

# Spin Transfer to $\Lambda$ Hyperons at CLAS12

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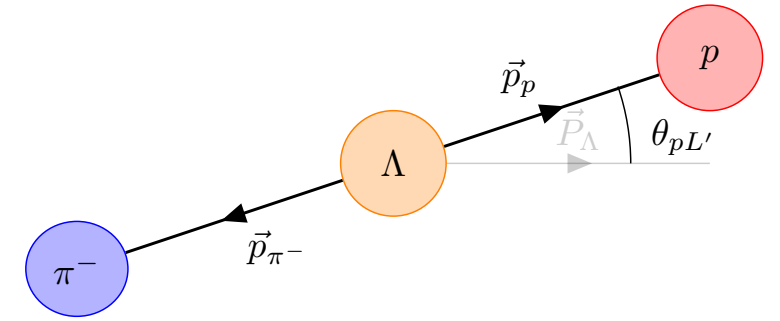
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# Longitudinal Spin Transfer

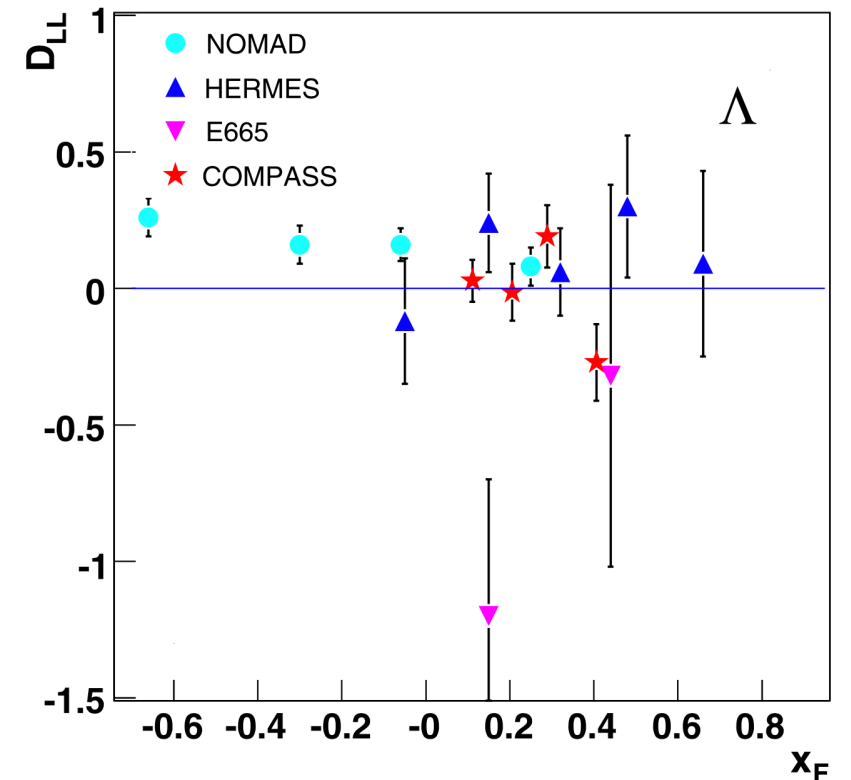
- $\Lambda$  polarization is easily accessible from the  $\Lambda \rightarrow p\pi^-$  channel:

$$\frac{dN}{d\Omega_p} \propto 1 + \alpha P_b D(y) D_{LL'}^\Lambda \cos \theta_{pL'}$$

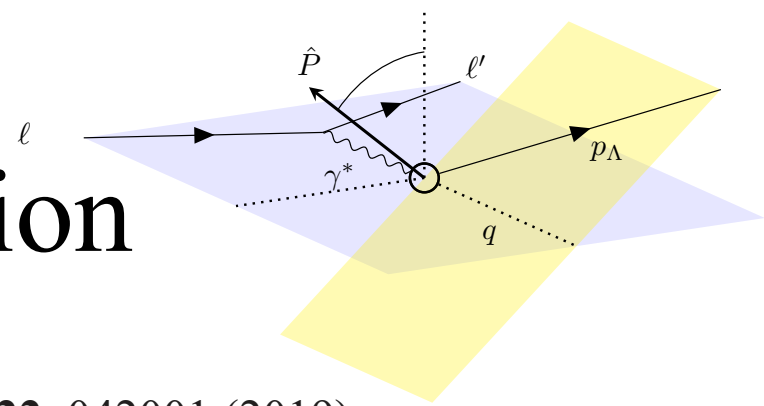
- $D_{LL'}^\Lambda$  describes probability for a quark to transfer its polarization to the  $\Lambda$
- Related to helicity FF  $G_1^\Lambda$



Eur. Phys. J. C (2009) **64**: 171–179



# Spontaneous Transverse Polarization



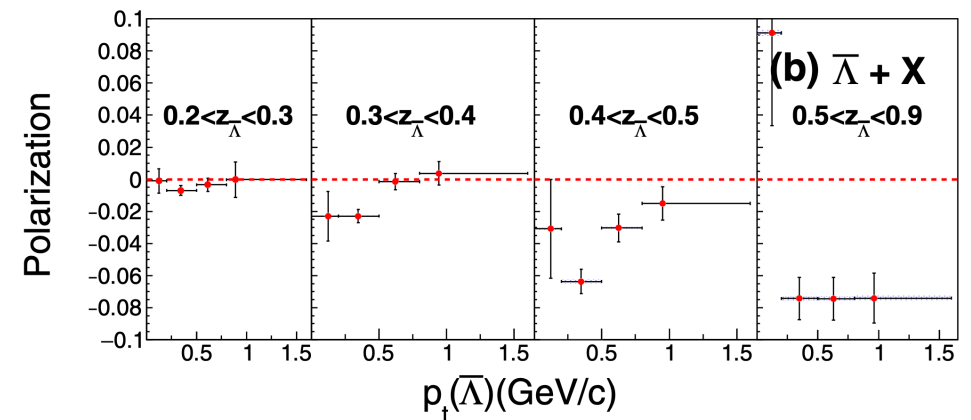
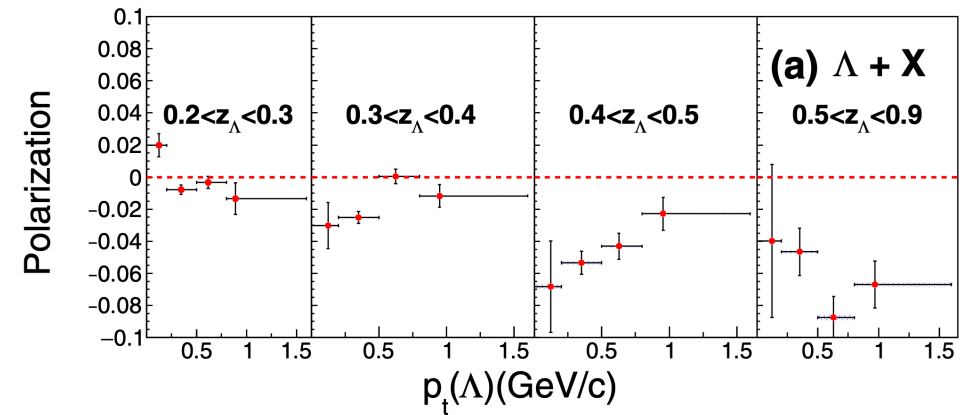
- Large transverse polarization of  $\Lambda$  observed in unpolarized proton collisions

$$\frac{dN}{d\Omega_p} \propto 1 + \alpha P_T^\Lambda \cos \theta_{pL'}$$

- Transverse polarization is related to FF  $D_{1T}^{\perp\Lambda}$ , see Isabella Garzia's talk
- Process-dependent sign is an important test of QCD gauge structure

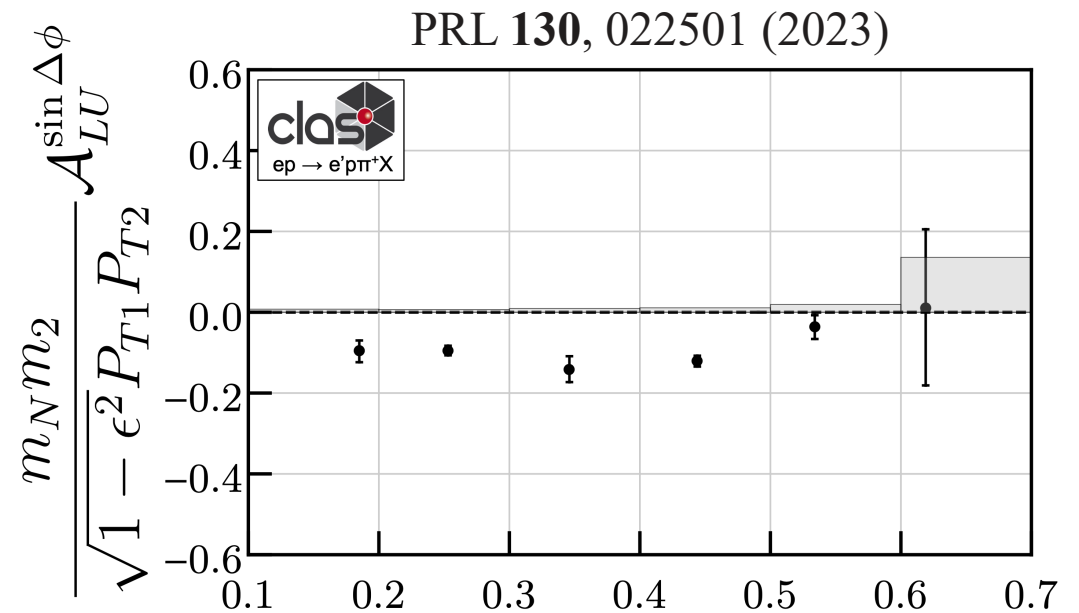
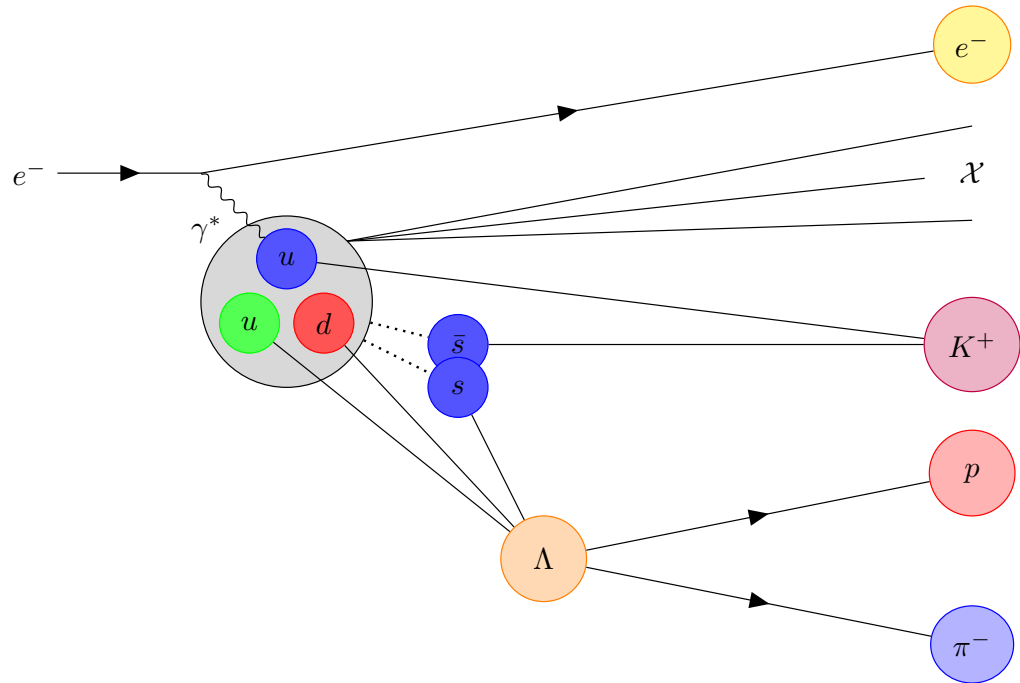
$$D_{1T}^{\perp SIDIS} = D_{1T}^{\perp e^+e^-} = -D_{1T}^{\perp DY}$$

PRL 122, 042001 (2019)



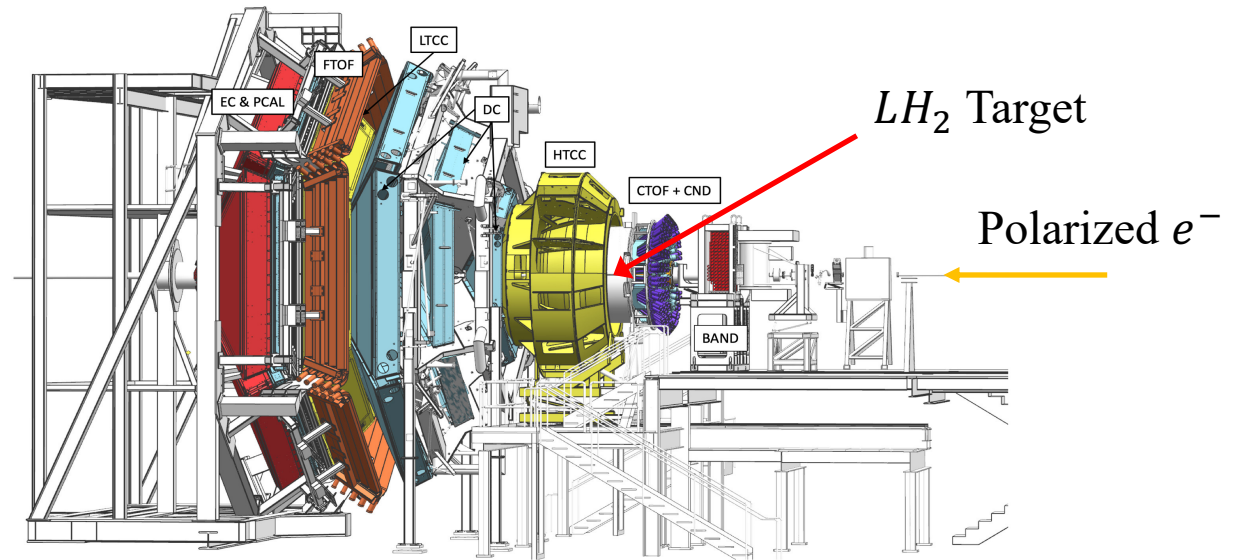
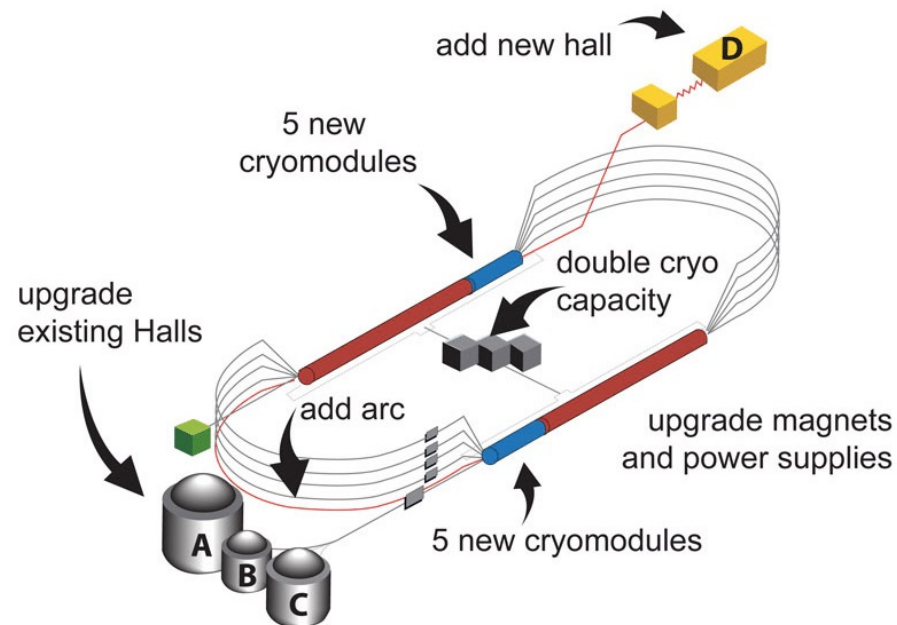
# Target Fragmentation Region (TFR) $\Lambda$ s

