Spin Transfer to Λ Hyperons at CLAS12

Matthew McEneaney, Duke University

matthew.mceneaney@duke.edu

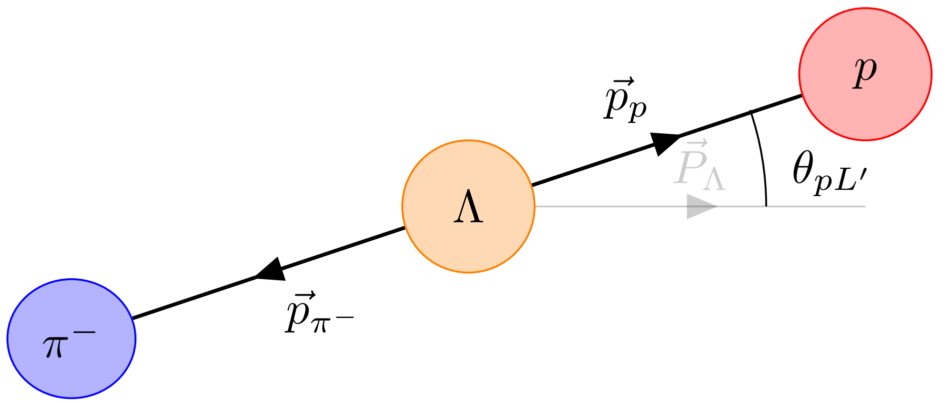
JINST ***18*** *P06002 2023*

Research supported by:

U.S. DEPARTMENT OF ENERGY | Office of Science

25th International SPIN Symposium, September 26, 2023

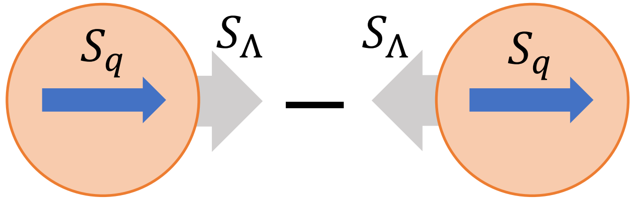
Λ Hyperons

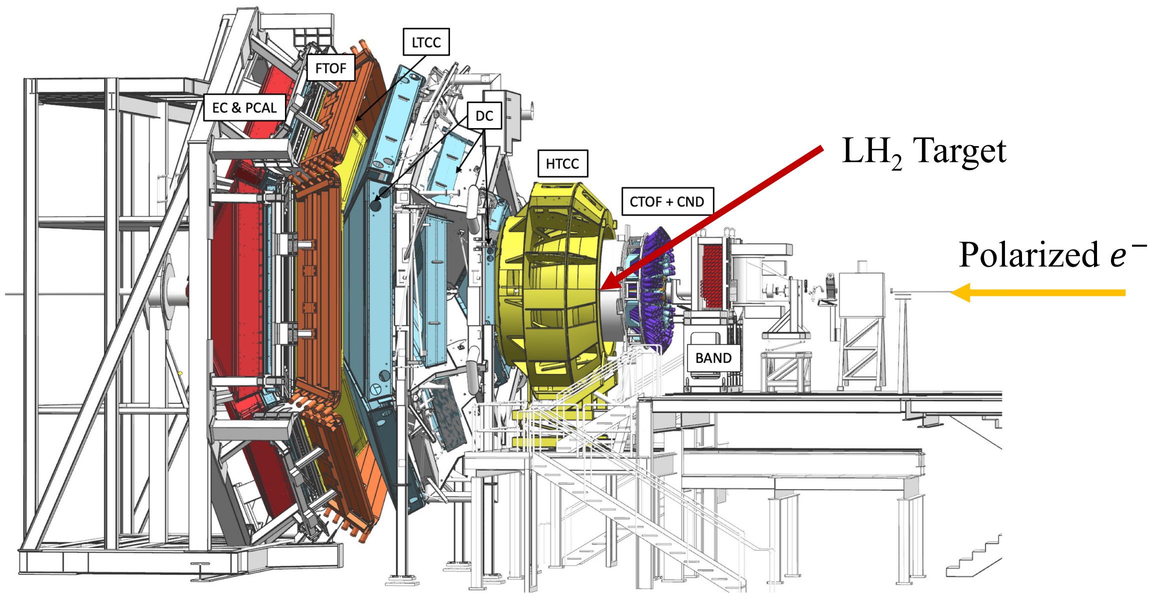


- Λ polarization is easily accessible from the $\Lambda \to p\pi^-$ channel:

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

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

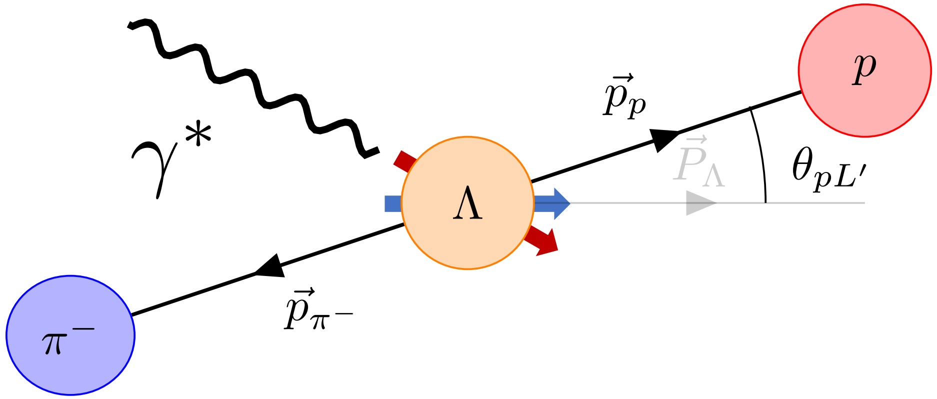
$G_1^{\Lambda} \propto ($  $)$



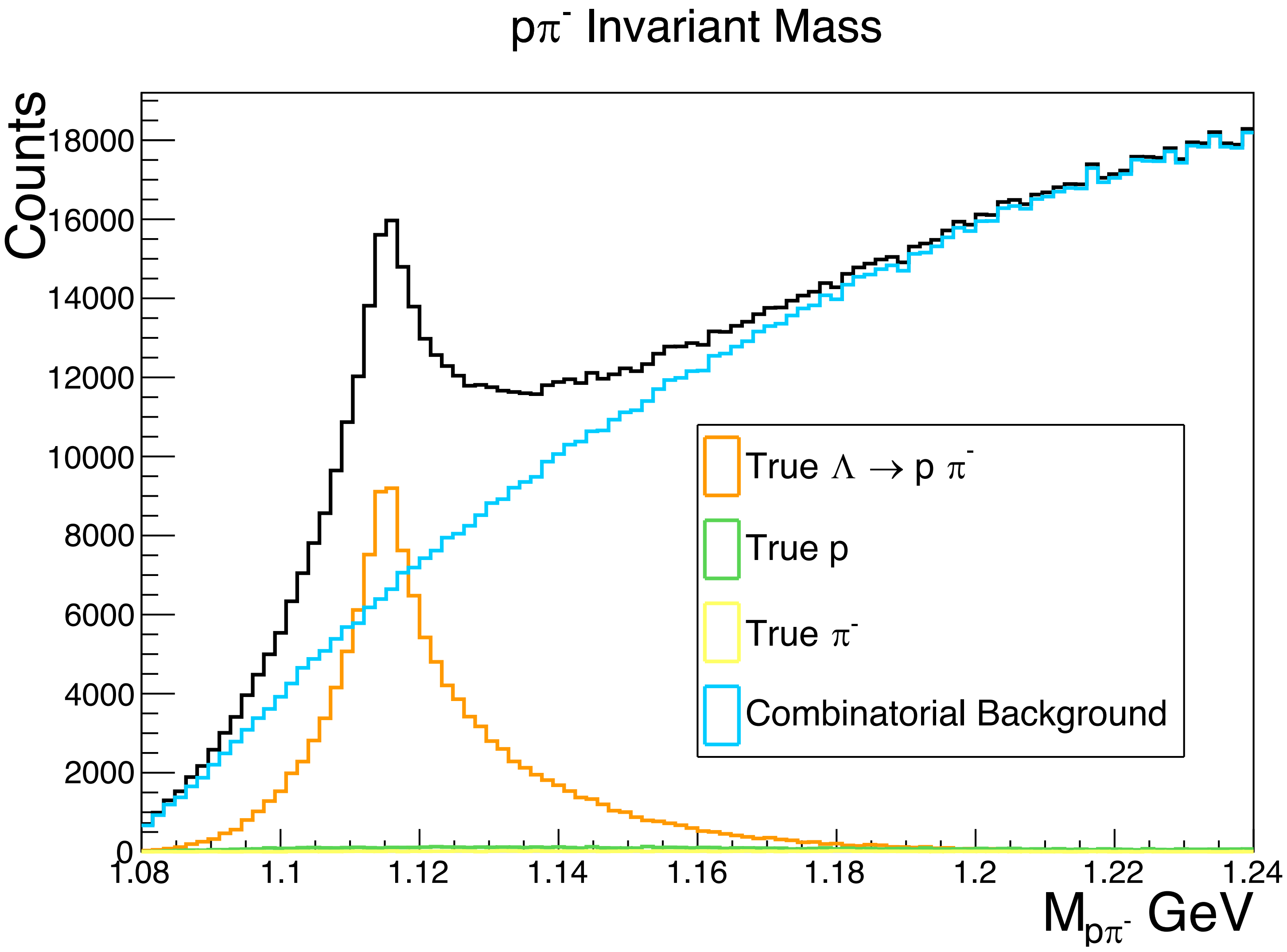
V. Burkert, et al. NIM A 2020.

