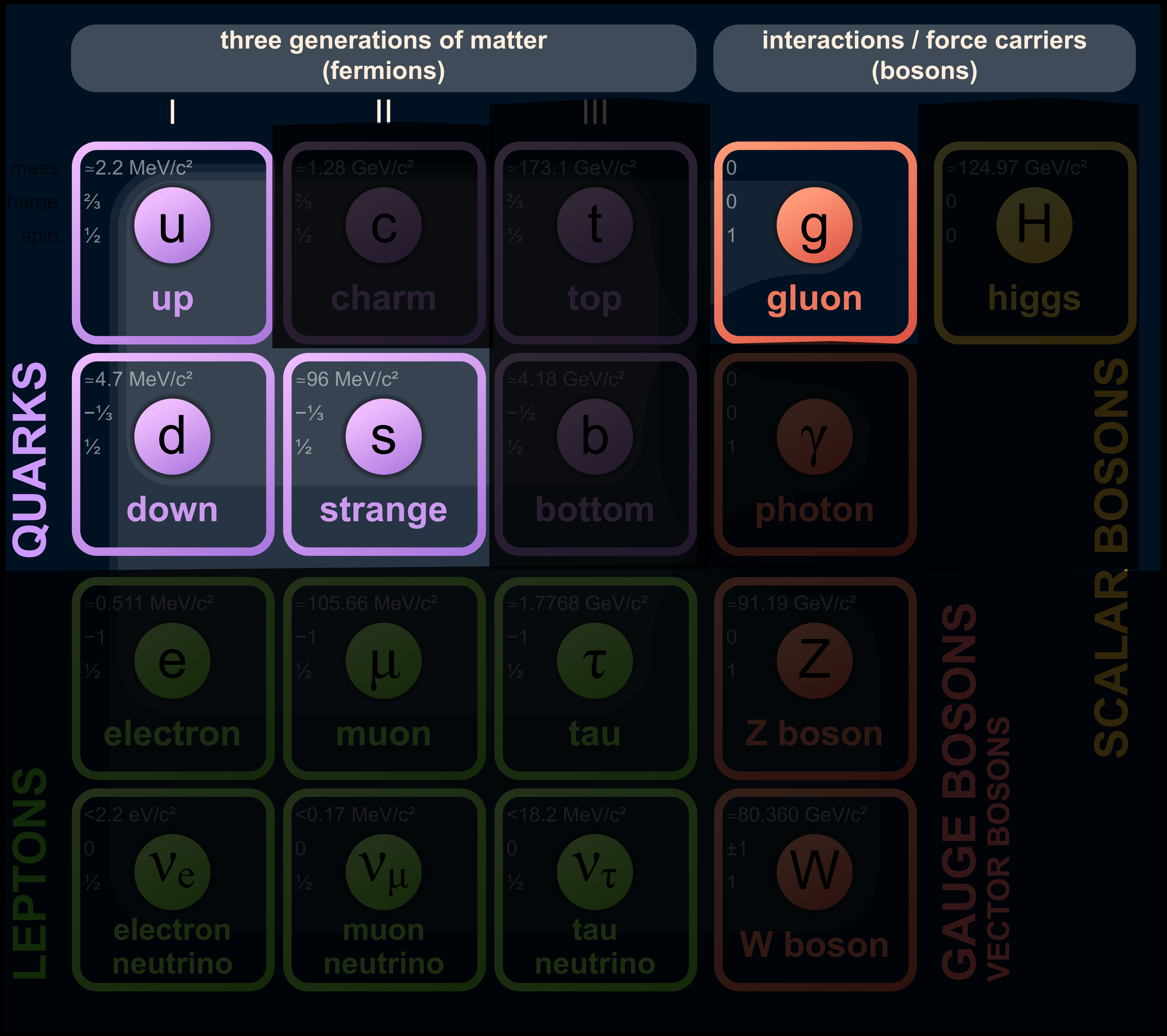
$J^P = ([1^+]^+, [1^-]^+)$ — **Benchmark dsratio**