- Correlations arise due to momentum, spin conservation between a produced  $q\bar{q}$  pair
- Provide a means to study the hadronization process in the TFR



# CLAS12 Experiment at JLab

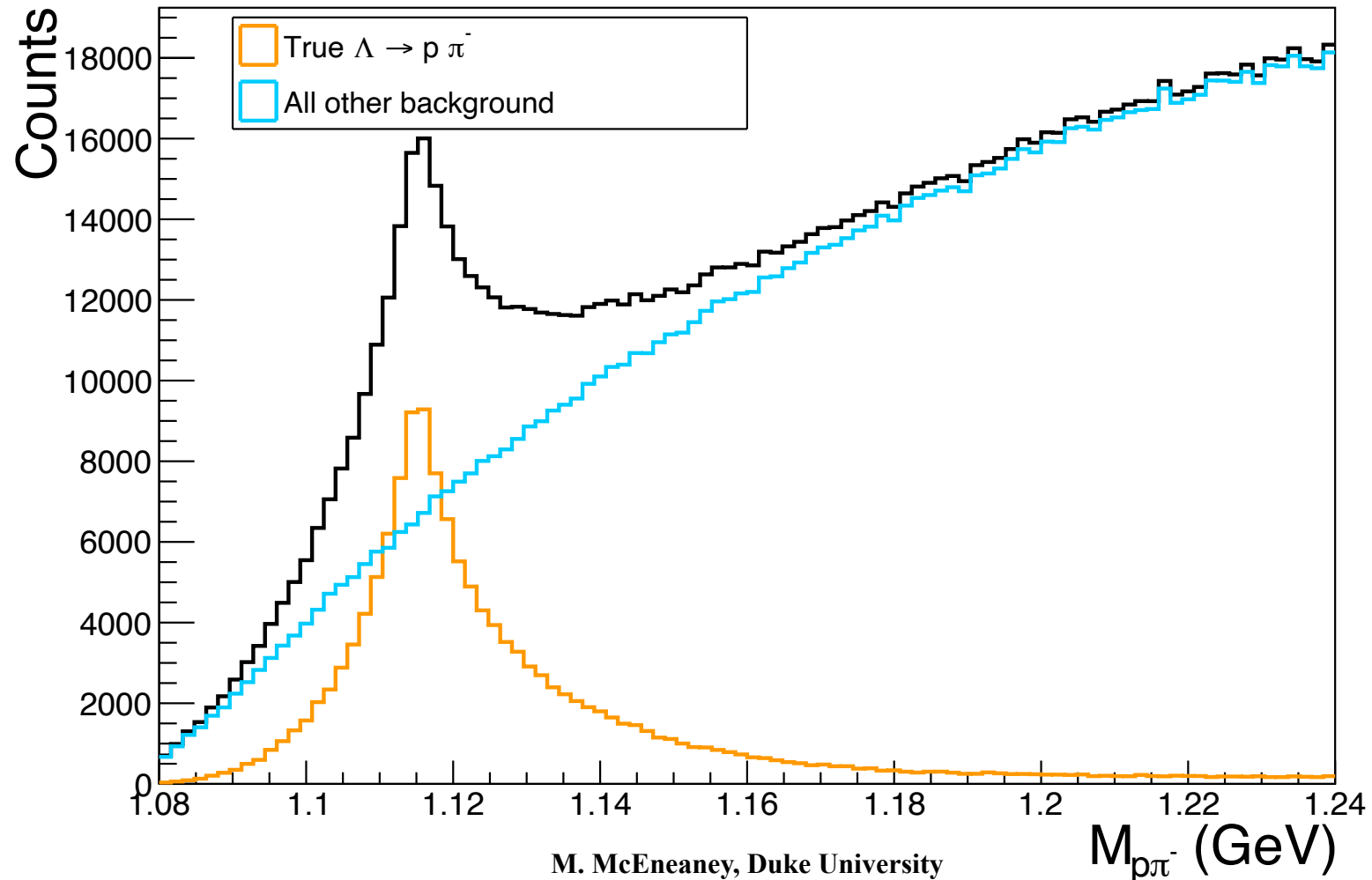
- CEBAF provides highly polarized  $e^-$  beam at 10.6 GeV
- CLAS12 has excellent momentum resolution and PID with full azimuthal coverage



V. Burkert, et al. NIM 2020.

# Signal Decomposition MC

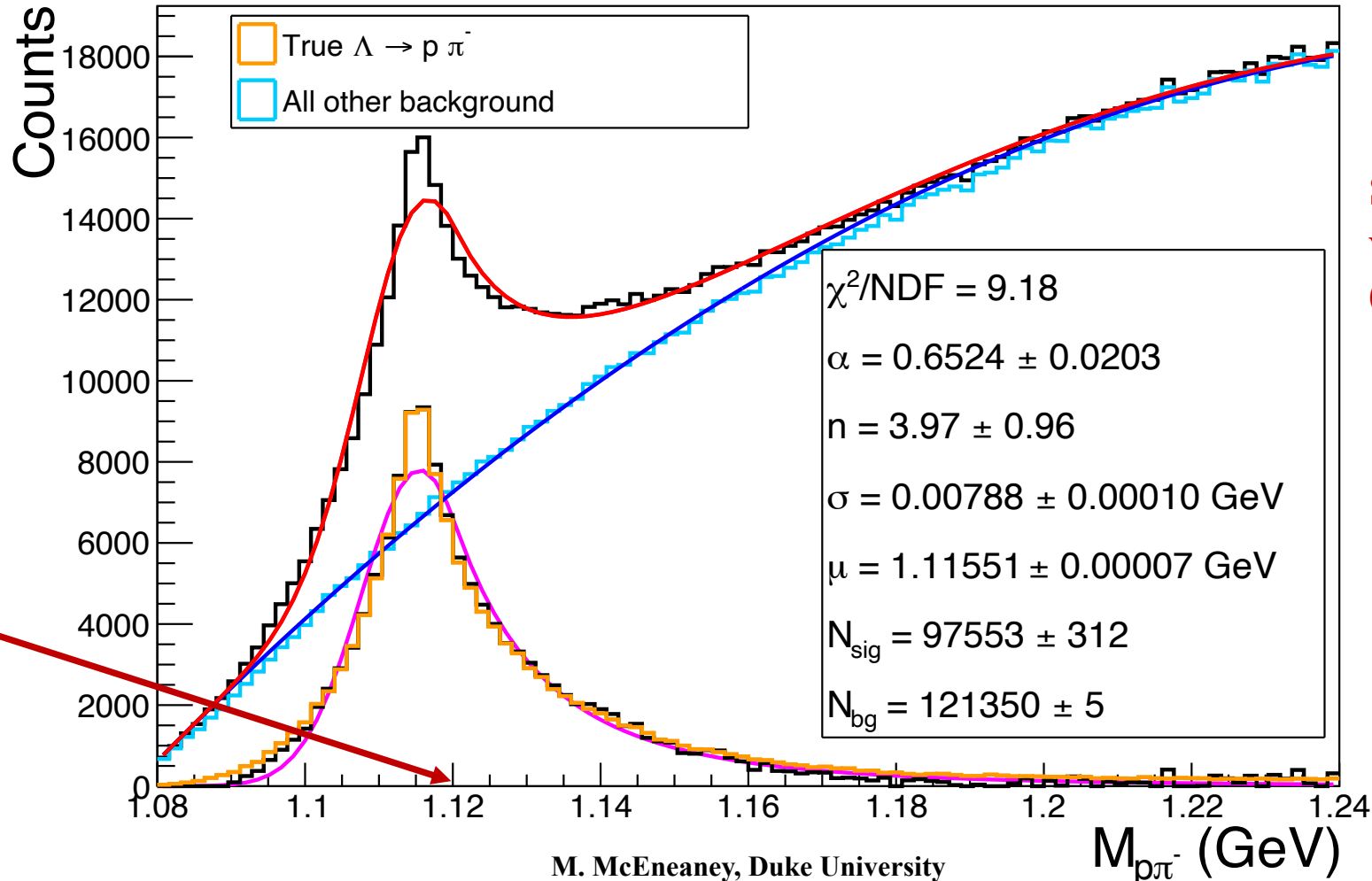
$\rho\pi^-$  Invariant Mass



# Signal Decomposition MC

$\rho\pi^-$  Invariant Mass

$$f(x; \alpha, n, \mu, \sigma) = N \begin{cases} \exp -\frac{(x-\mu)^2}{2\sigma^2}, & \frac{x-\mu}{\sigma} > \alpha \\ A(B - \frac{x-\mu}{\sigma})^{-n}, & \frac{x-\mu}{\sigma} \leq \alpha \end{cases}$$



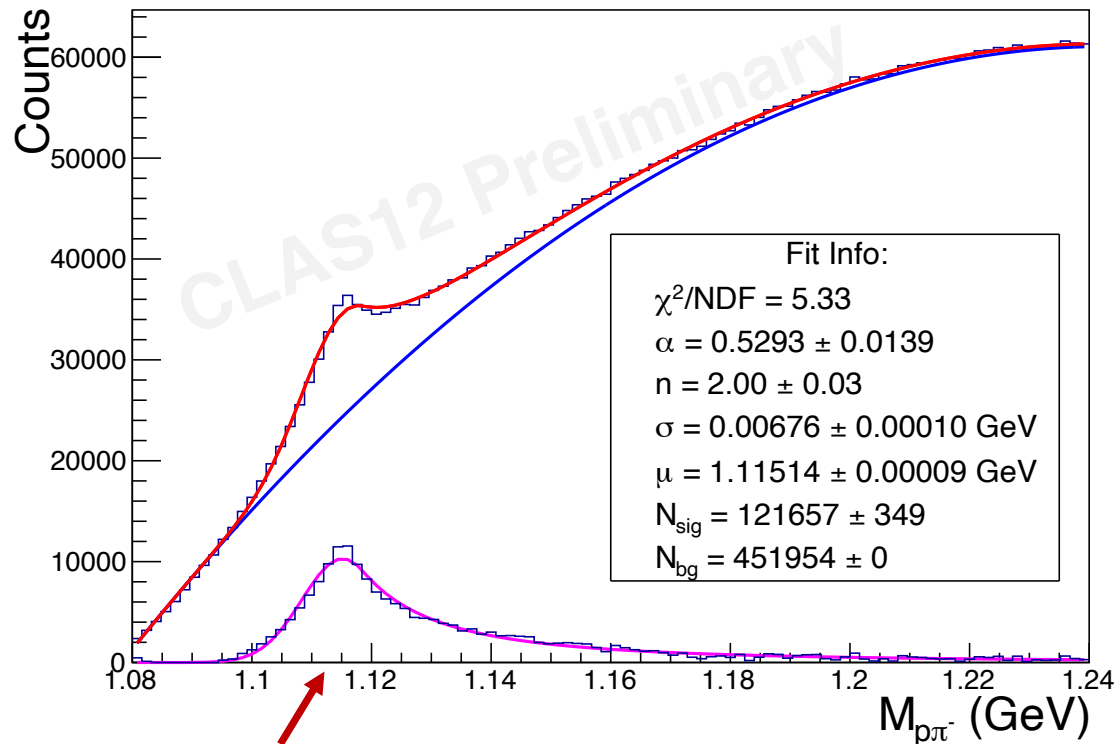
Signal Fit: Gaussian Peak with power law tail (Crystal Ball)

Integrate from 1.10 – 1.13 GeV

# Signal Fit on Data

Data

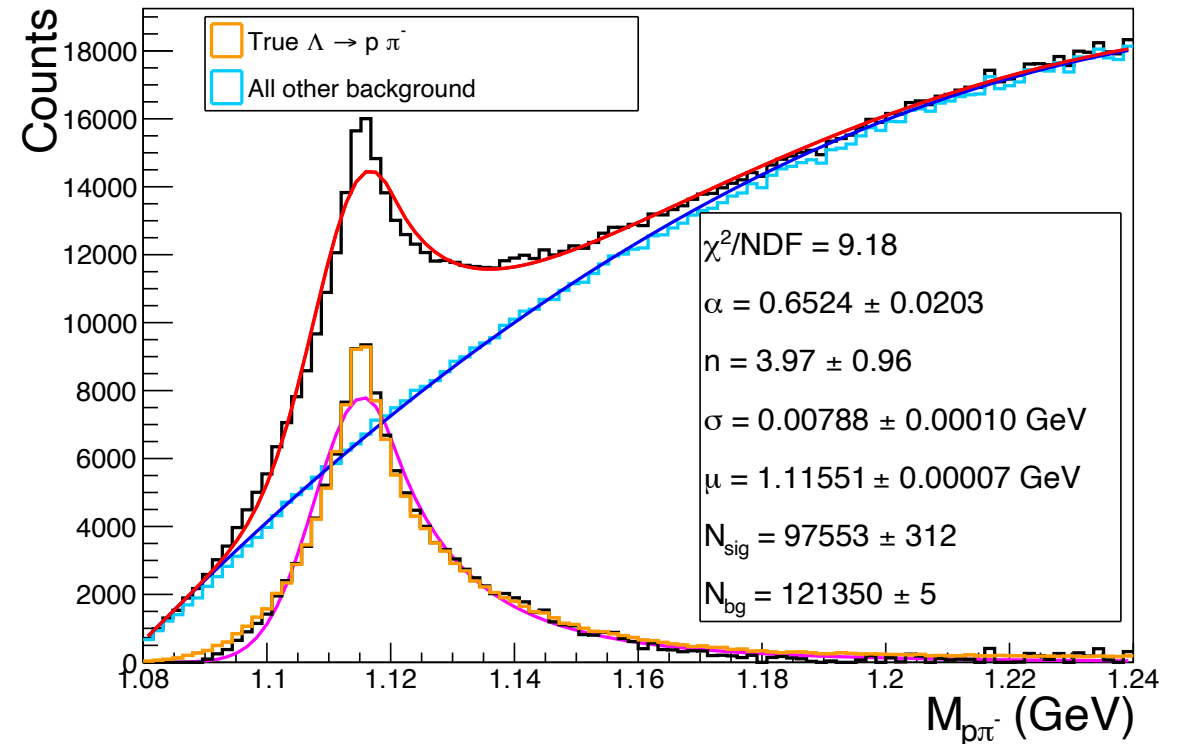
$\rho\pi^-$  Invariant Mass



Integrate from 1.10 – 1.13 GeV

MC

$\rho\pi^-$  Invariant Mass



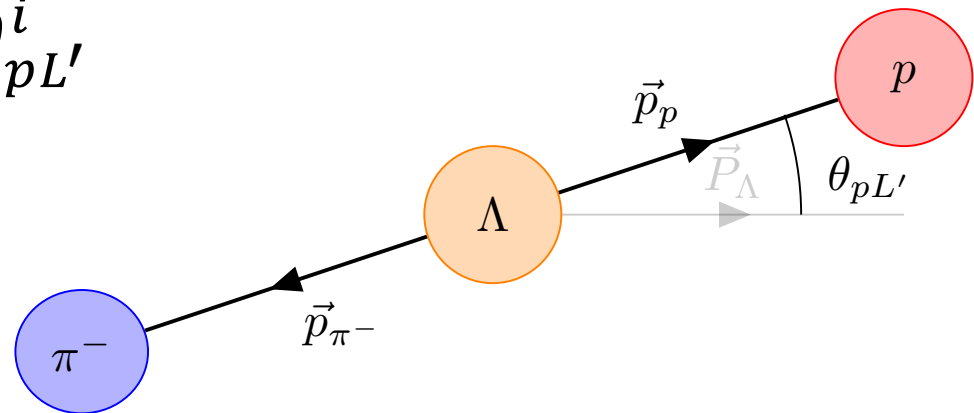


# $D_{LL'}$ Extraction

- Linear fit to cross-section requires **acceptance correction**
- Maximum Likelihood (ML) method requires **equal** amounts of positive and negative helicity events