Choice of Λ Polarization Axis

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



Signal Decomposition in MC



Event selection:

$p\pi^-$ and scattered e^-

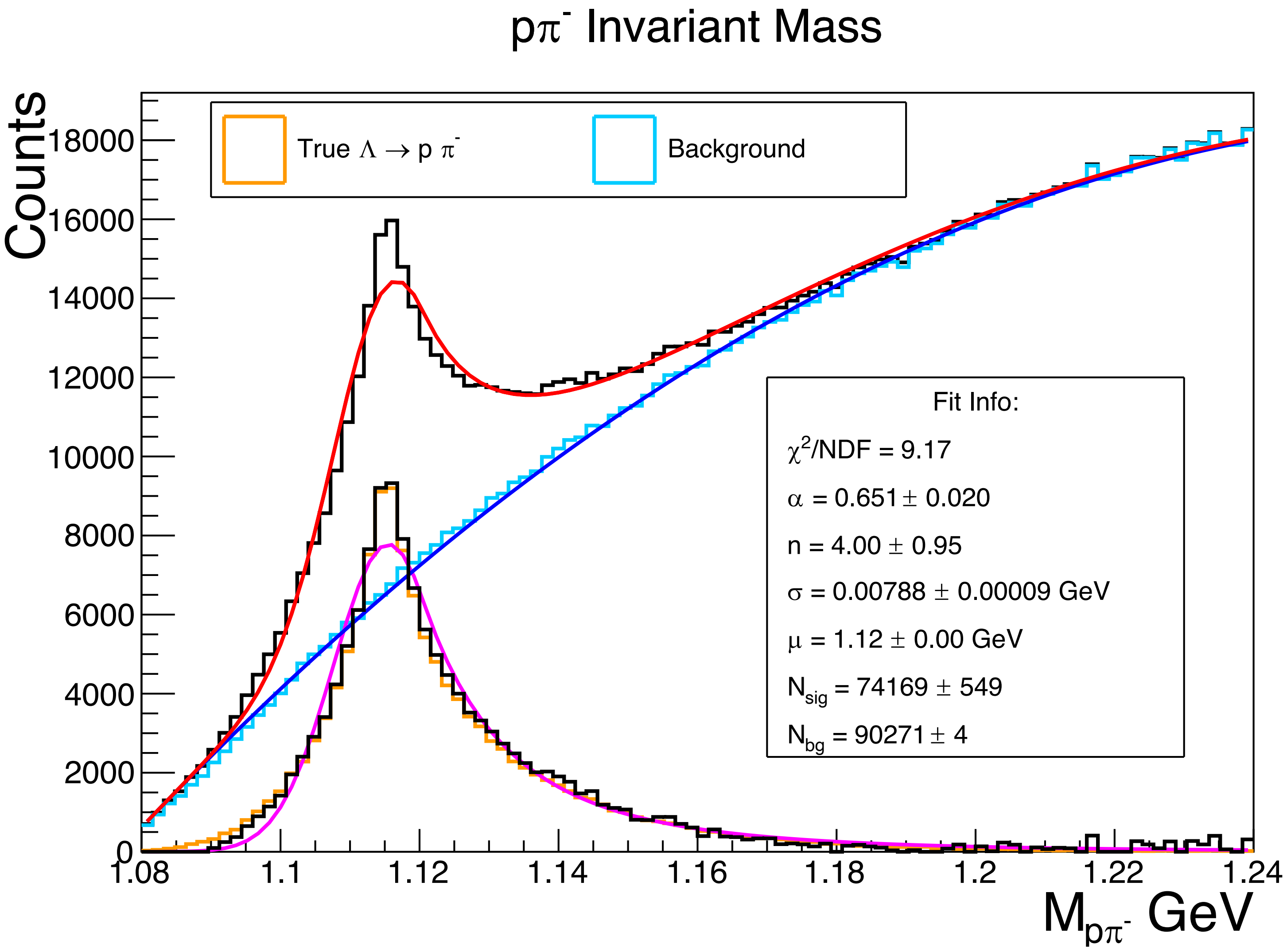
Kinematic Cuts:

$Q^2 > 1$ & $W > 2$ & $y < 0.8$

Λ Cuts:

$x_F > 0$ & $z_{p\pi^-} < 1$

Signal Fit in MC



Event selection:

$p\pi^-$ and scattered e^-

Kinematic Cuts:

$Q^2 > 1$ & $W > 2$ & $y < 0.8$

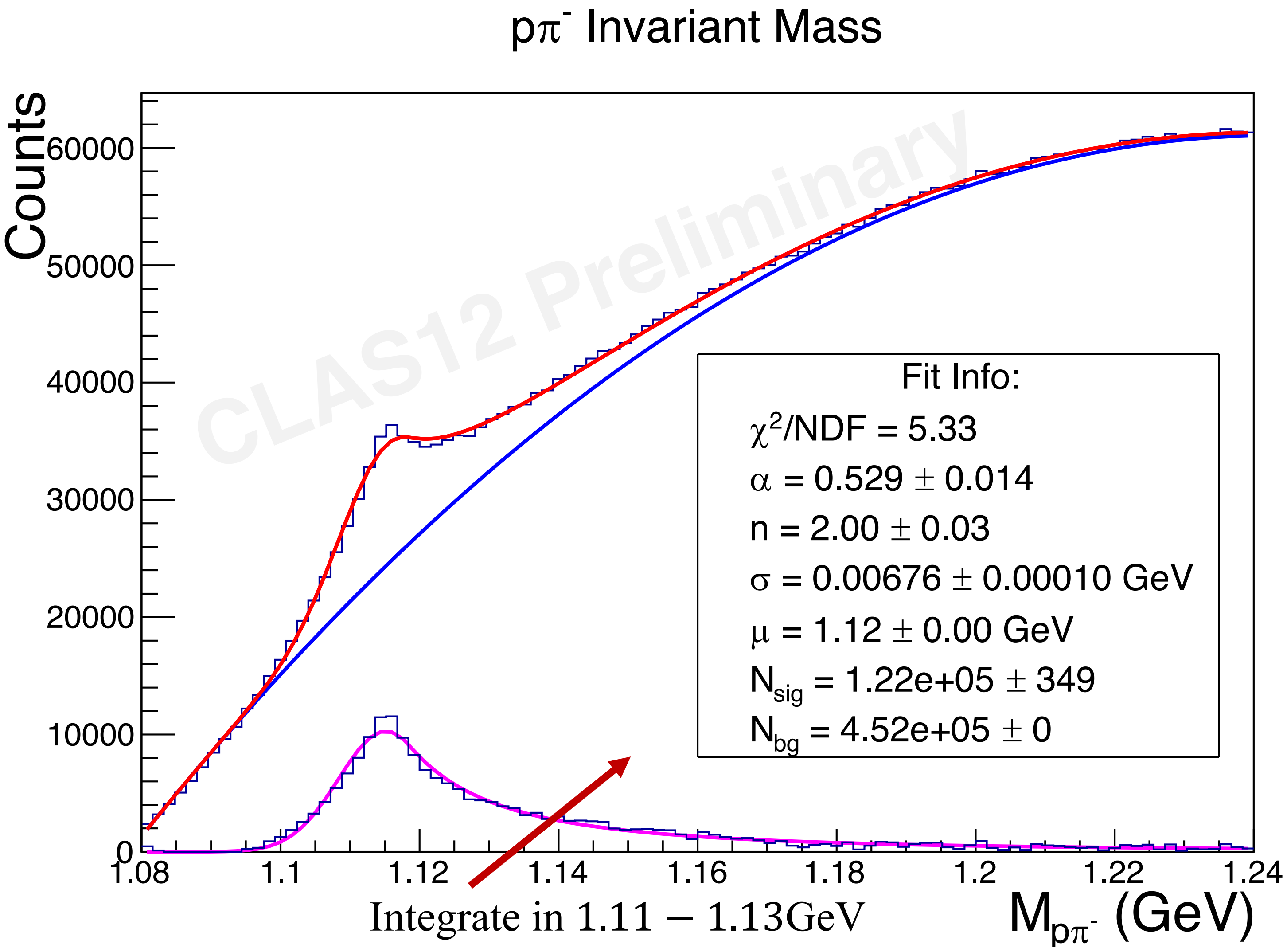
Λ Cuts:

$x_F > 0$ & $z_{p\pi^-} < 1$

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

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

Signal Fit in Data



Integrate in 1.11 – 1.13GeV

Event selection:

$p\pi^-$ and scattered e^-

Kinematic Cuts:

$Q^2 > 1$ & $W > 2$ & $y < 0.8$

Λ Cuts:

$x_F > 0$ & $z_{p\pi^-} < 1$

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

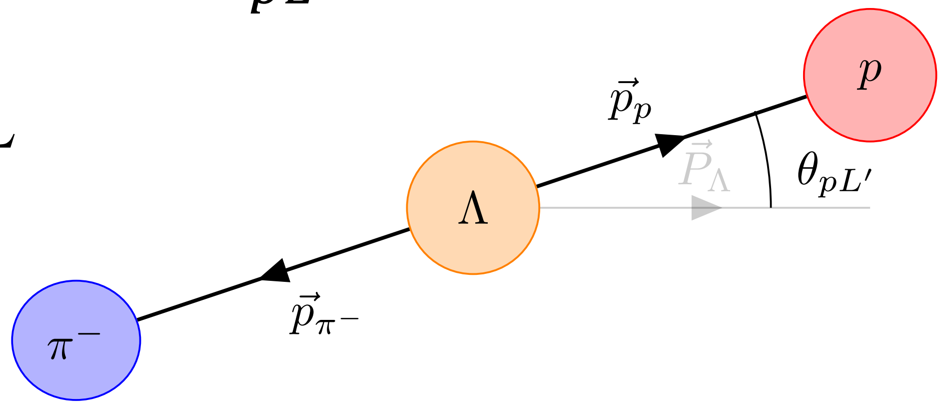
Fit Function: Gaussian Peak with power law tail (Crystal Ball)