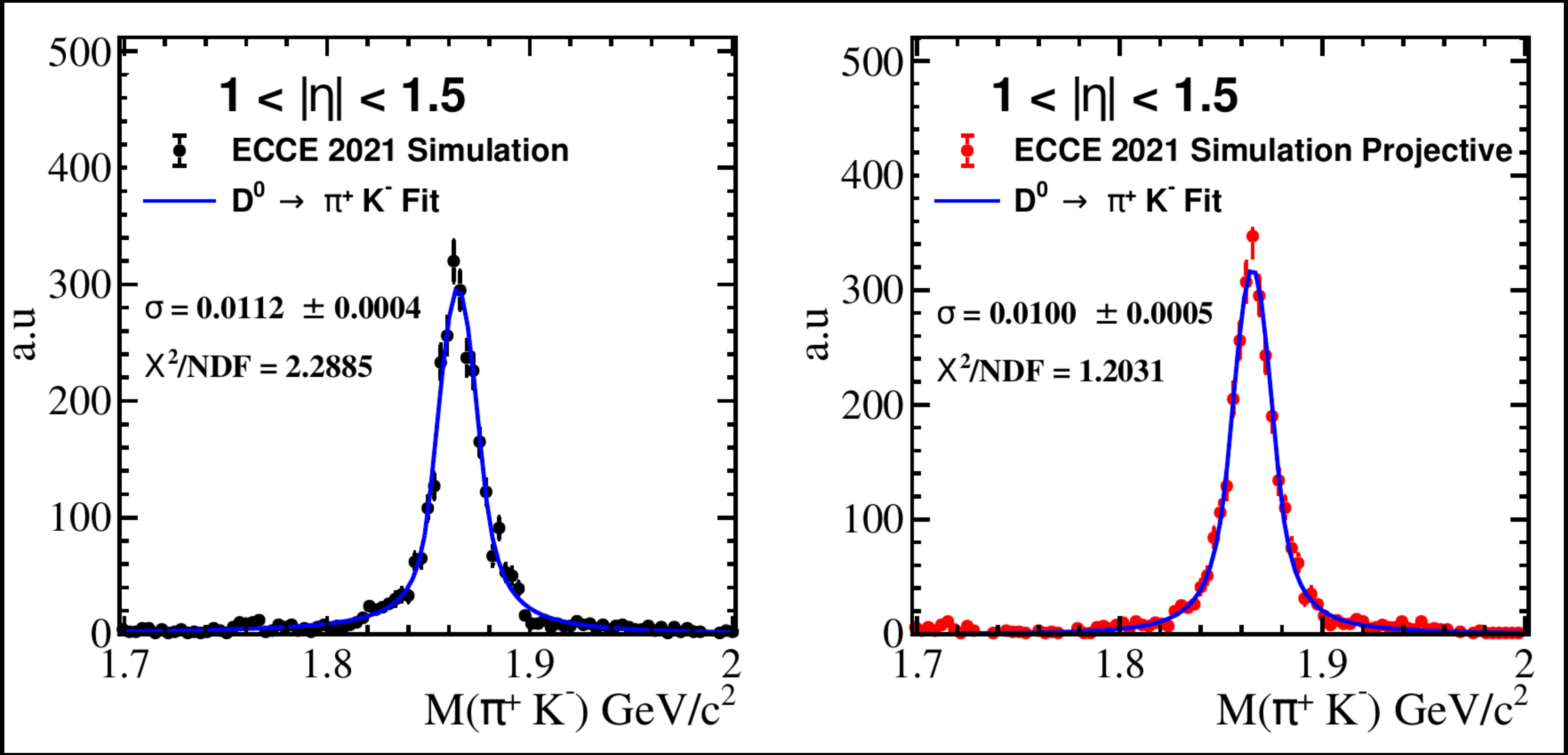


The Standard Model of Physics

This talk focuses on
Light Hadron Spectroscopy



Post-hoc validation on physics observables



The π^+K^- invariant mass obtained from the SIDIS events with updated baseline and optimized projective geometry. A region of eta that is sensitive due to considerable materials for support structure was also taken in to account for this optimization.