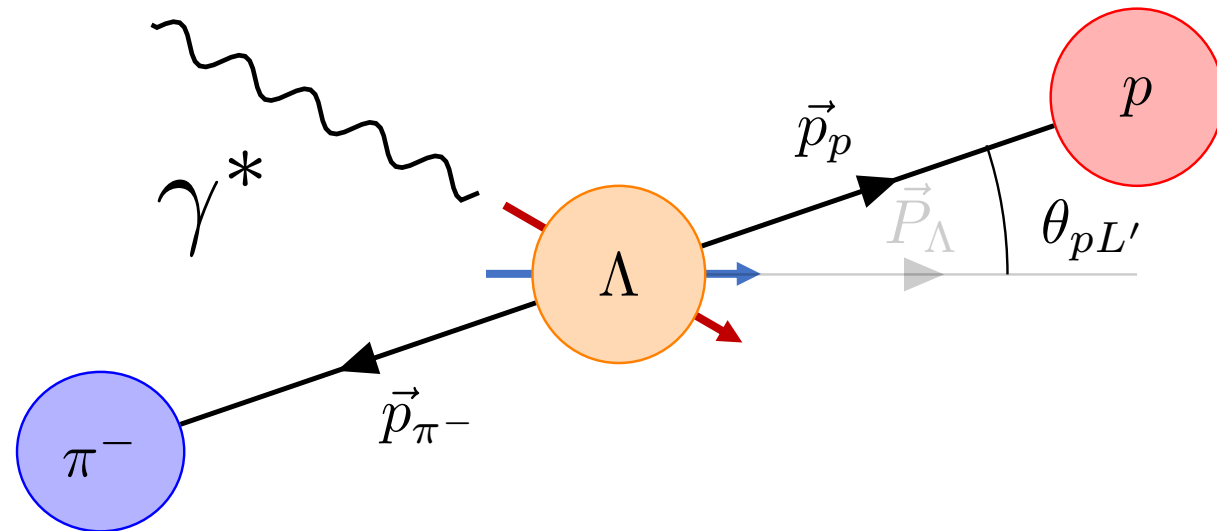
$$D_{LL'}^{\Lambda} = \frac{1}{\alpha P_b^2} \cdot \frac{\sum_{i=1}^{N_{\Lambda}} P_{b,i} D(y_i) \cos \theta_{pL'}^i}{\sum_{i=1}^{N_{\Lambda}} D^2(y_i) \cos^2 \theta_{pL'}^i}$$

- **No acceptance correction** needed for ML



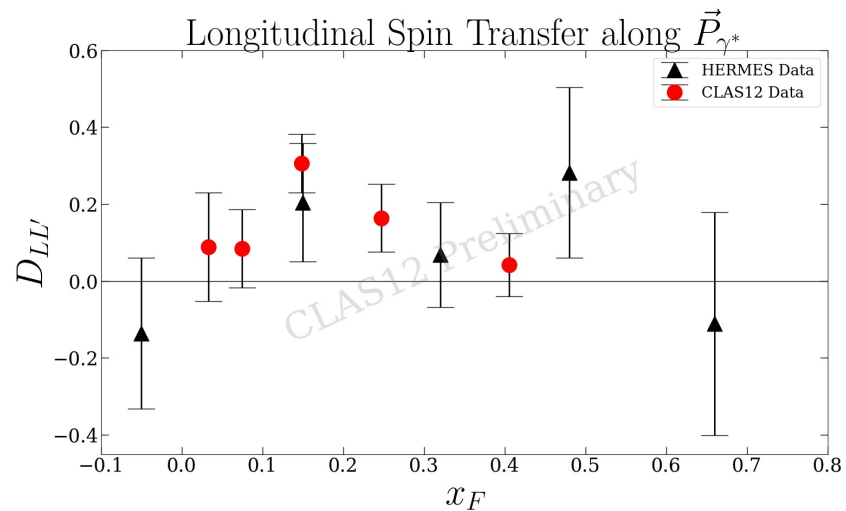
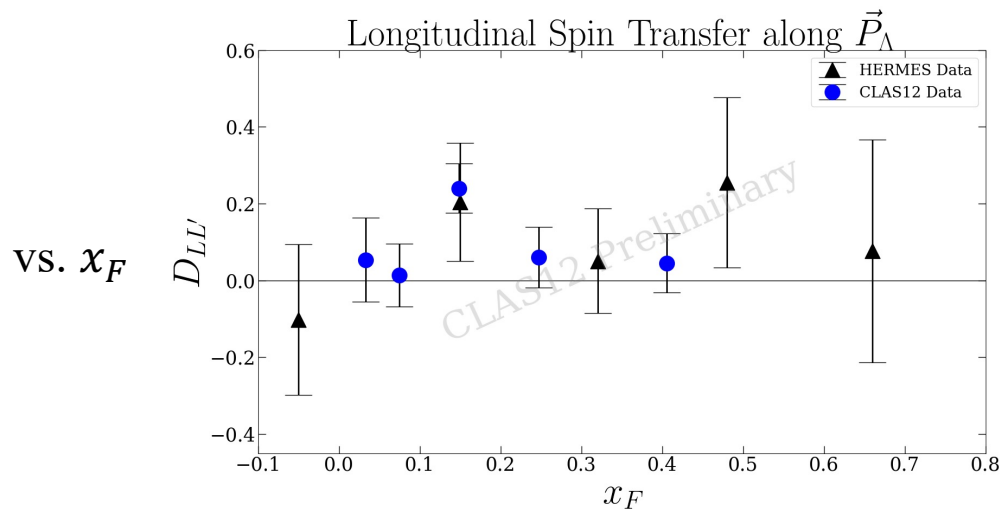
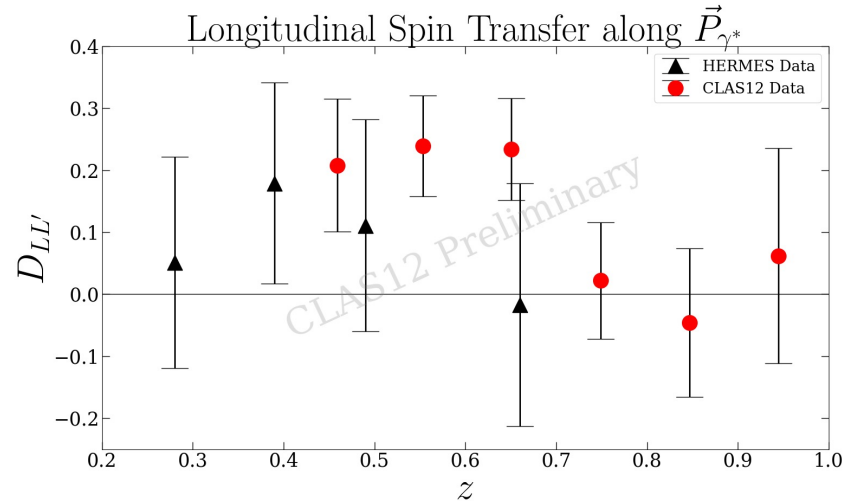
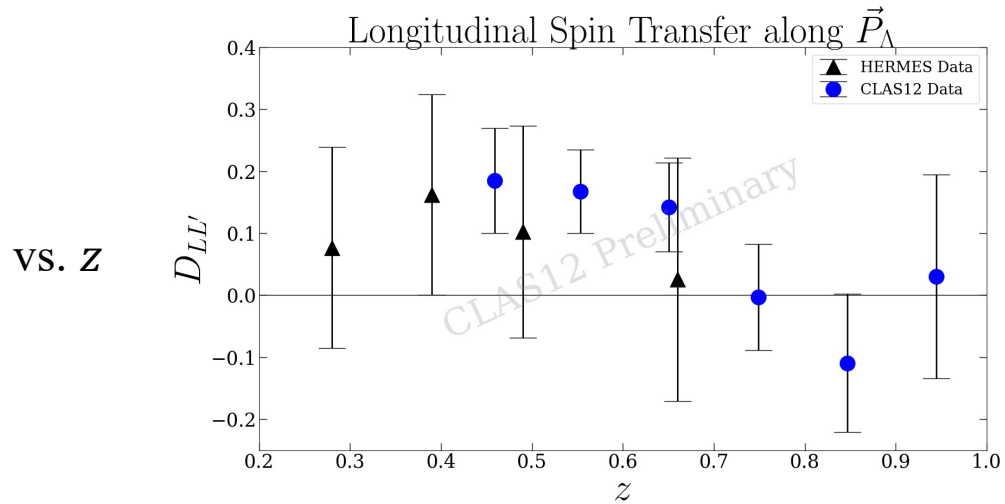
# Choice of $\Lambda$ Polarization Axis

- $\cos \theta_{pL'}$  is the angle between the proton momentum and the  $\Lambda$  polarization axis  $L'$
- Two choices used for  $L'$ 
  - Along  $P_\Lambda$
  - Along  $P_{\gamma^*}$



# Maximum Likelihood (ML) Results

$$D_{LL'}^{\Lambda} = \frac{D_{LL' sig} - \epsilon D_{LL' bg}}{1 - \epsilon}$$

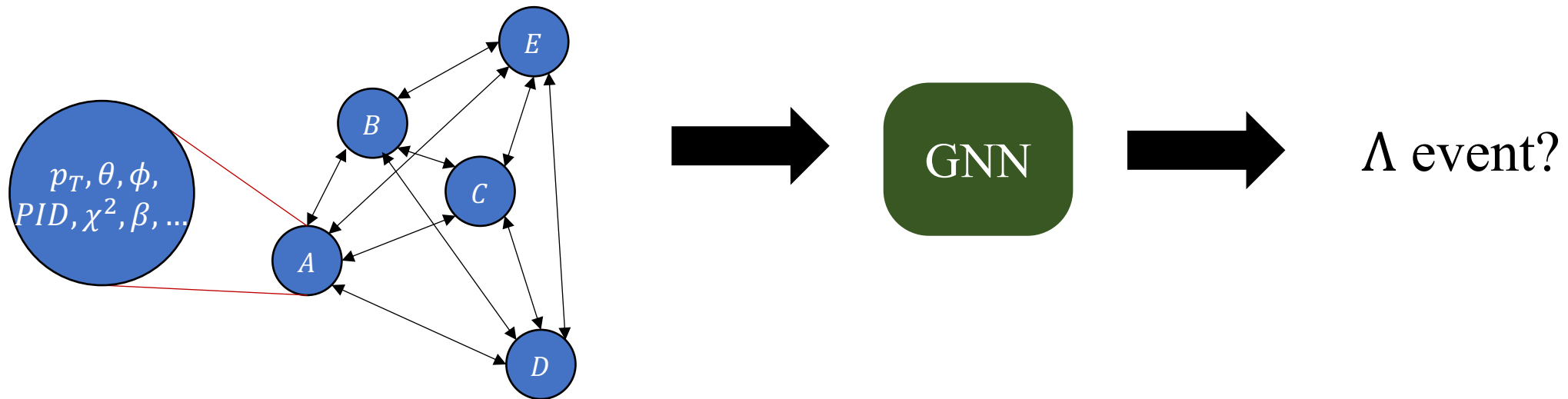


**Note:** errors are solely statistical

HERMES results from PRD, 74(7), Oct 2006

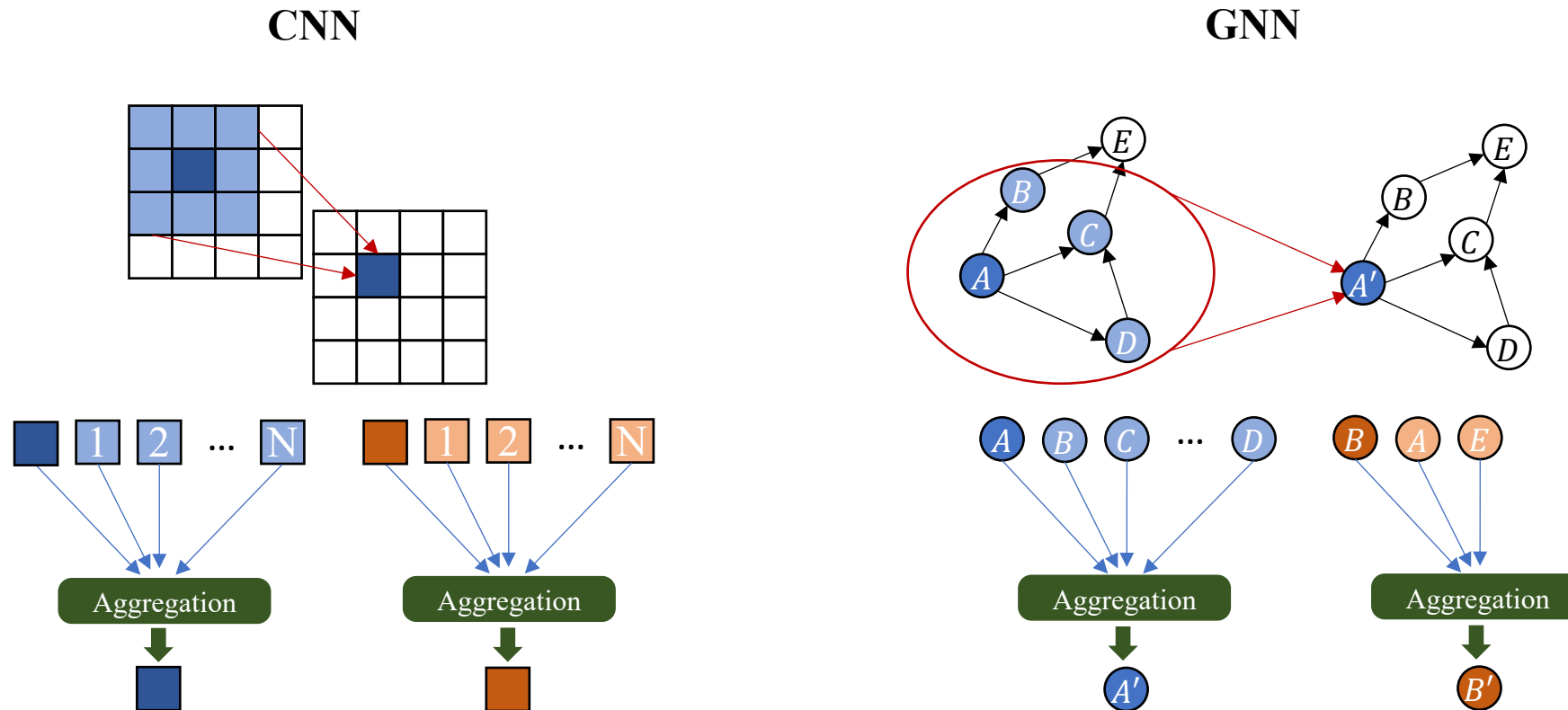
# Graph Neural Networks (GNNs)

- **Idea:** use GNN to reduce background in invariant mass spectrum on event-by-event basis
- Pass each event as fully-connected, bidirectional graph
- Each particle is a node with its own data:  $p_T, \theta, \phi$ , etc.