$D_{LL'}^{\Lambda}$ Extraction

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

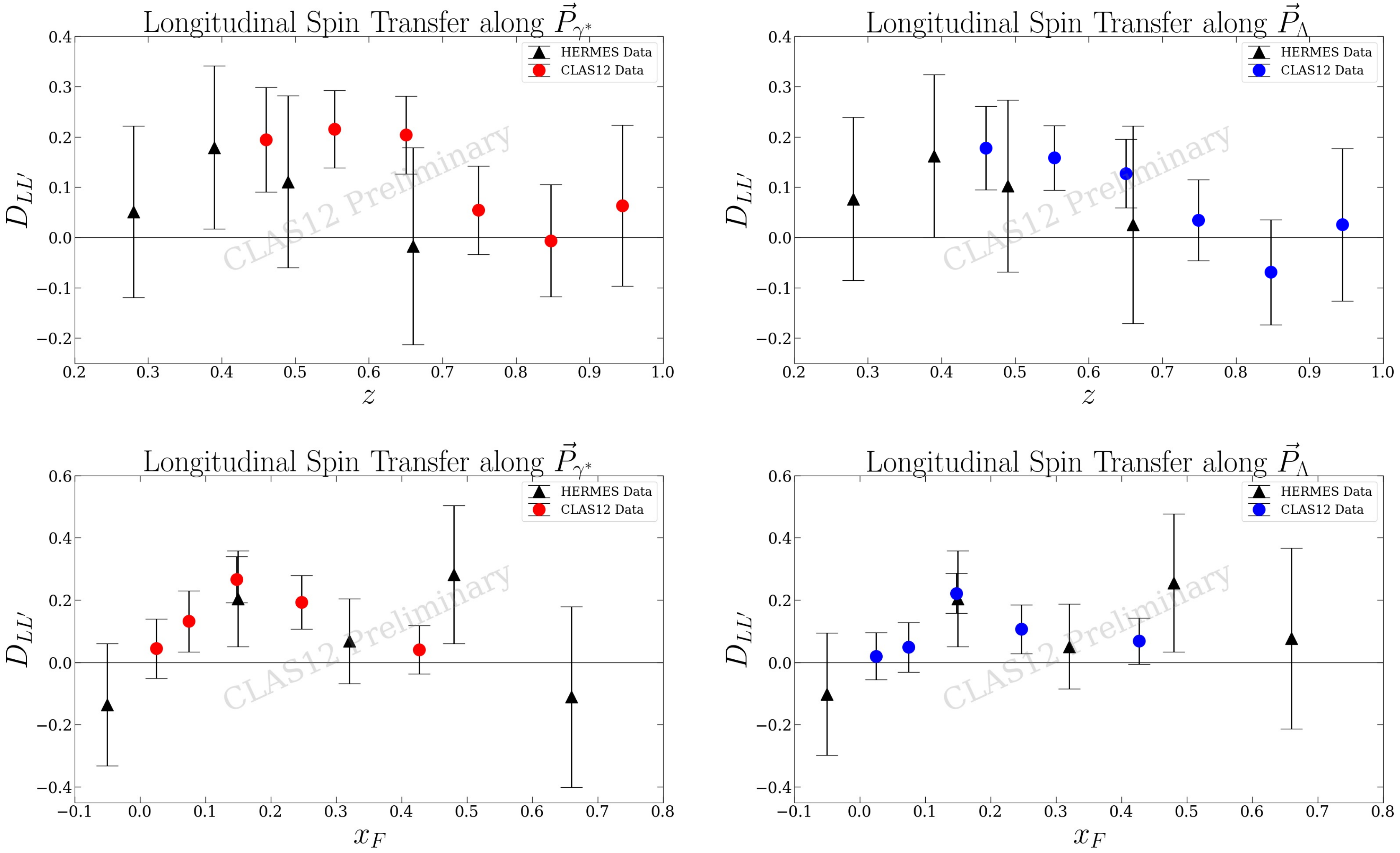
$$D_{LL'}^{\Lambda} = \frac{1}{\alpha \overline{P_b^2}} \cdot \frac{\Sigma_{i=1}^{N_\Lambda} P_{b,i} D(y_i) \cos\theta_{pL'}^i}{\Sigma_{i=1}^{N_\Lambda} D^2(y_i) \cos^2\theta_{pL'}^i}$$

- No acceptance correction needed for ML



Maximum Likelihood Results

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

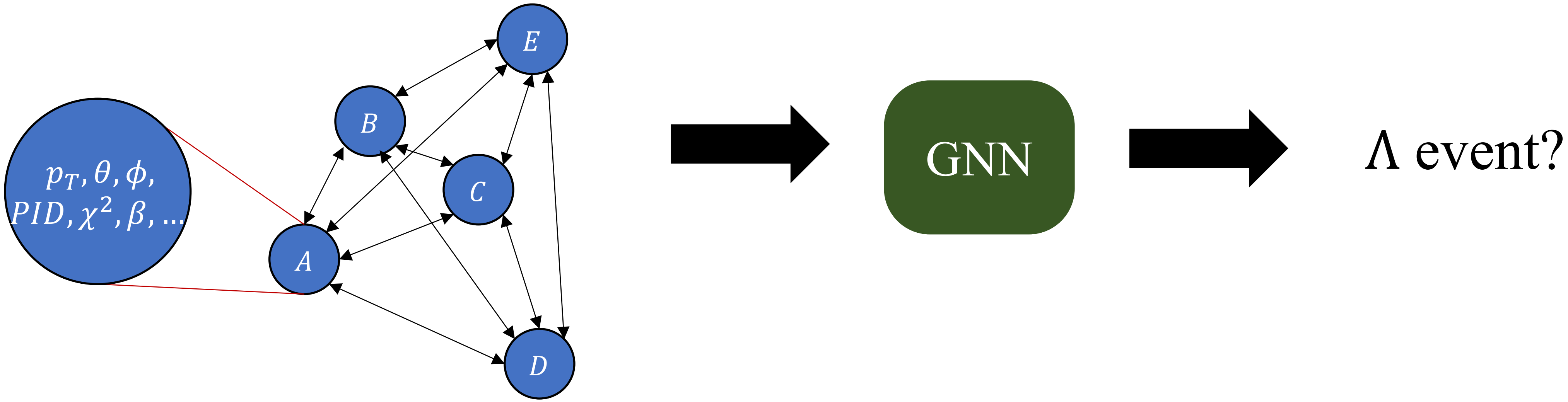


Note: Errors are solely statistical

HERMES Results from: A. Airapetian, et al. Physical Review D, 74(7), Oct 2006.

Graph Neural Networks (GNNs)

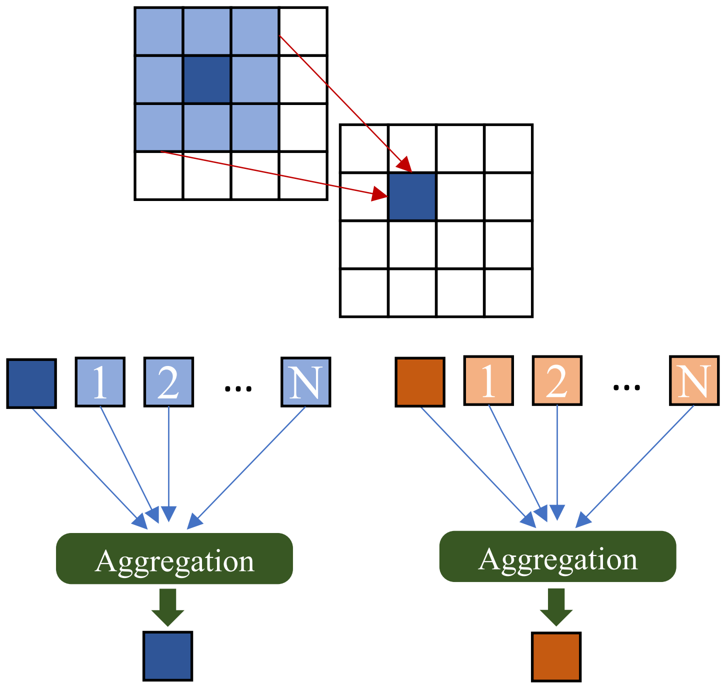
- **Idea**: use GNN to reduce background in invariant mass spectrum on event-by-event basis
- Pass each event as fully-connected, bidirectional graph
- Each particle is a node with its own data: p_T, θ, ϕ, etc.



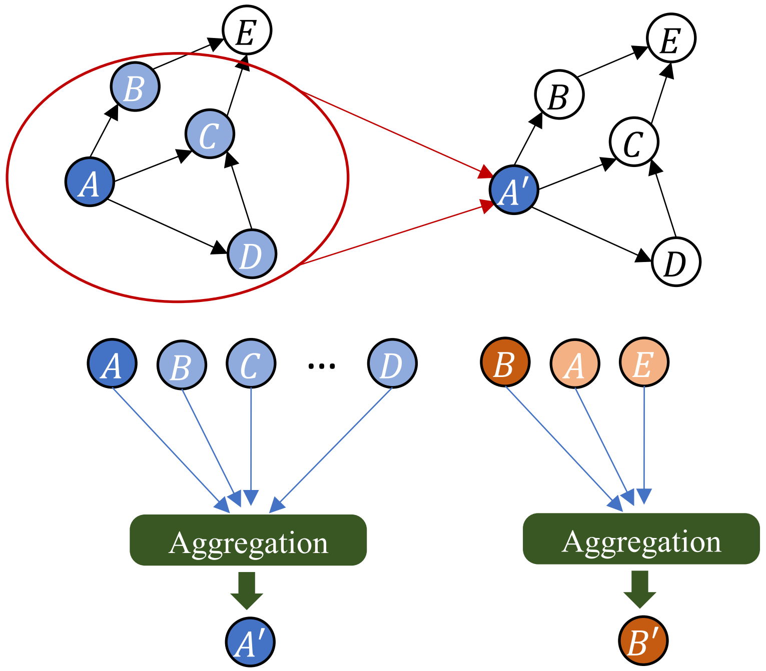
Graph Neural Networks (GNNs)