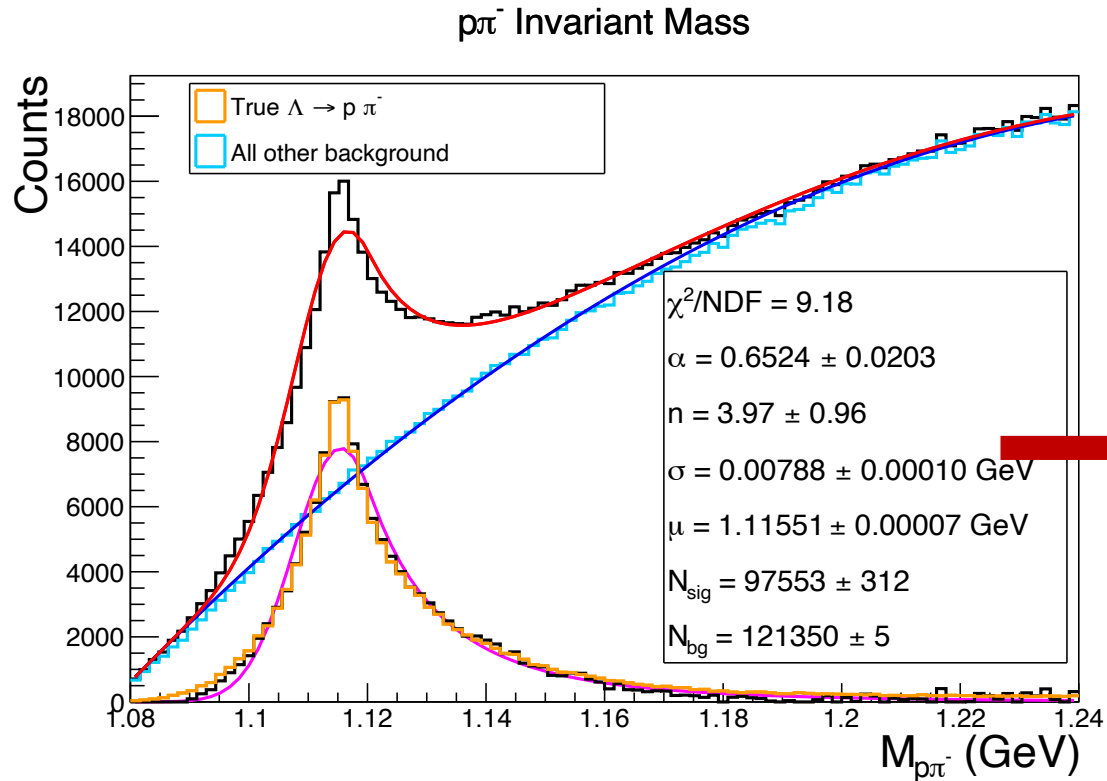


# Graph Neural Networks (GNNs)

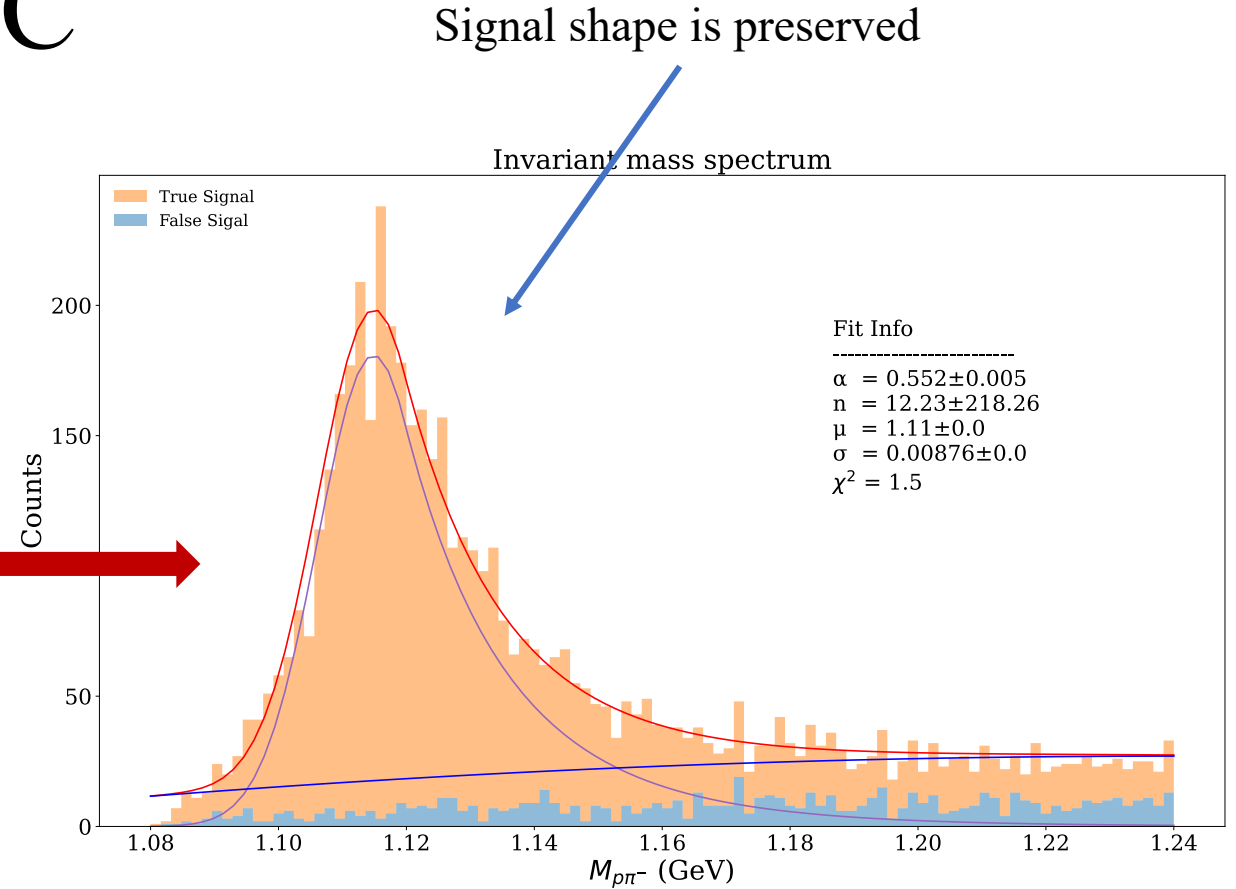
- At basic level, function as generalized form of CNNs



# GIN Evaluation on MC



Before NN

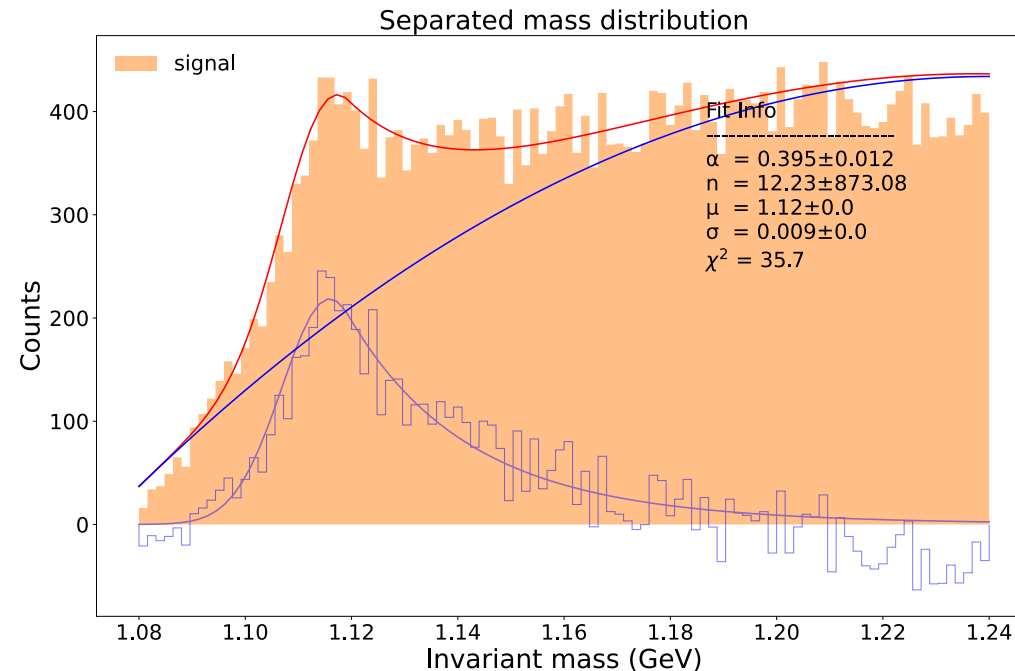


After NN

83.7% Test accuracy and background is significantly reduced!

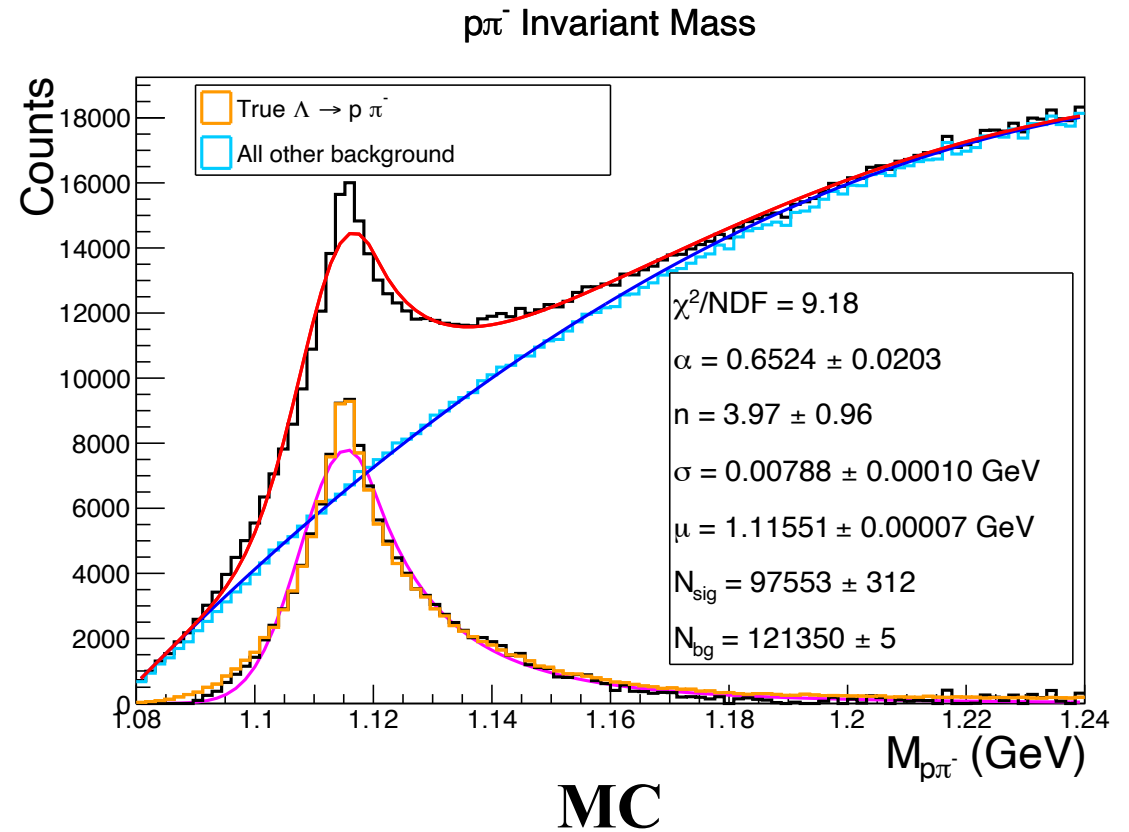
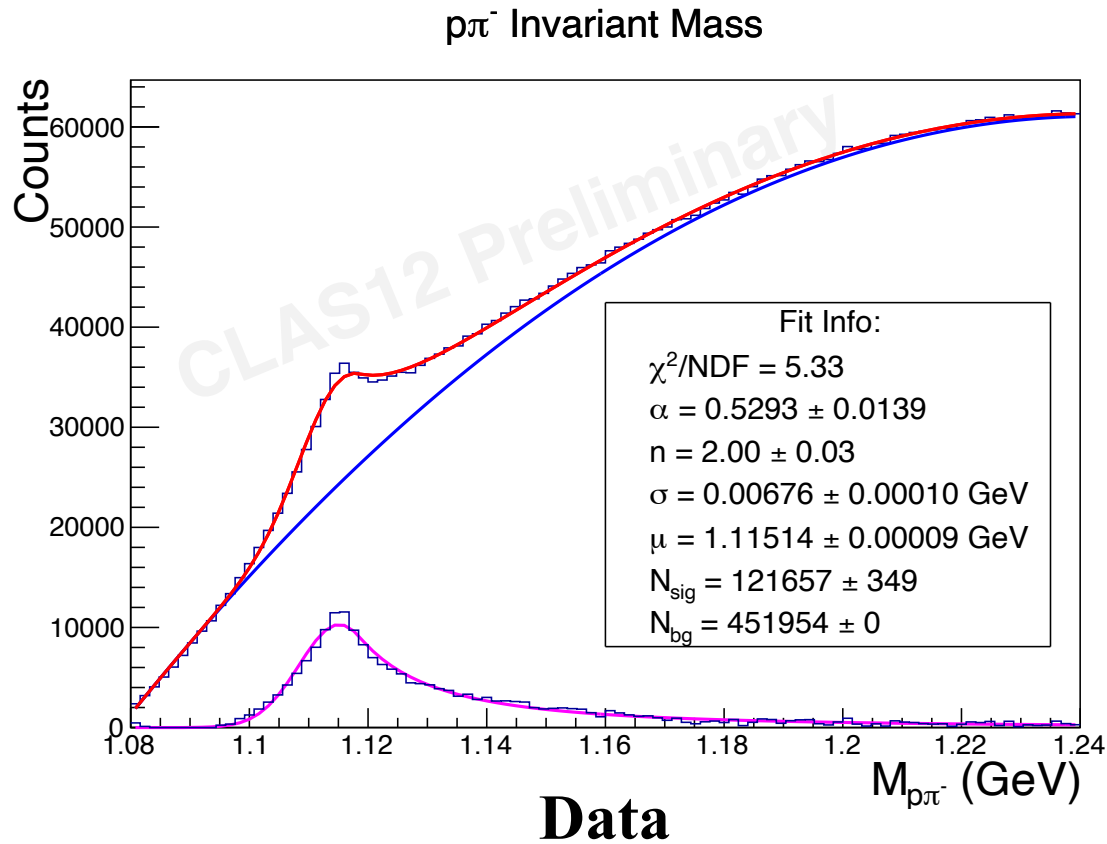
# GIN Evaluation on Data