- At basic level, function as generalized form of CNNs

CNN

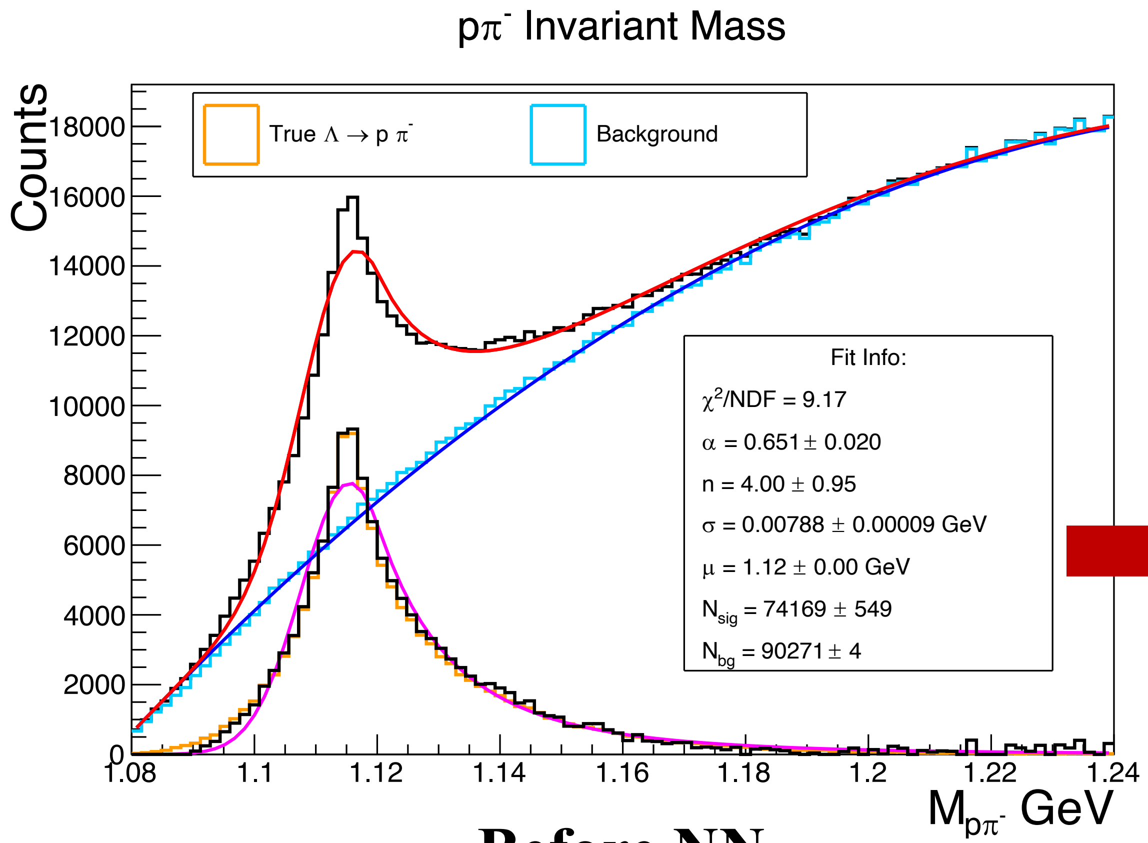


GNN

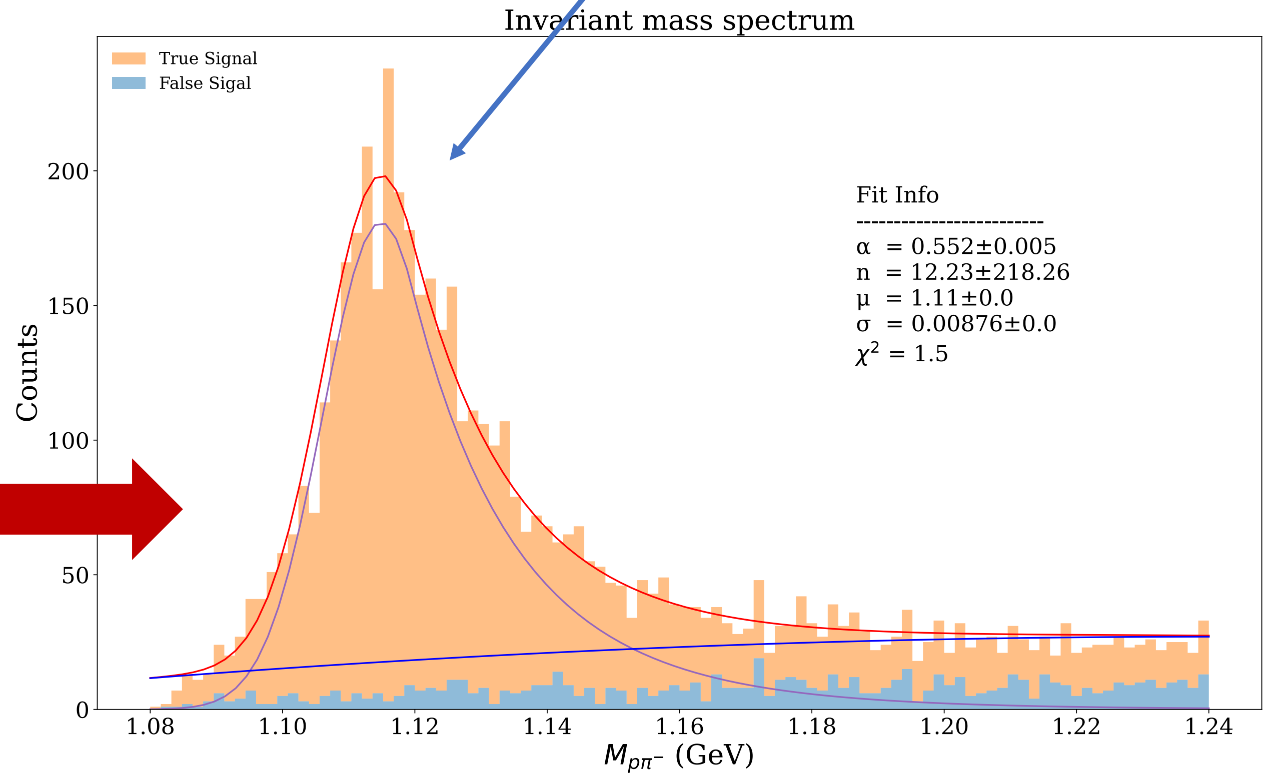


GNN Evaluation on MC

Signal shape preserved



Before NN

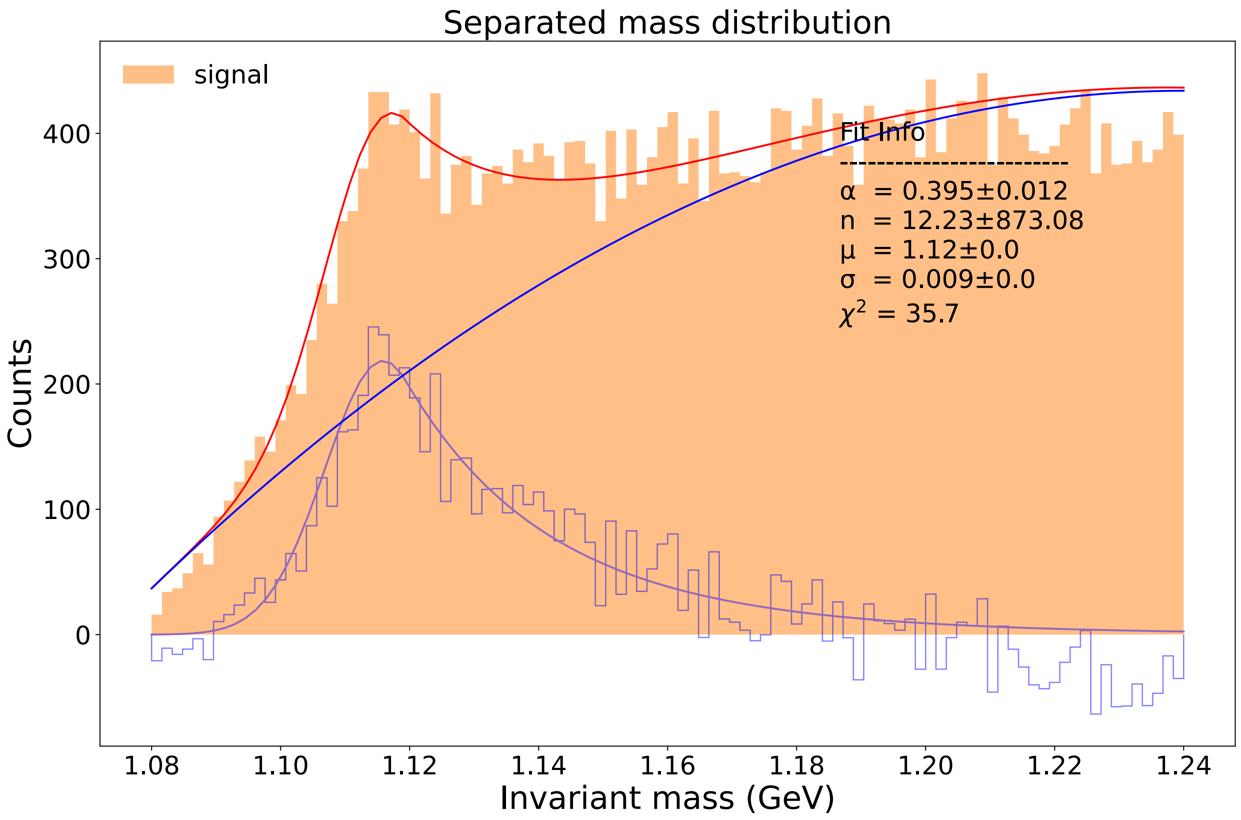


After NN

83.7% Test accuracy and background is significantly reduced!