- Evaluate on 24k events
- $FOM = N_{sig} / \sqrt{N_{tot}}$  is 65.74 compared to 34.11 without the GIN



# Domain Adaptation

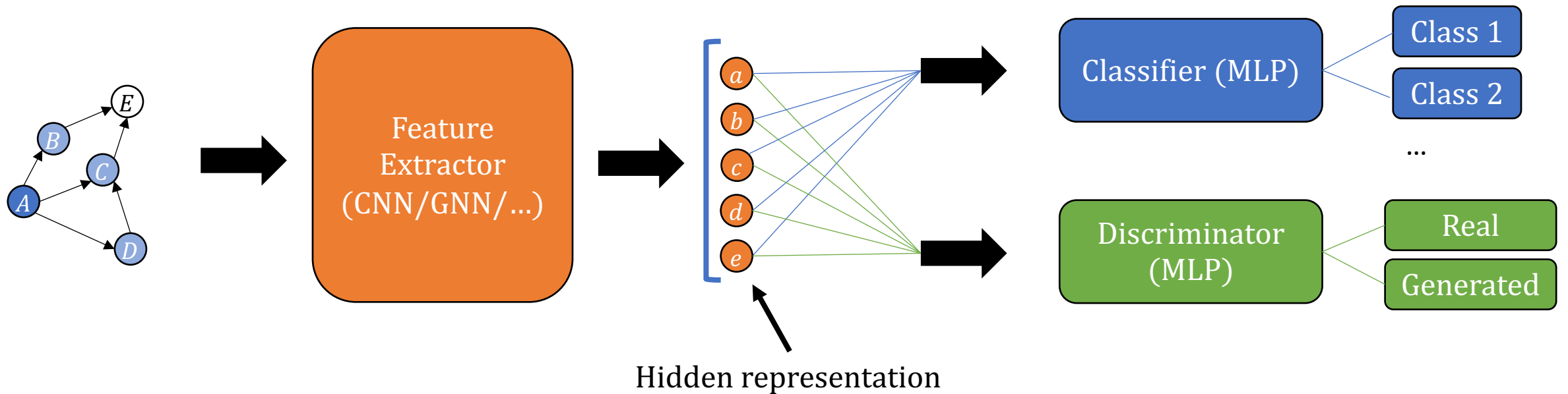
- **Problem:** target domain does not match source domain





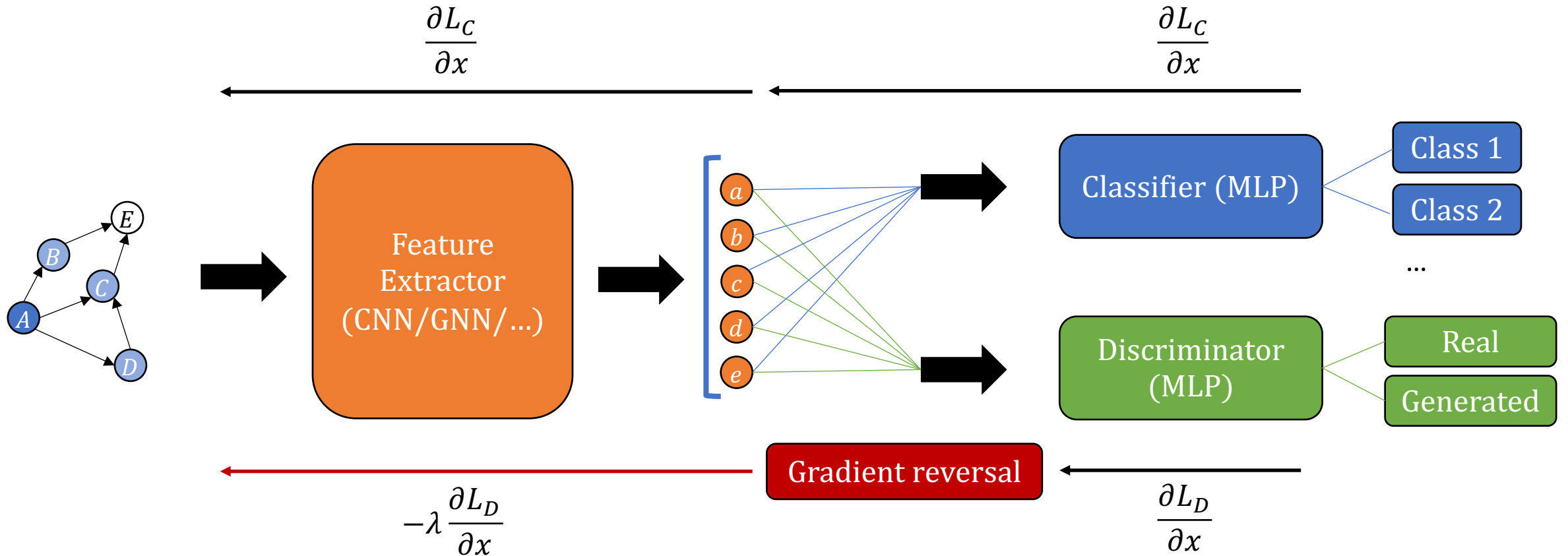
# Domain Adversarial NNs

- Minimizes distinction between real and training data
- Two objectives: classification task and domain discrimination

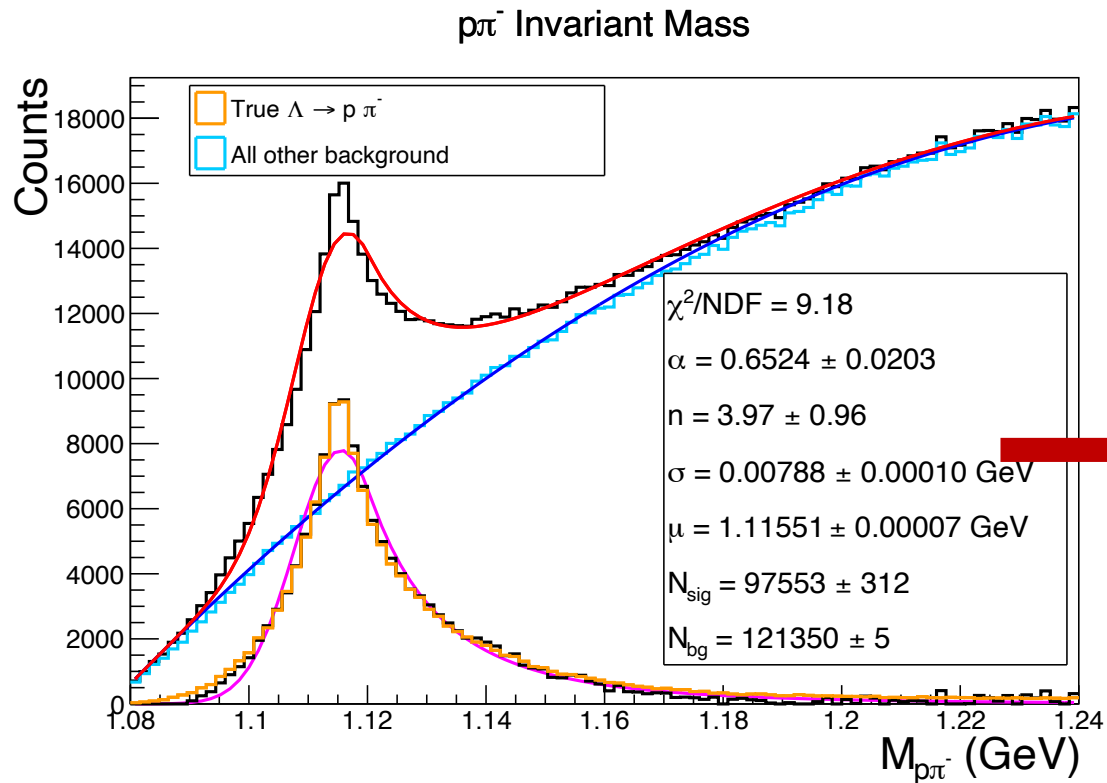


# Domain Adversarial NNs

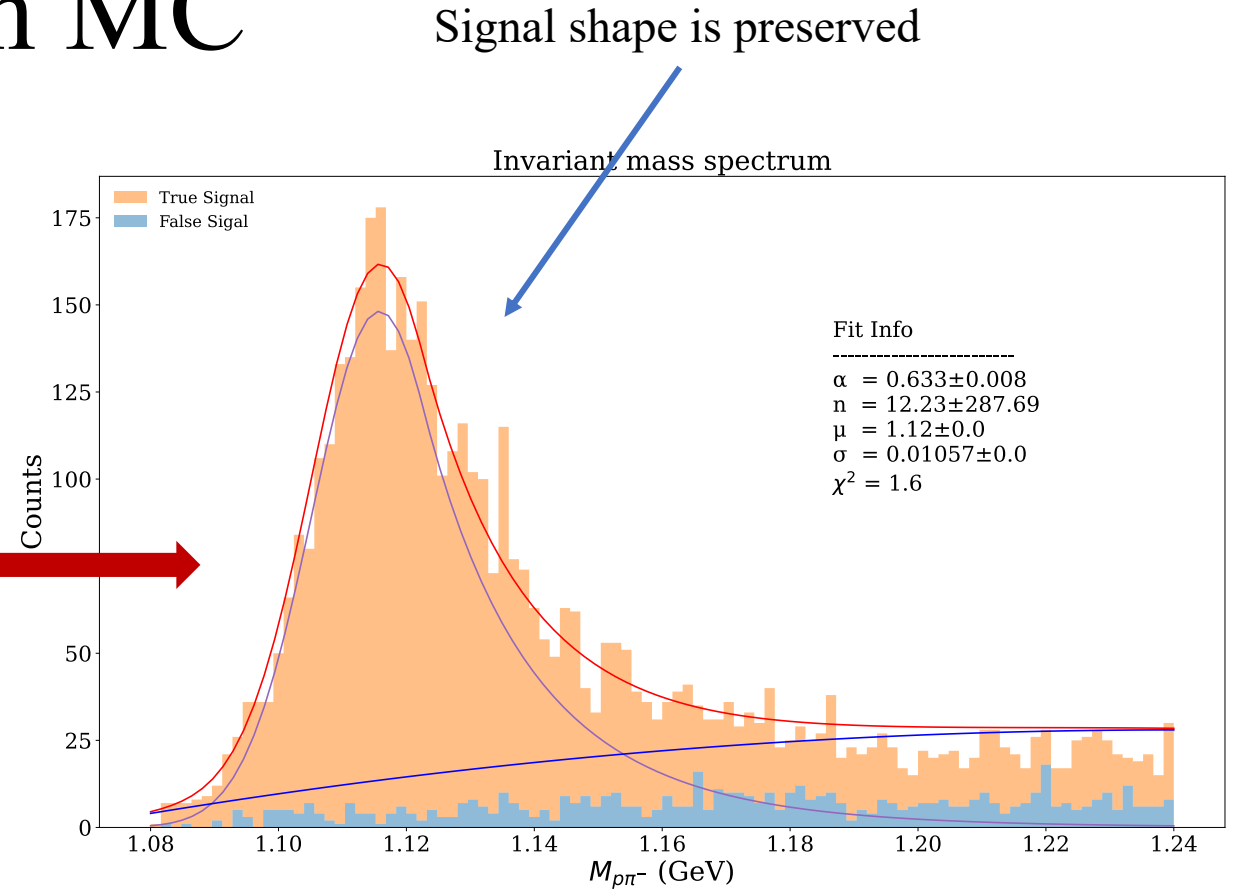
- Reverse gradient from discriminator loss during backpropagation



# DAGIN Evaluation on MC



Before NN

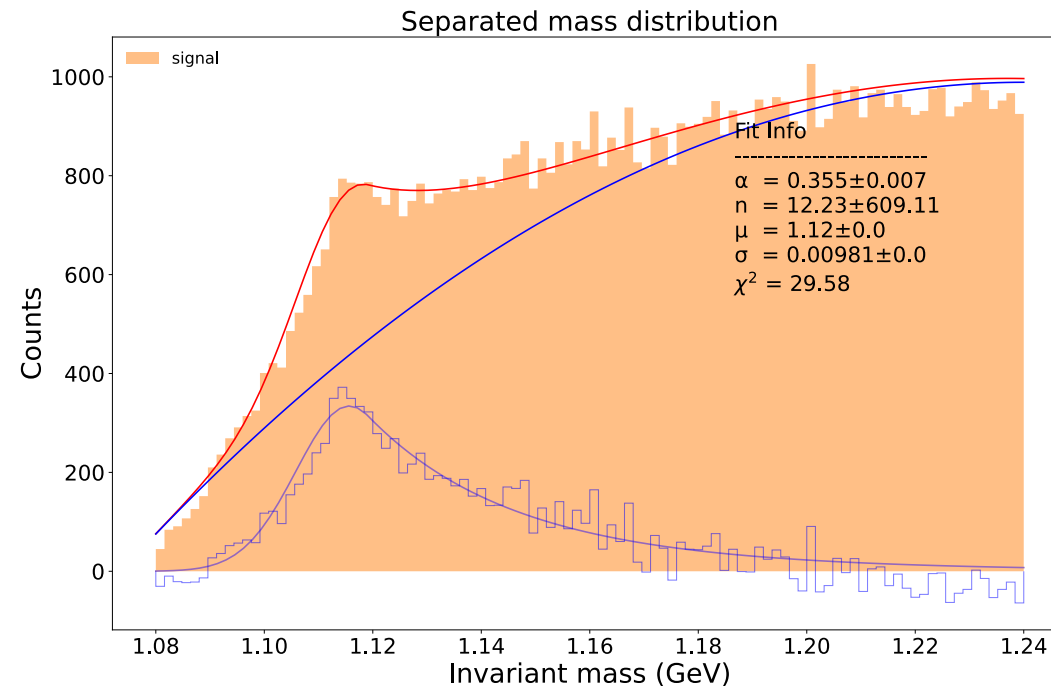


After NN

82.9% Test accuracy and background is significantly reduced!