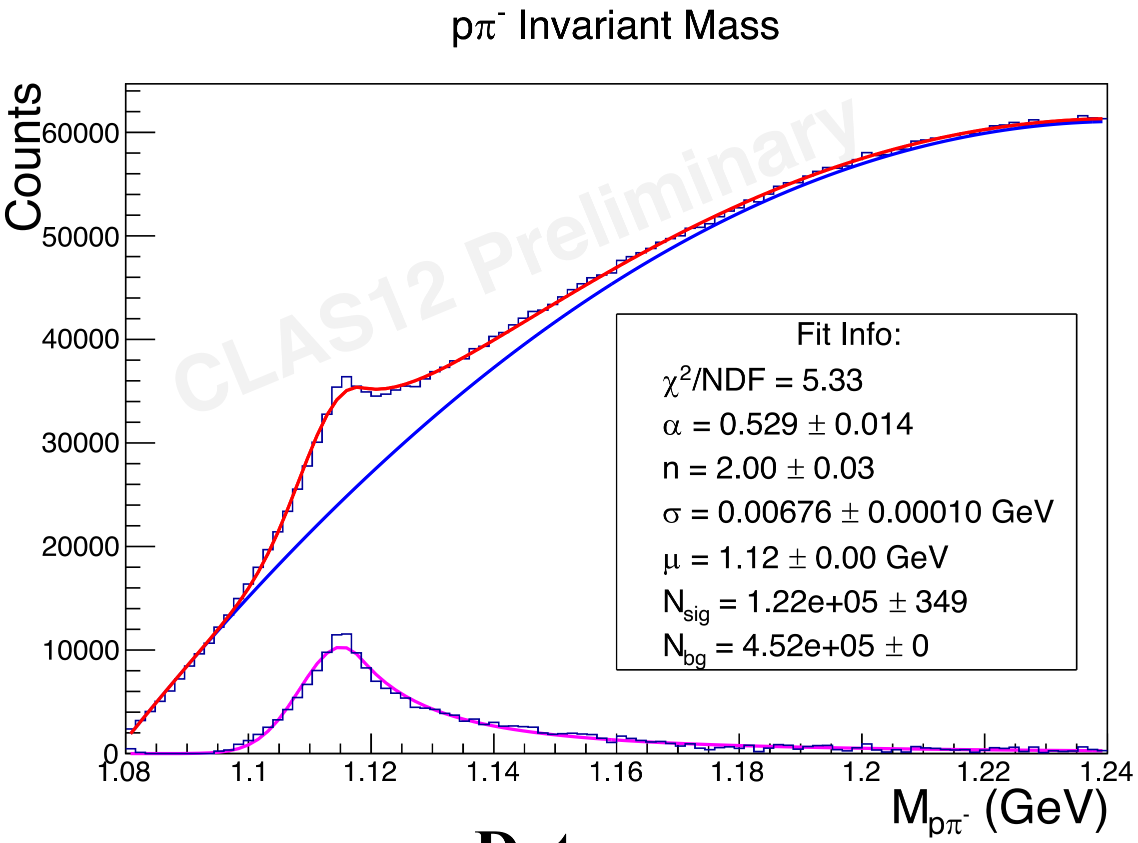
GNN Evaluation on Data

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

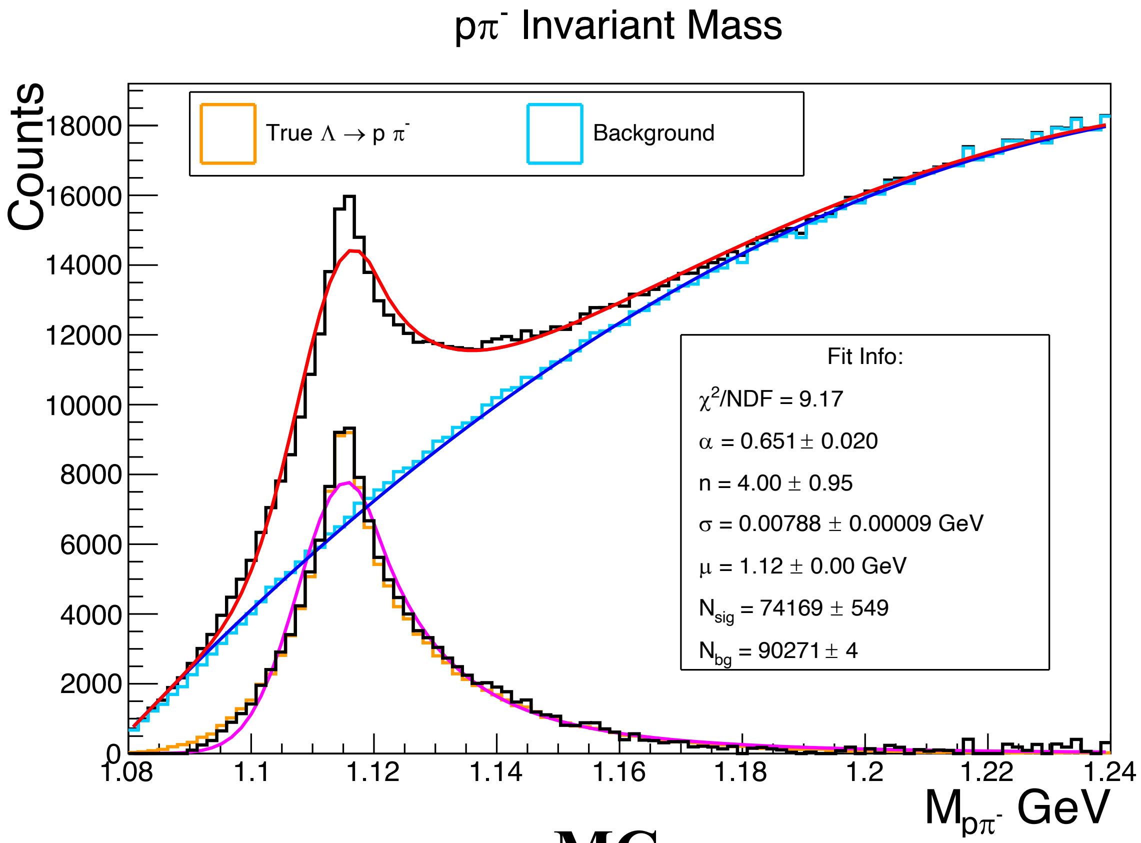


Domain-Adaptation

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



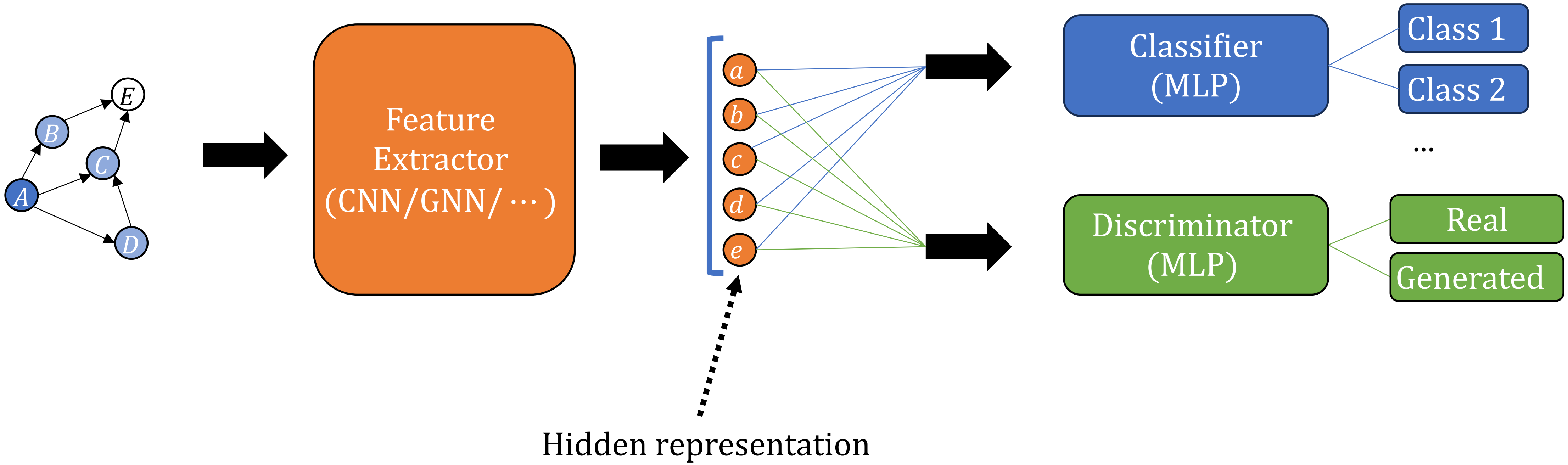
Data



MC

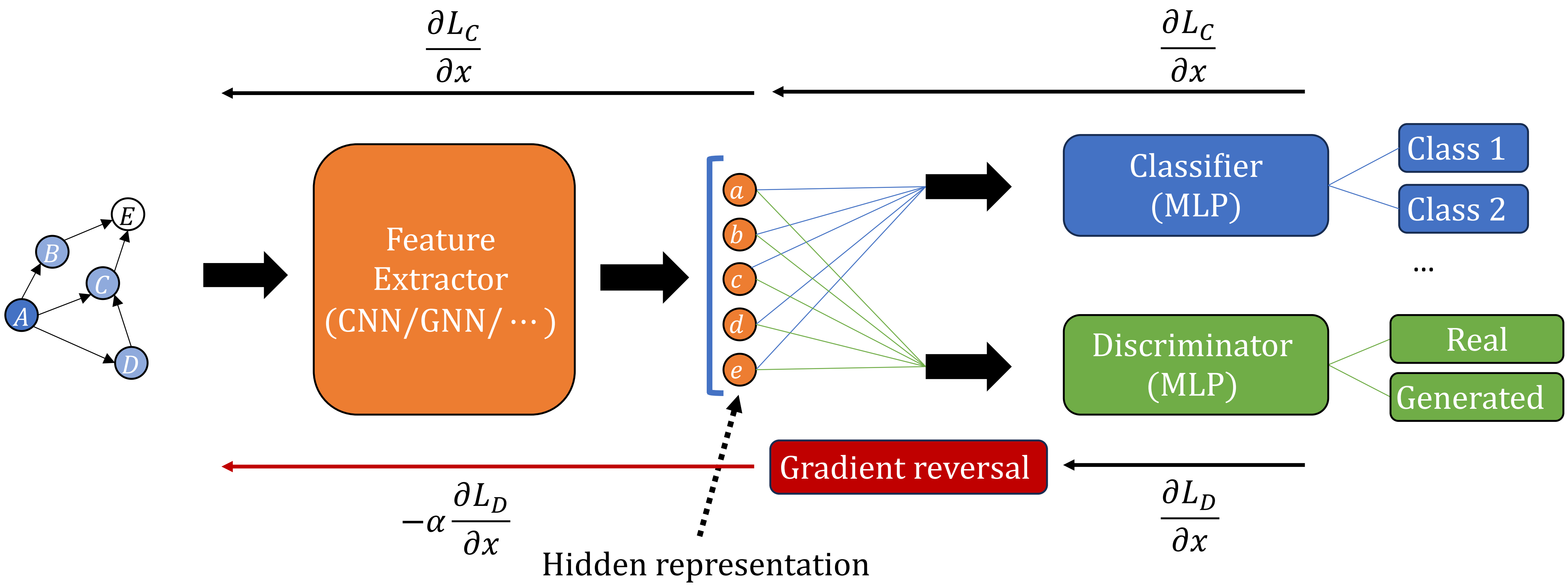
Domain-Adaptation