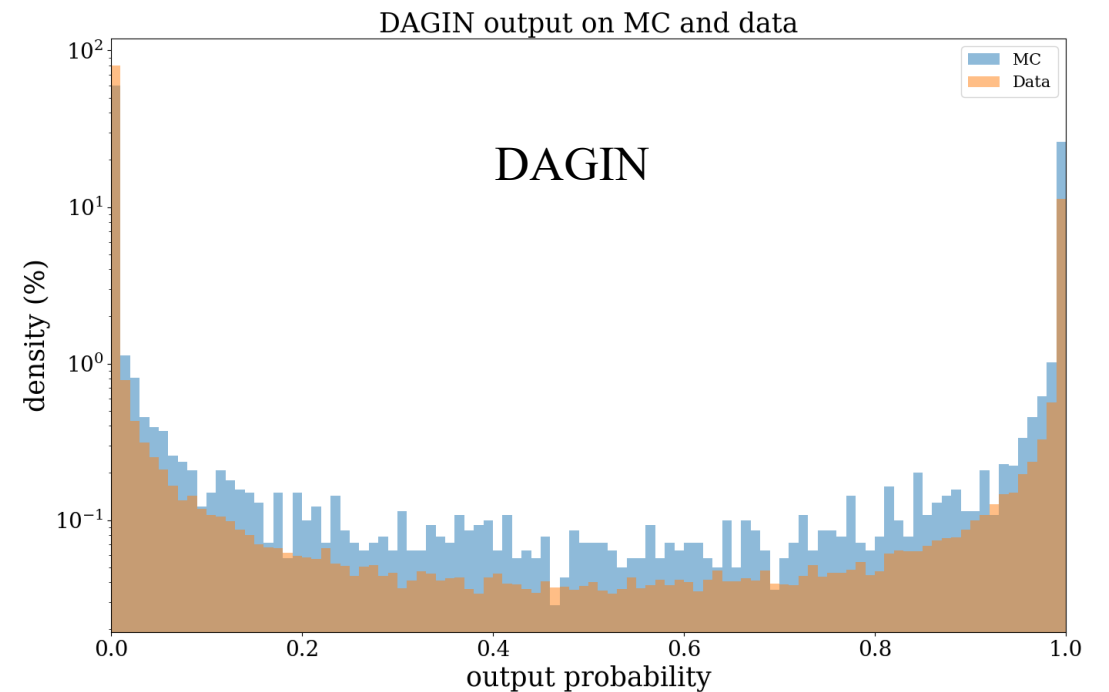
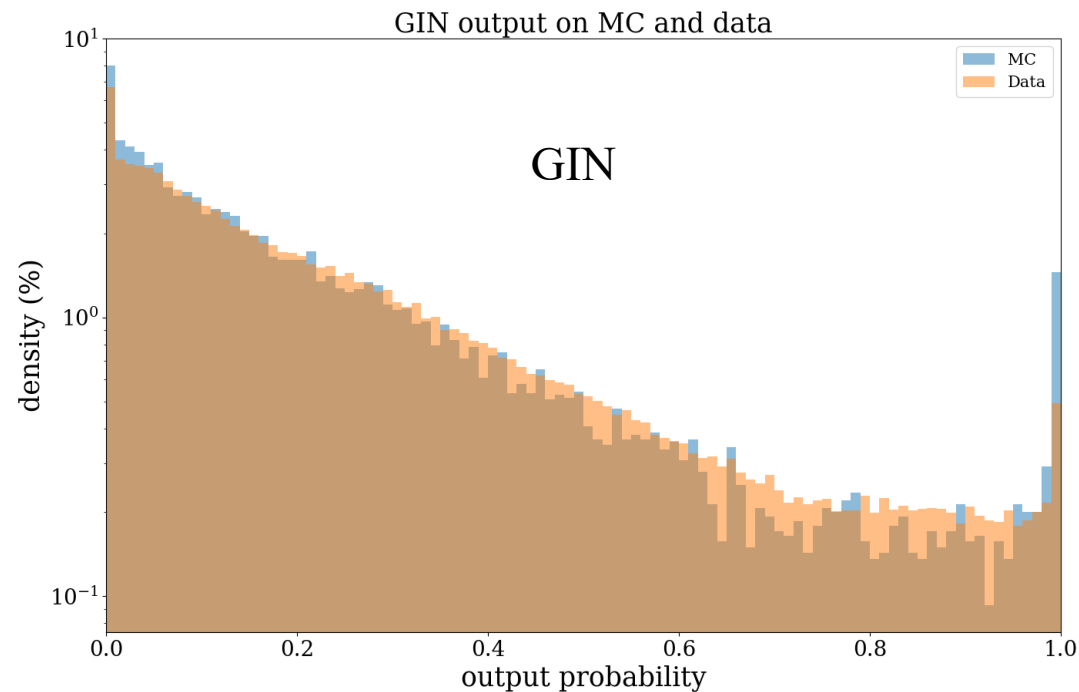
# DAGIN Evaluation on Data

- Evaluate on 24k events
- $FOM = N_{sig} / \sqrt{N_{tot}}$  is 42.09 compared to 34.11 without the GIN



# NN Output on Data and MC

- Kolmogorov-Smirnov statistic is 0.035 for GIN and 0.261 for DAGIN



# Summary and Next Steps

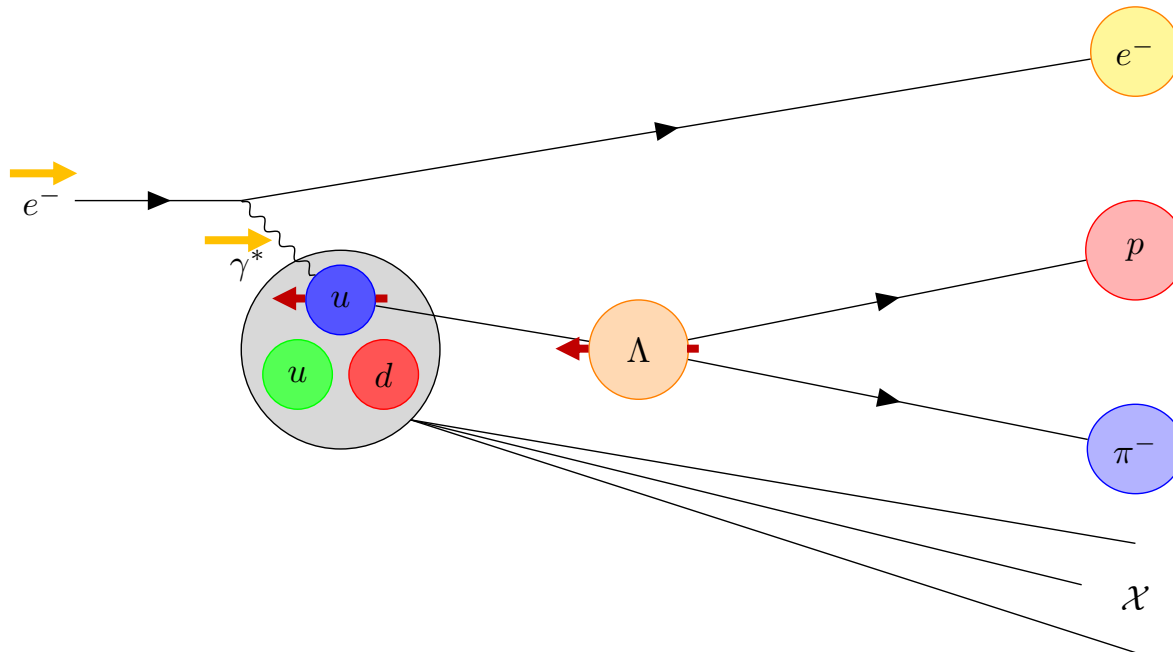
- Preliminary extraction of  $\langle D_{LL'}^\Lambda \rangle = 0.0618 \pm 0.0963(stat)$  is consistent with previous measurements
- Machine learning methods need further validation
- Next steps:
  - Secondary vertex reconstruction method recently implemented
  - Measurement of  $\Lambda$  spontaneous transverse polarization
  - $\Lambda K$  spin orbit correlations

Thank you!



# Longitudinal Spin Transfer

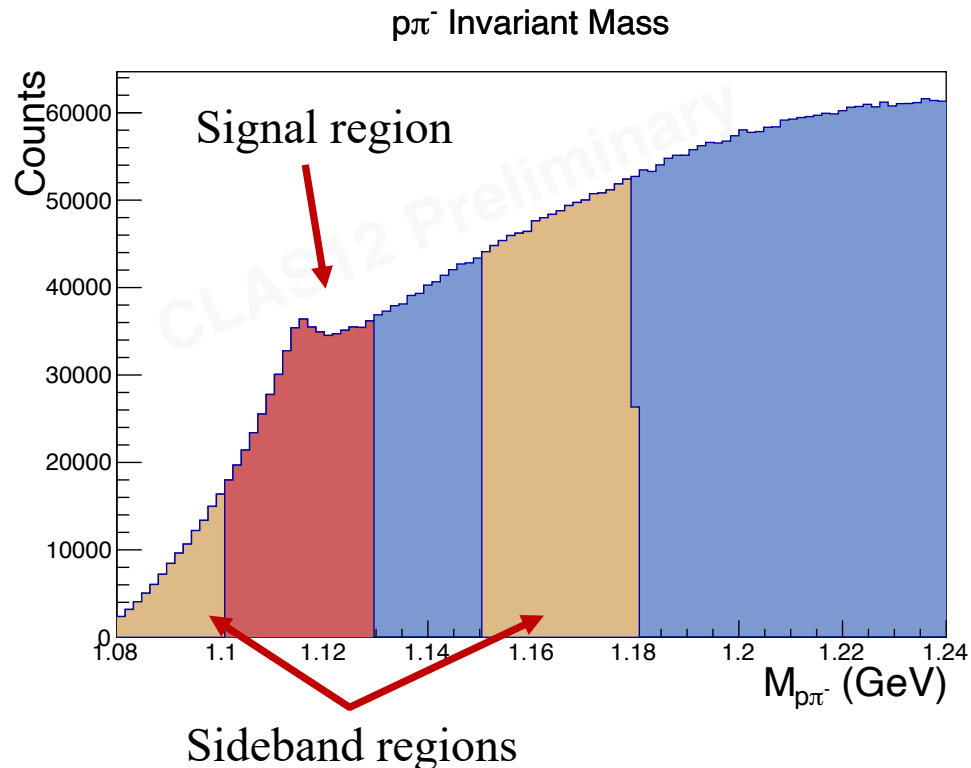
- Polarized electron selects a quark with the opposite spin
- Polarization of quark is transferred to hadrons after fragmentation





# Sideband Background Correction

- Assume background polarization is independent of  $M_{p\pi^-}$
- Subtract polarization computed in sideband regions

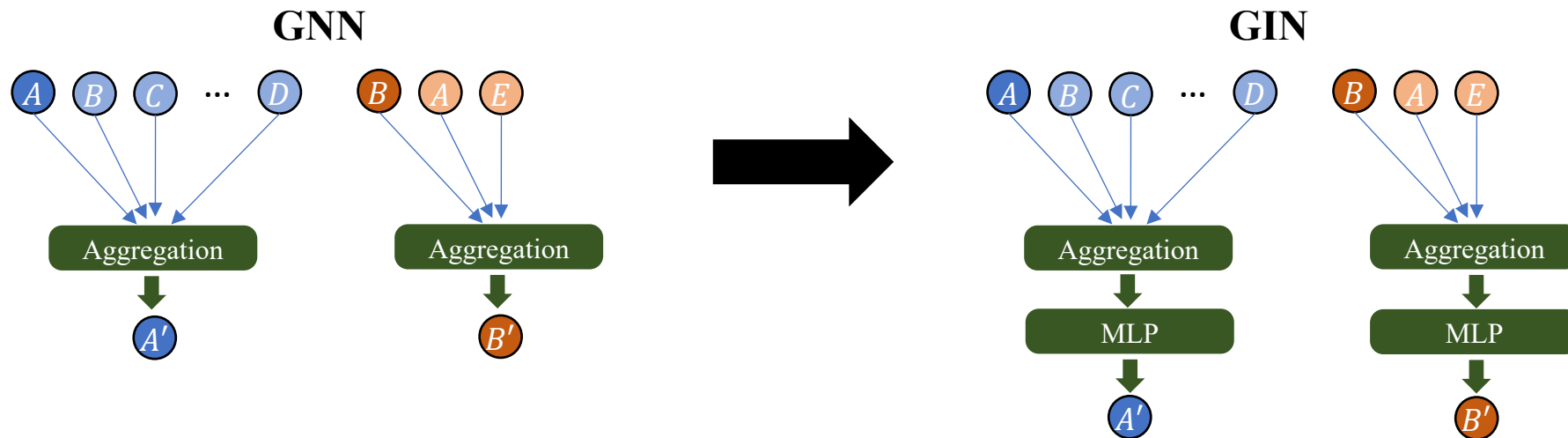


$$D_{LL'}^{\Lambda} = \frac{D_{LL' sig} - \epsilon D_{LL' bg}}{1 - \epsilon}$$

# Graph Isomorphism Network (GIN)

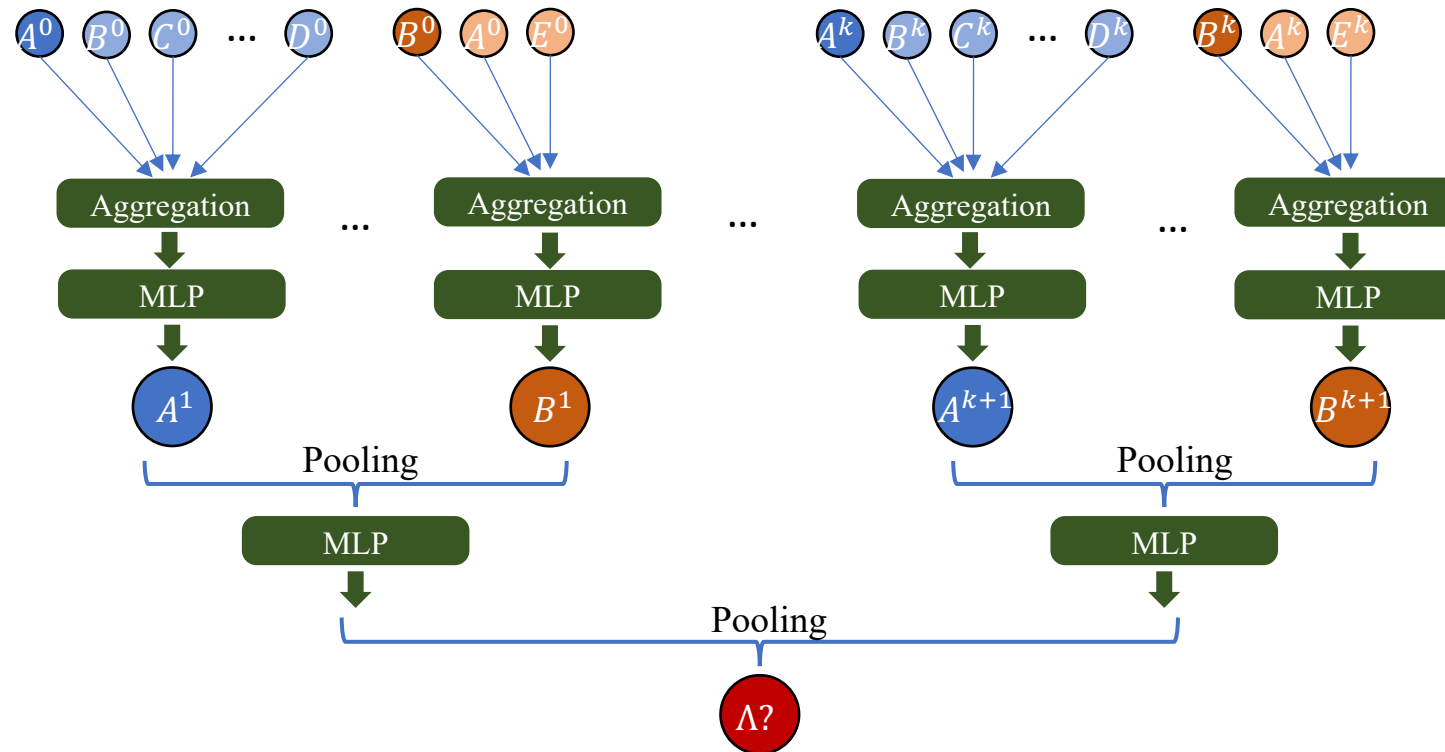
- Similar to Weisfeiler-Lehman (WL) Test, essentially ensures aggregation is injective
- Compare with basic GNN convolution:

$$h_v^{(k)} = \text{MLP}^{(k)} \left( \left( 1 + \epsilon^{(k)} \right) \cdot h_v^{(k-1)} + \sum_{u \in \mathcal{N}(v)} h_u^{(k-1)} \right)$$



# Graph Isomorphism Network (GIN)

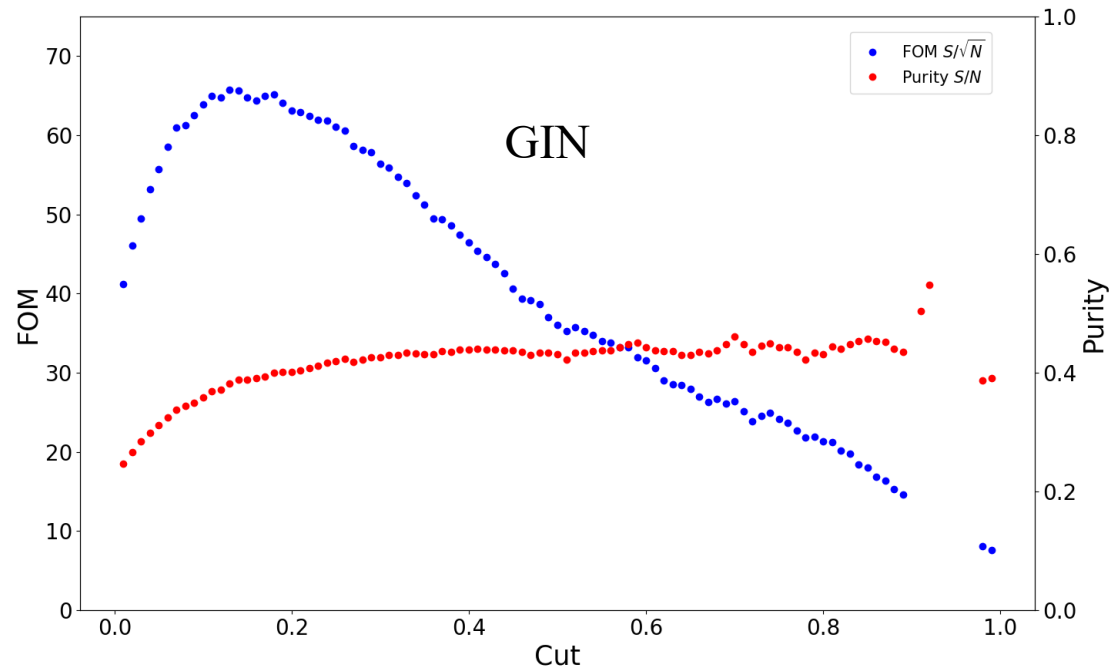
- Aggregation in final layer is across all previous layers/iterations



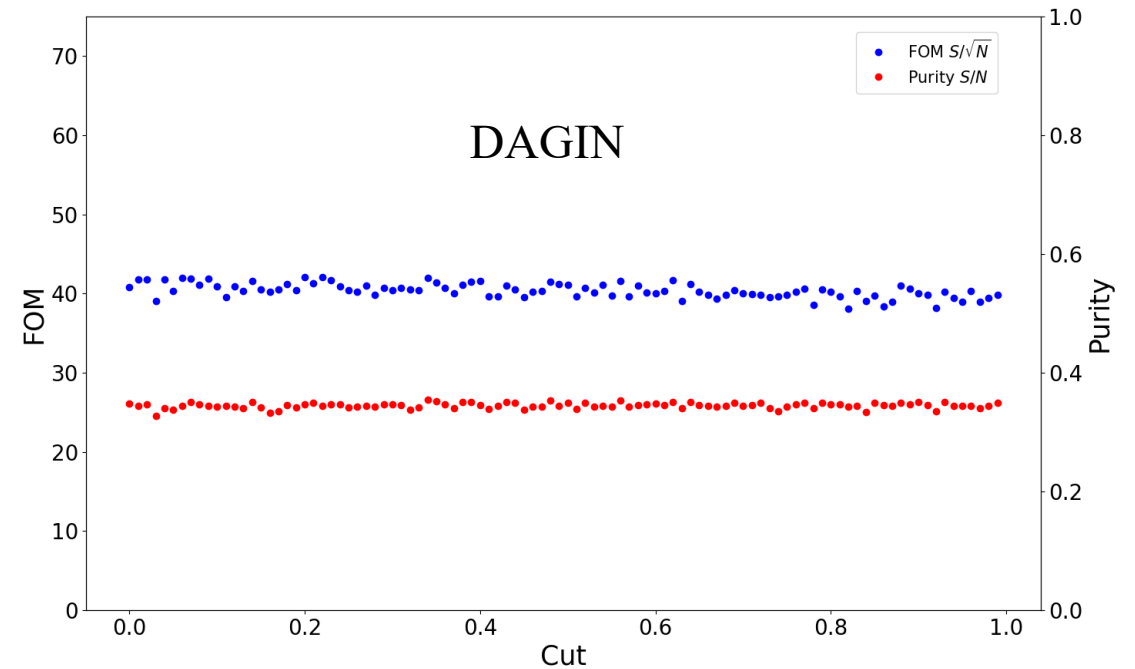
# Optimization of NN Cut

- Scan FOM and purity as a function of NN cut

Metrics vs. cut on NN output

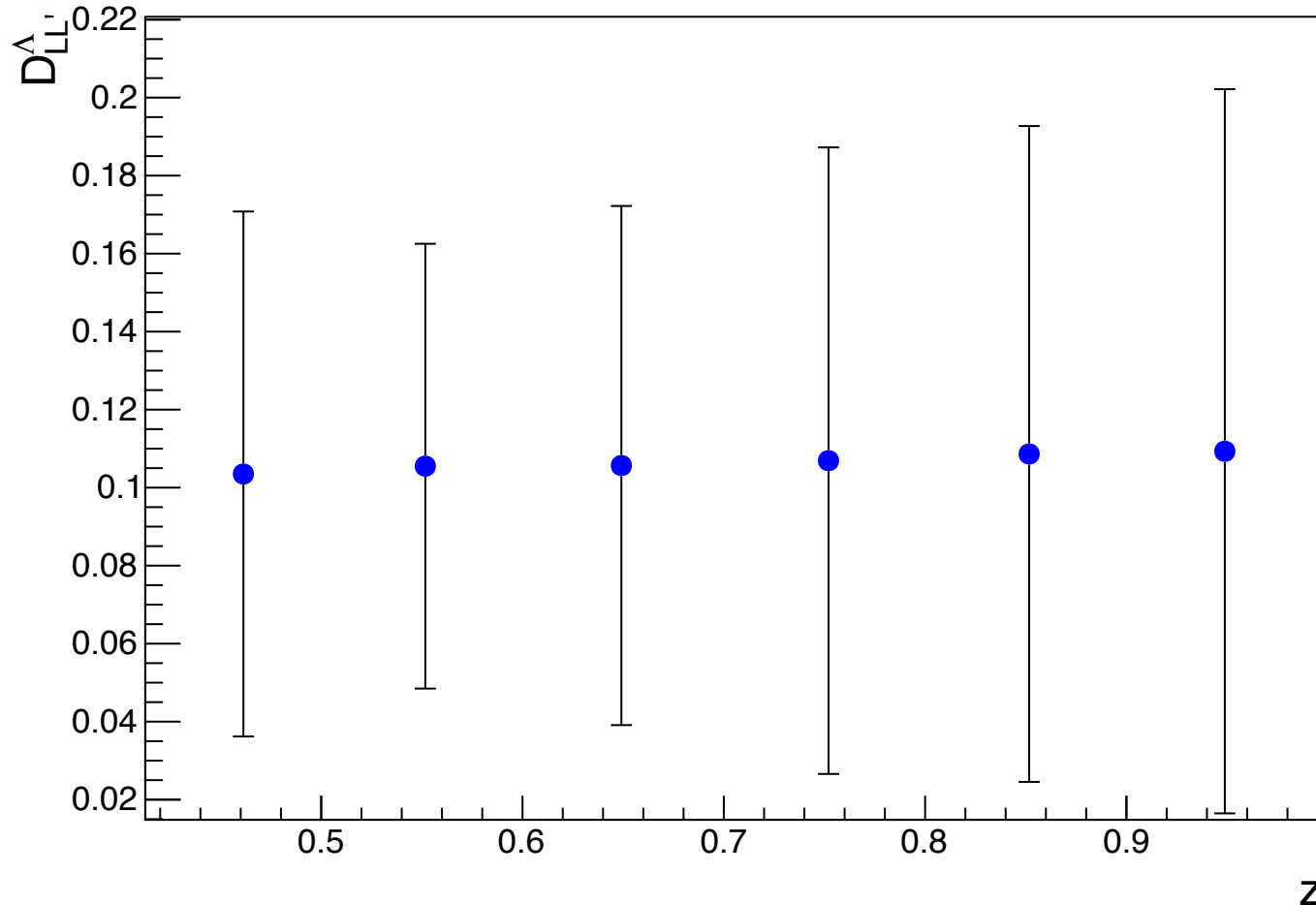


Metrics vs. cut on NN output



# Asymmetry Injection

Longitudinal Spin Transfer along  $\vec{p}_\Lambda$



Weight  $\cos\theta_{REC}$  by :