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



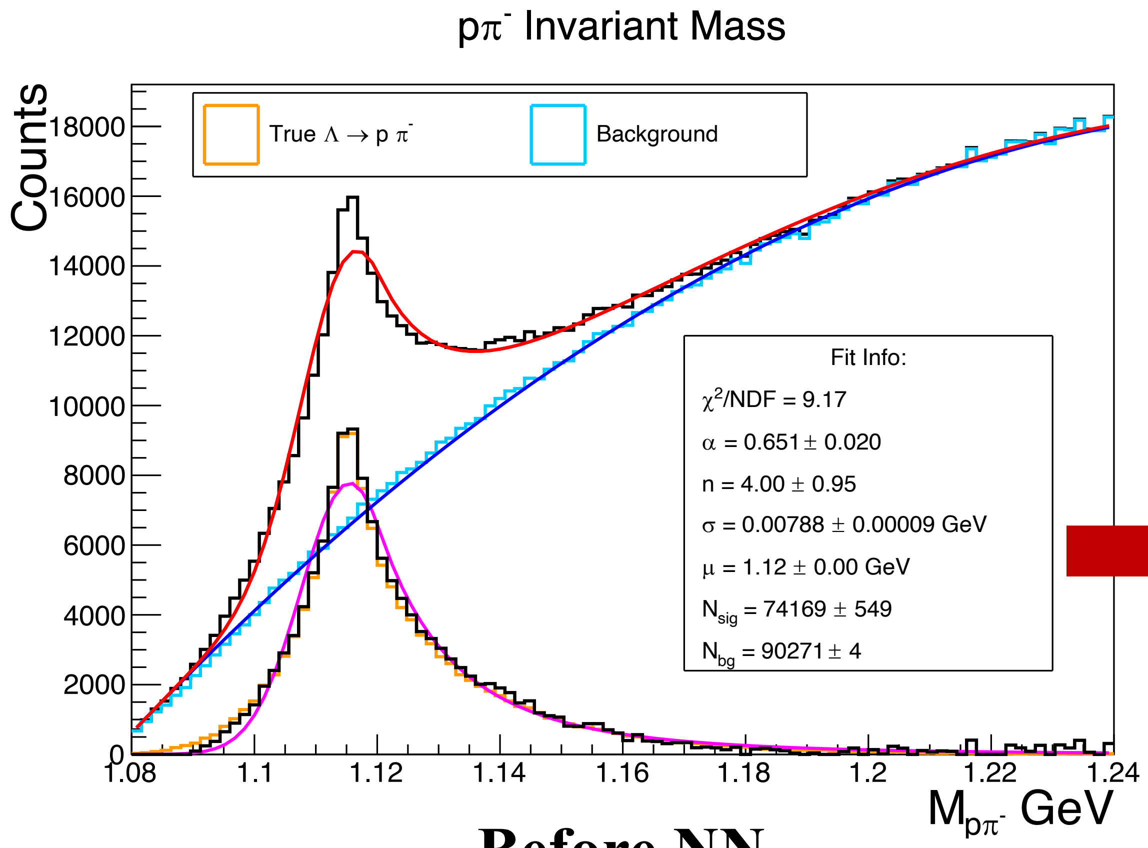
Domain-Adaptation

- Reverse gradient from discriminator loss during backpropagation

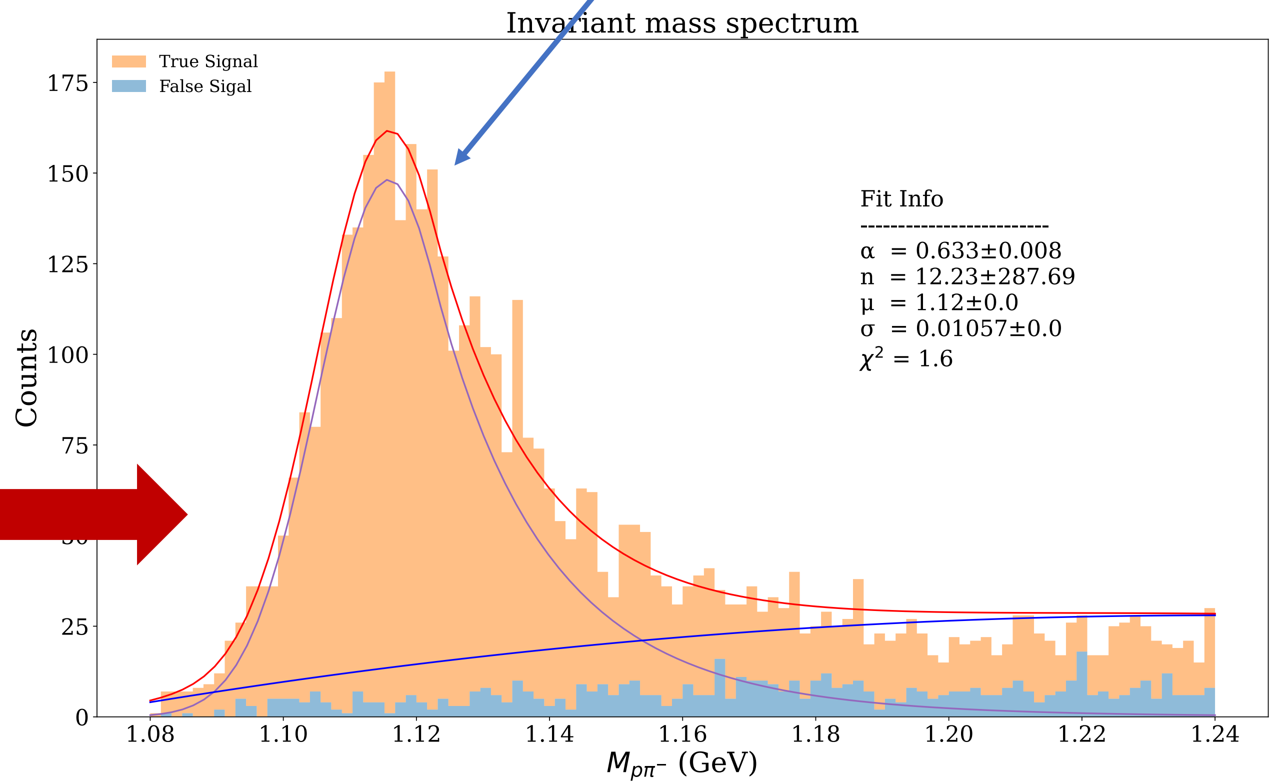


DAGNN Evaluation on MC

Signal shape preserved



Before NN

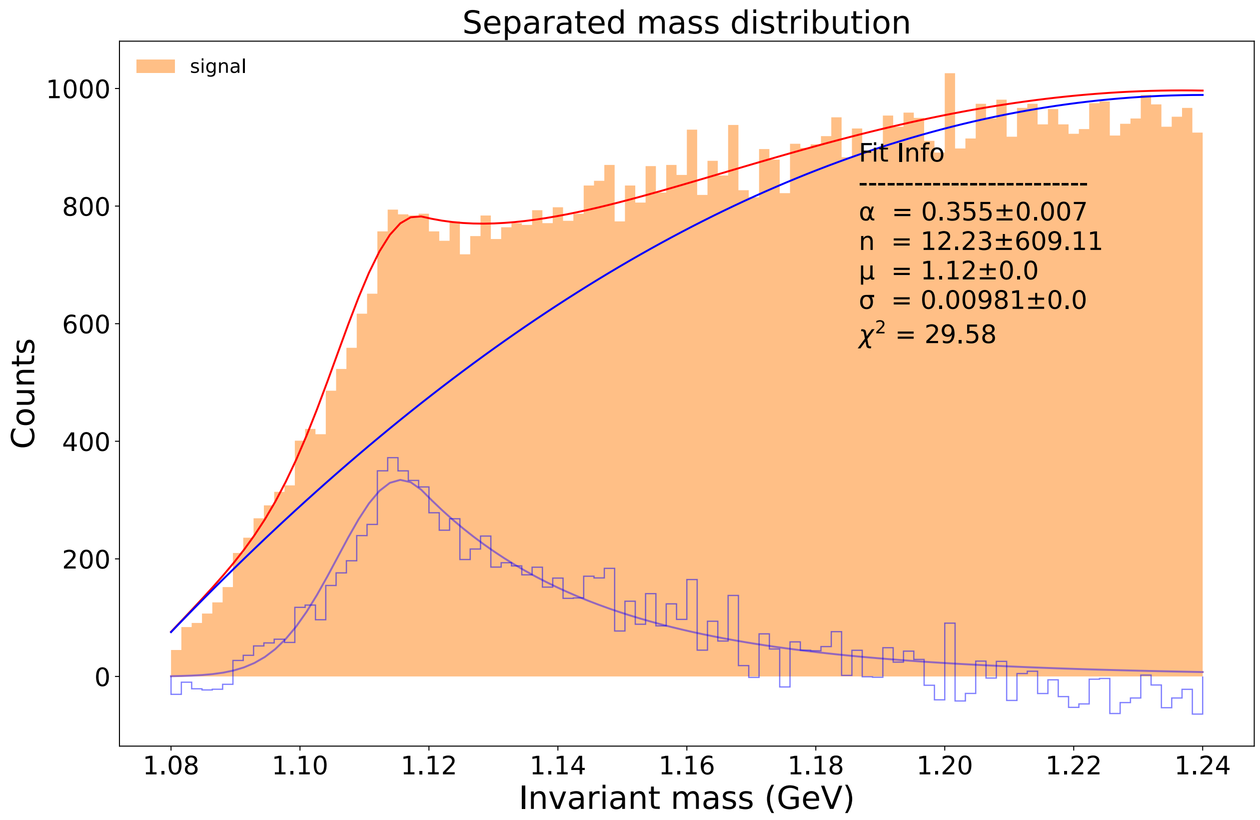


After NN

82.9% Test accuracy and background is significantly reduced!