$$1 + \alpha D(y) P_b D_{LL',injected} \cos\theta_{MC}$$

$D_{LL',injected} = 0.1$  for Signal and

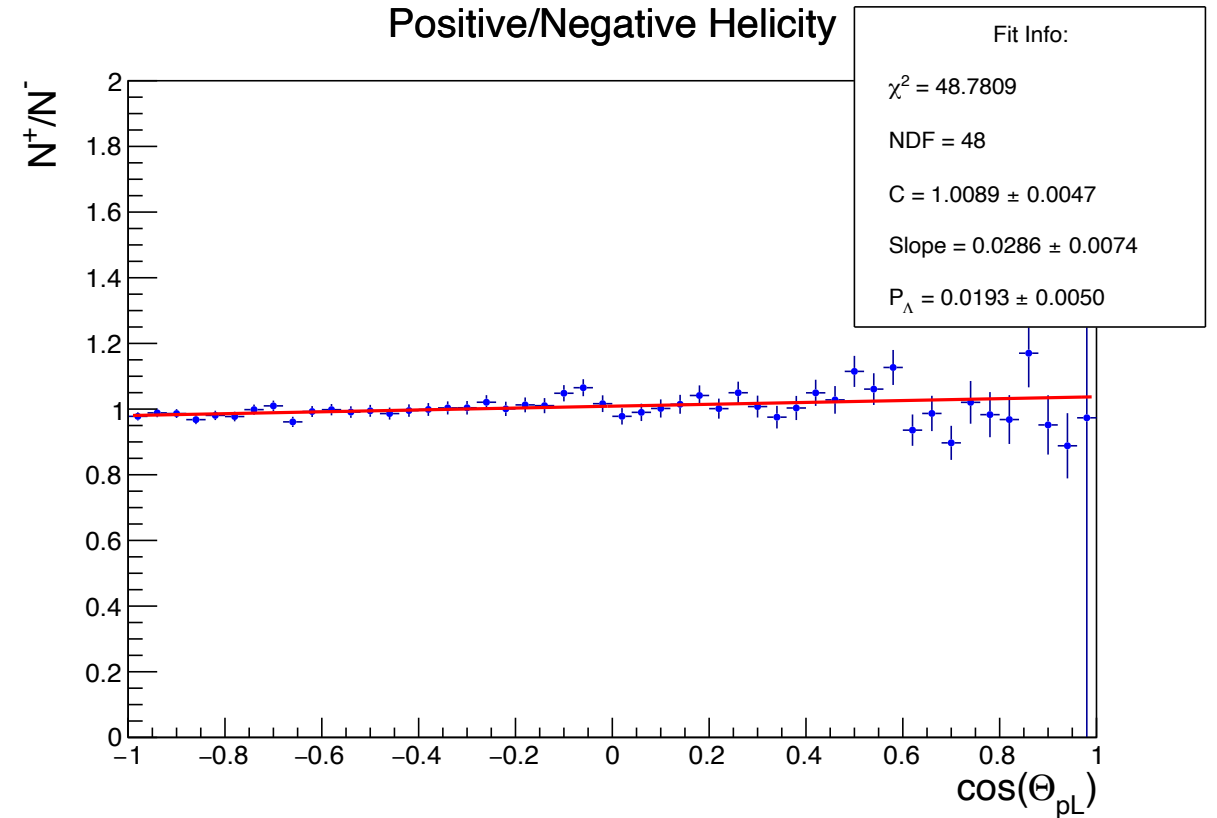
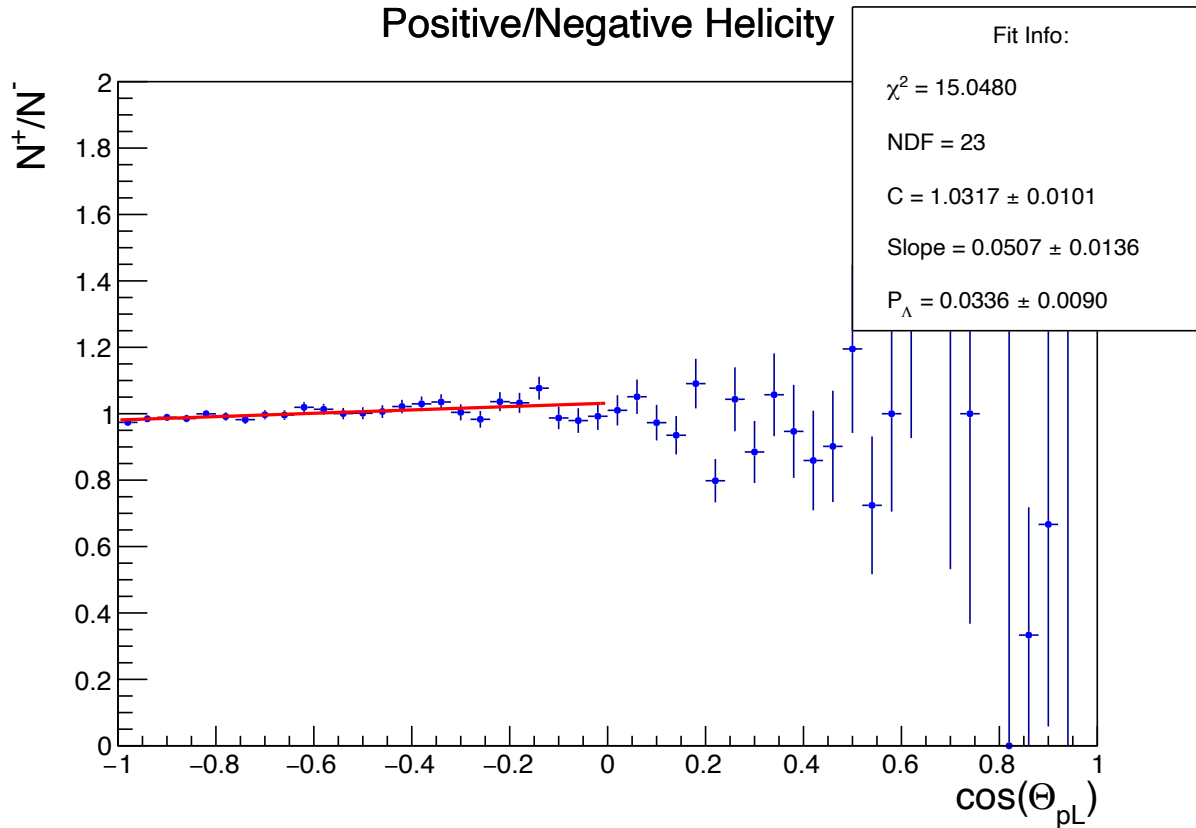
$D_{LL',injected} = 0.01$  for Background

Averaged result is:

$$D_{LL',REC} = 0.107 \pm 0.078$$

# Fit $\cos\theta$ (acceptance corrected)

$$P_{\Lambda} = \frac{1}{\alpha} \frac{\text{Slope}}{C}$$



**Note:** No GNN applied

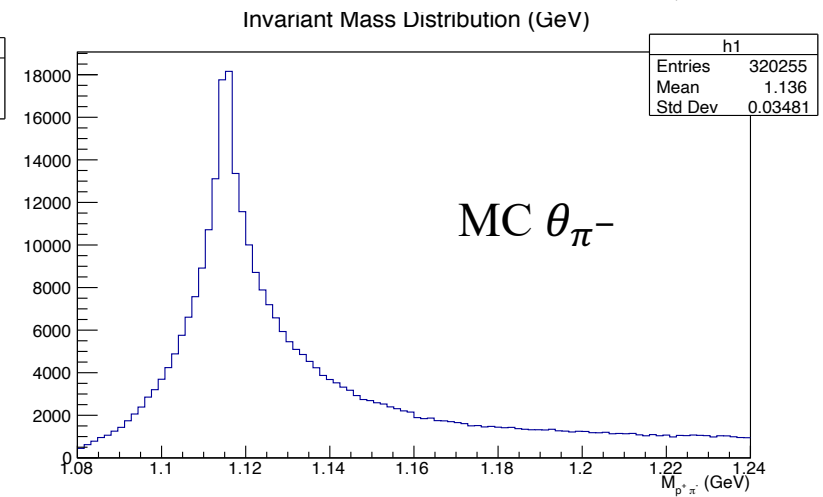
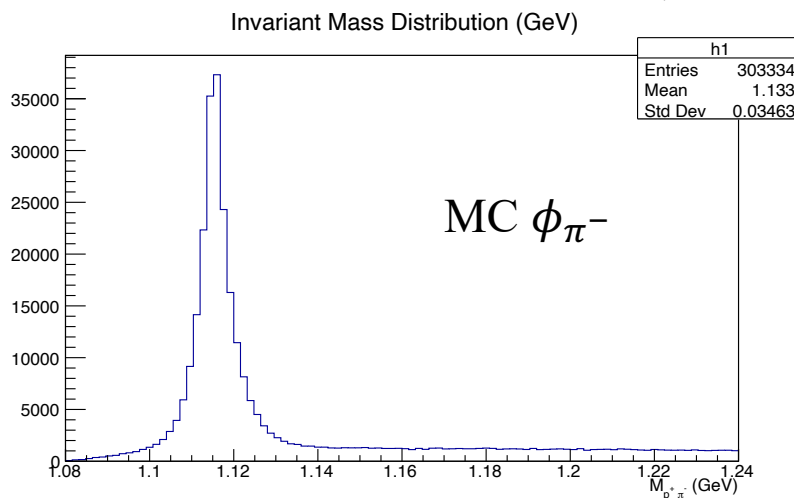
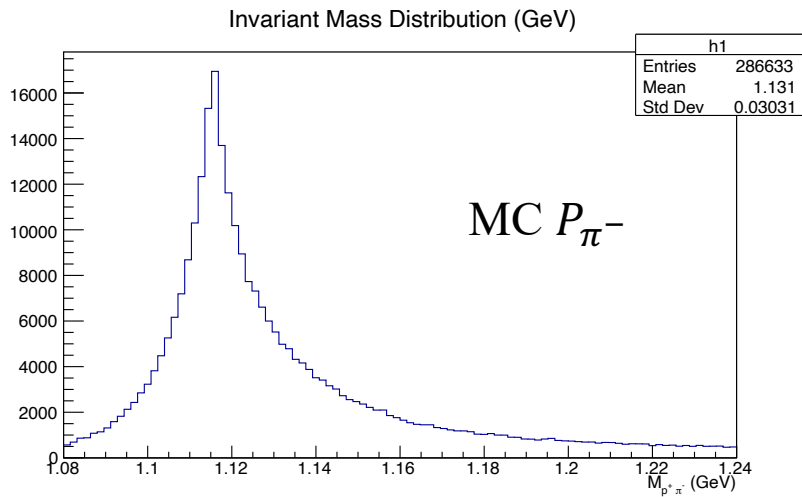
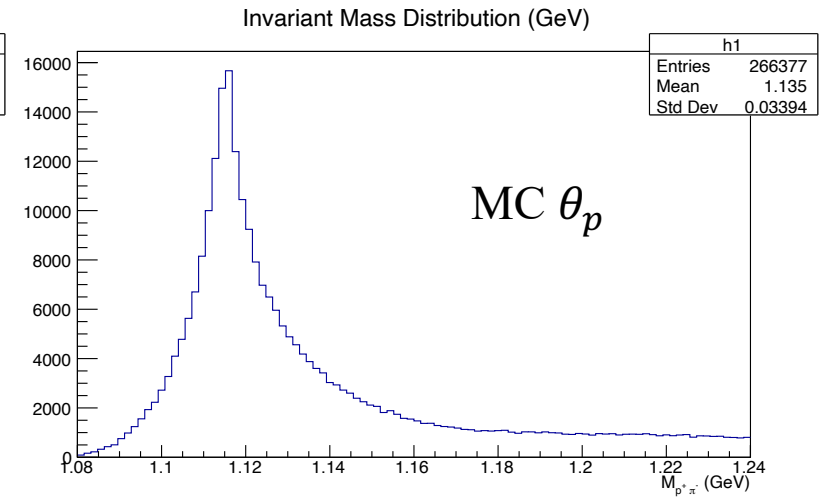
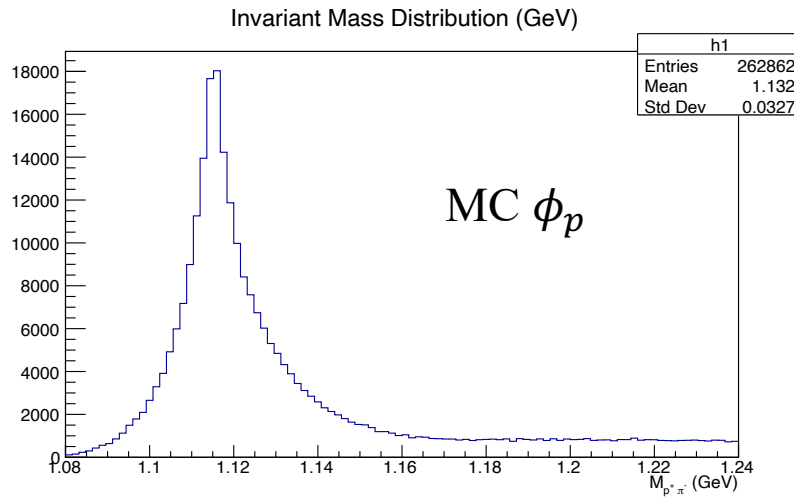
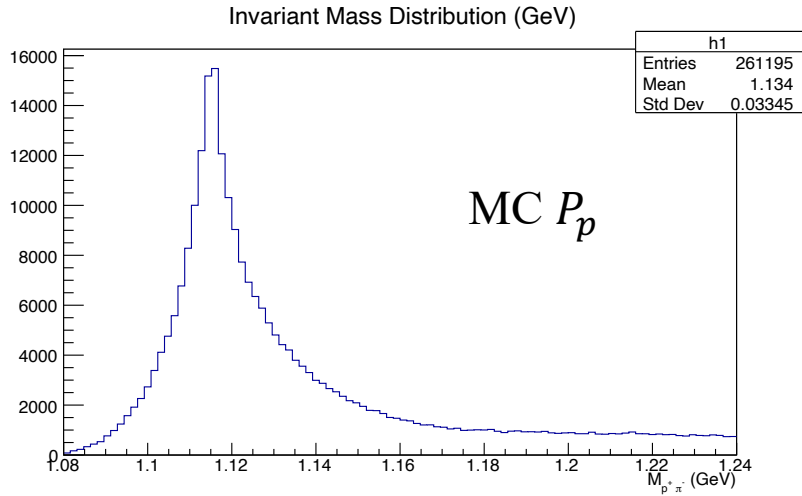
# Systematic Uncertainties

- Uncertainties from fit errors and incorrect particle PID were minimal ( $<0.001$ ).
- Spin transfer in sidebands is fairly small:

Preliminary Helicity Balance	
$\cos \theta_{pL'}$ along $\vec{p}_\Lambda$	$\cos \theta_{pL'}$ along $\vec{p}_\gamma$
$-0.00141 \pm 0.01293$	$0.00113 \pm 0.01387$

- Results from linear fit method are consistent within uncertainties but require better statistics.

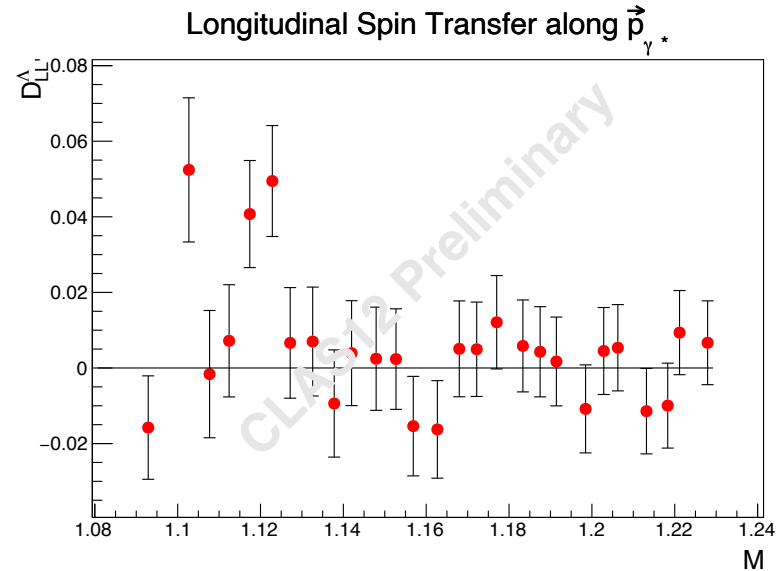
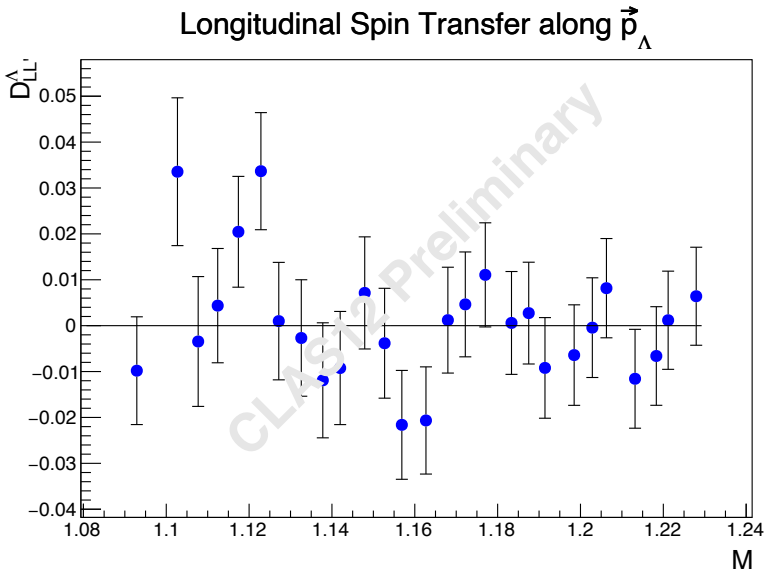
# REC/MC Mass Resolutions





# Helicity Balance vs. Invariant Mass

vs. Invariant  
Mass



**Note:** No GNN applied,  
errors are solely  
statistical