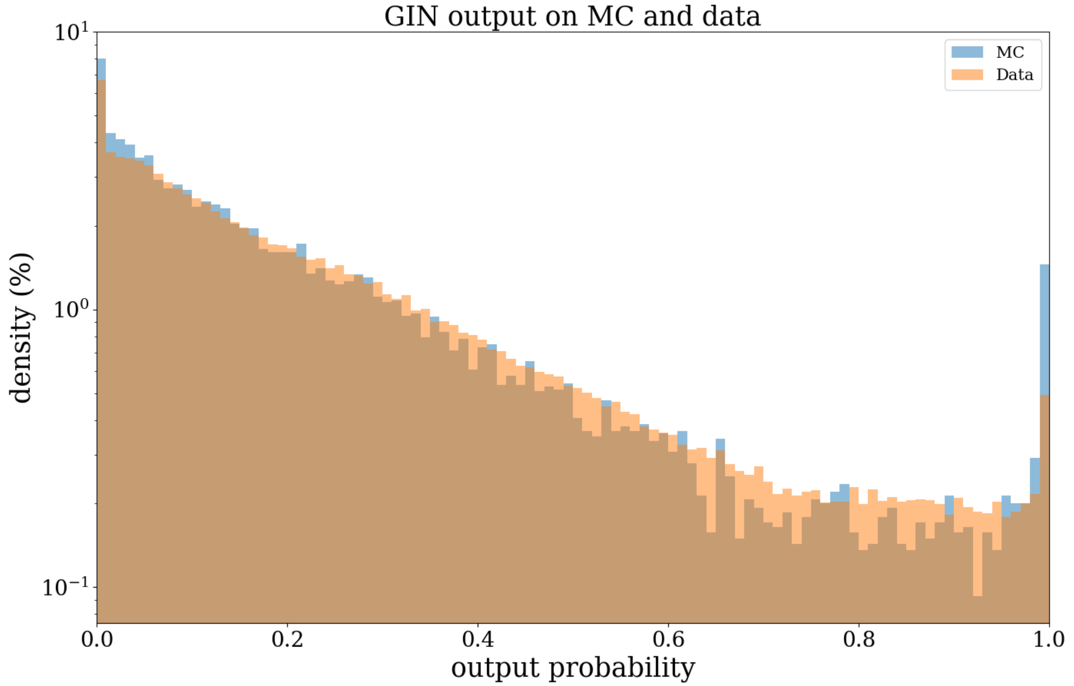
DAGNN Evaluation on Data

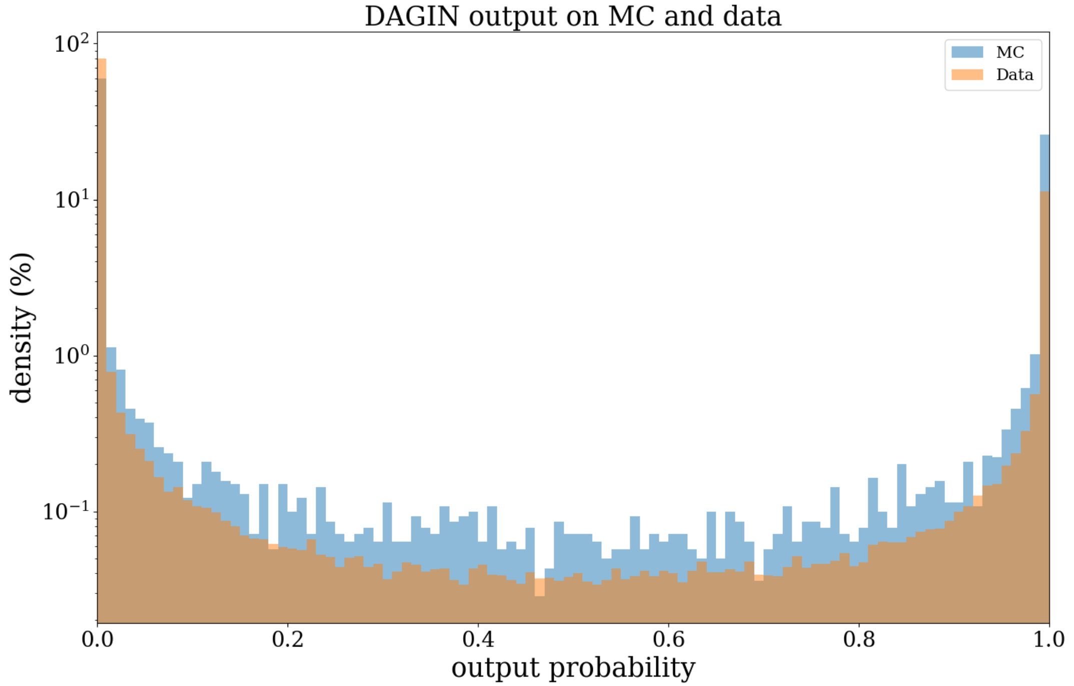
- $FOM = N_{sig}/\sqrt{N_{tot}}$ is 42.09 compared to 34.11 without the GIN



NN Output on Data and MC

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





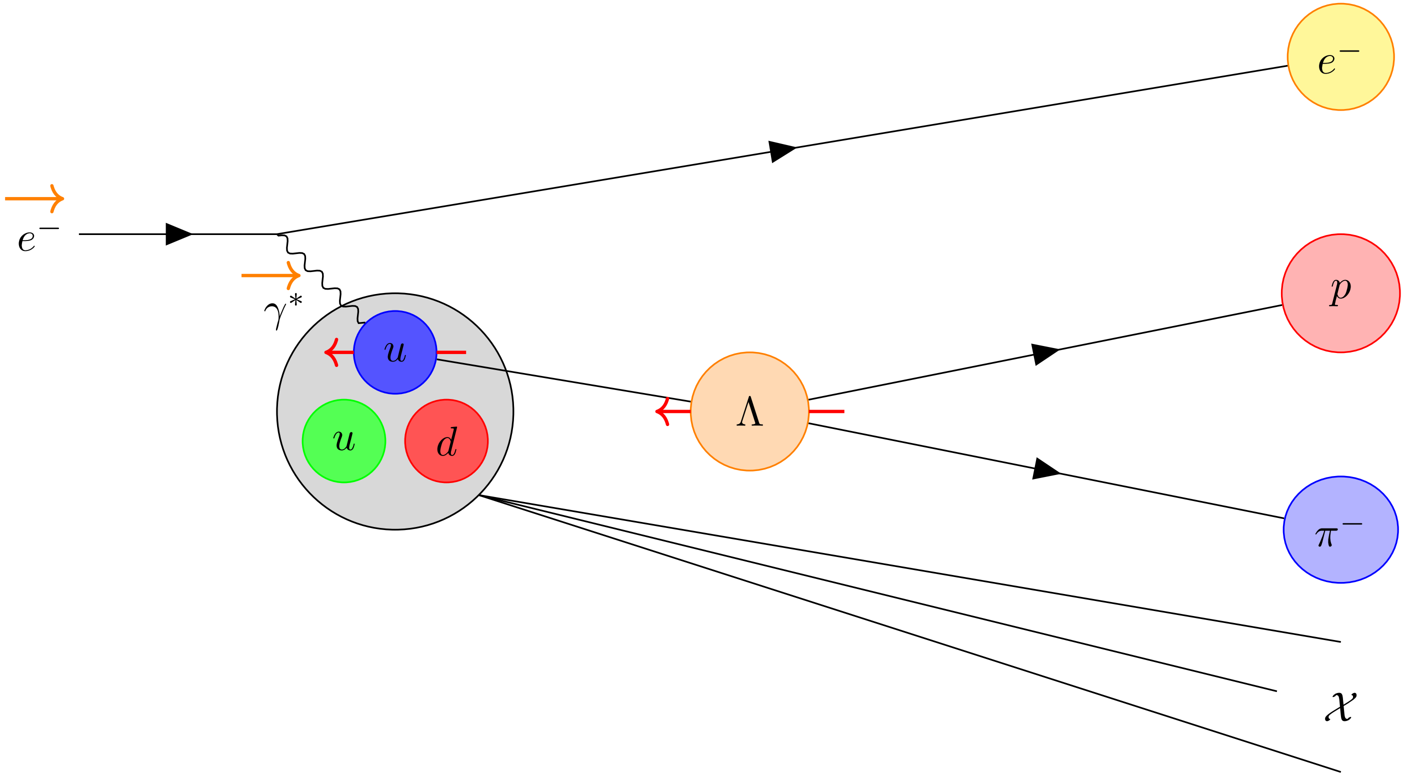
Summary and Next Steps

- 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
- Other approaches: normalizing flows, transformers
- Next steps:
  - Secondary vertex reconstruction method recently implemented
  - Measurement of Λ spontaneous transverse polarization
  - ΛK spin orbit correlations

Thank you!

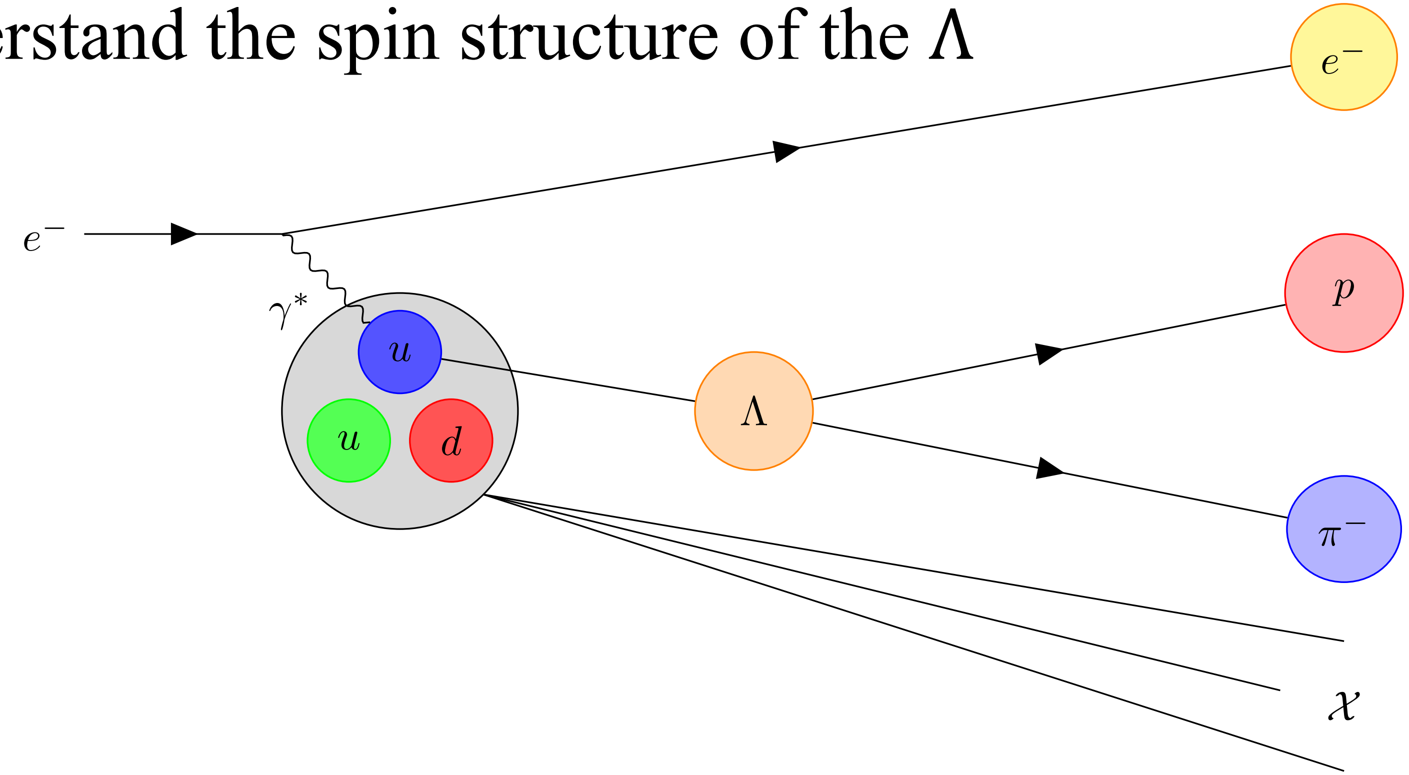
Longitudinal Spin Transfer

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



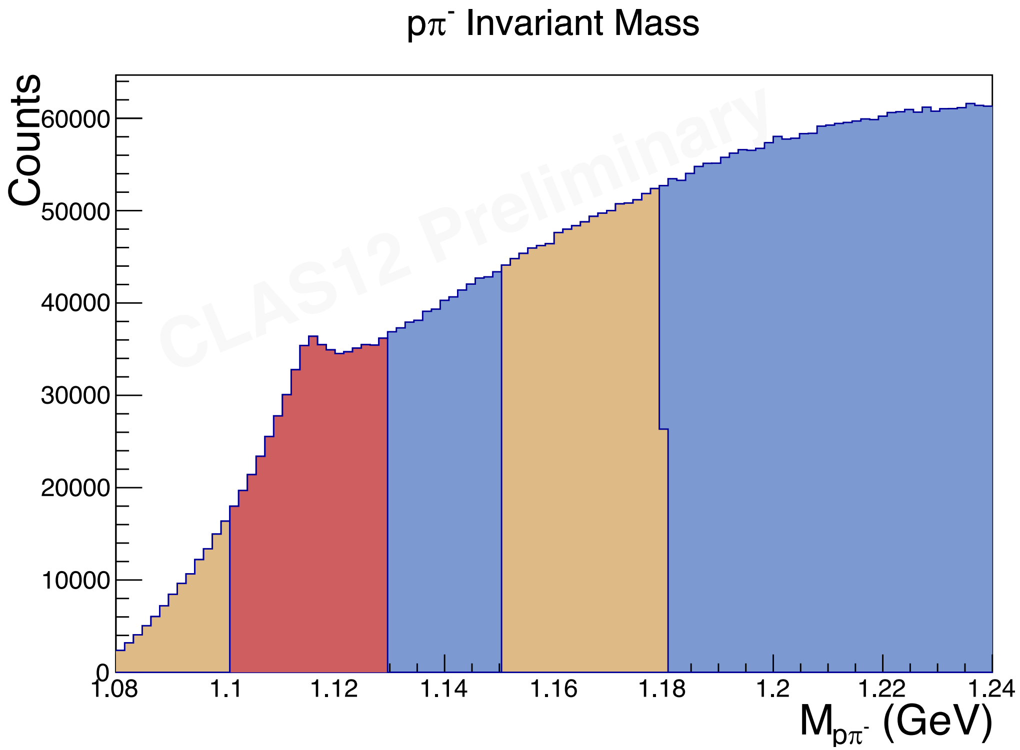
Interpretation of $D_{LL'}^{\Lambda}$

- In the naïve quark model, the strange quark carries the Λ spin
- By measuring the light quark spin contribution, we can better understand the spin structure of the Λ



Sideband Background Correction

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



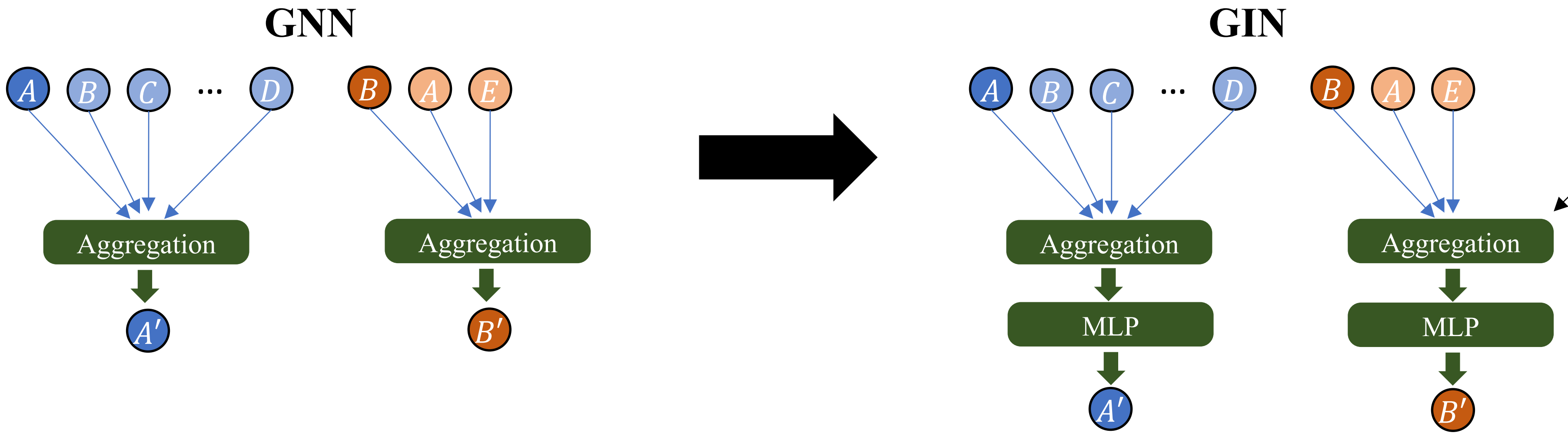
$$D_{LL'}^{\Lambda} = \frac{D_{LL'\,sig} - \epsilon D_{LL'\,bg}}{1 - \epsilon}$$

MC

Graph Isomorphism Network (GIN)

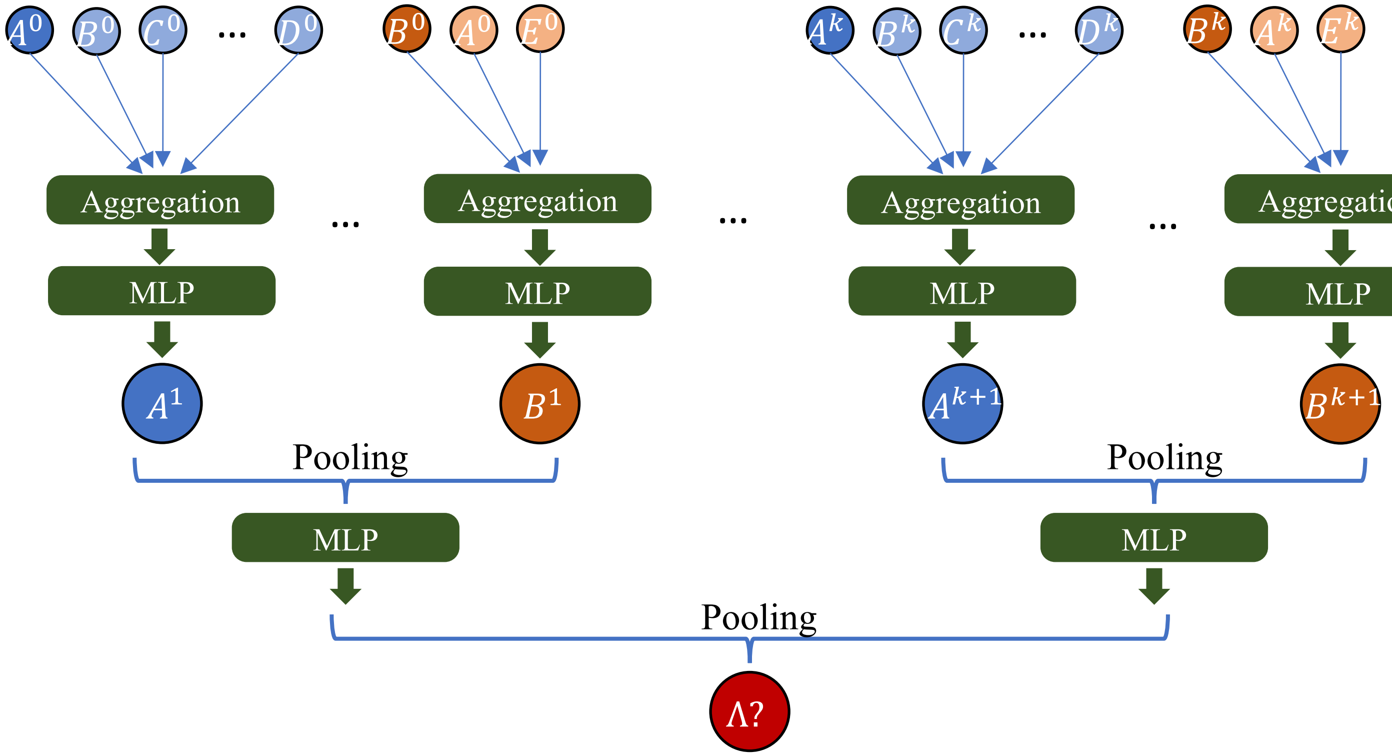
- Based on Weisfeiler-Lehman (WL) Test, essentially ensures aggregation is injective
- Compare with basic GNN convolution:

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



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 cut on NN output