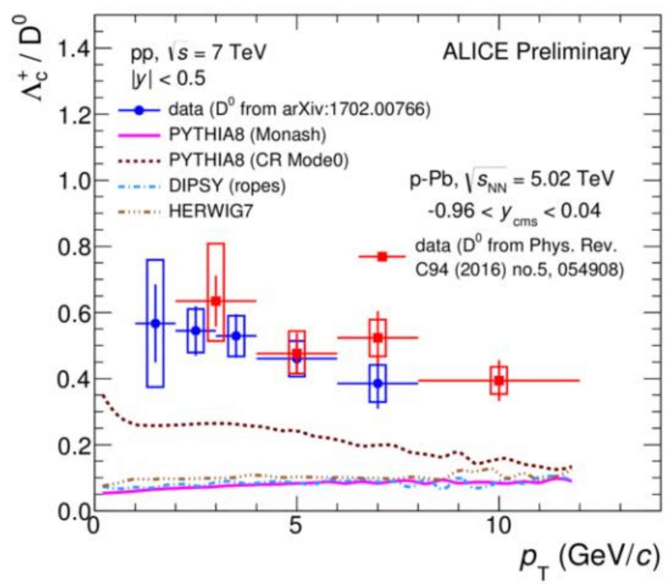
Status of Ξ_c^+ Hadronic Channel topological study

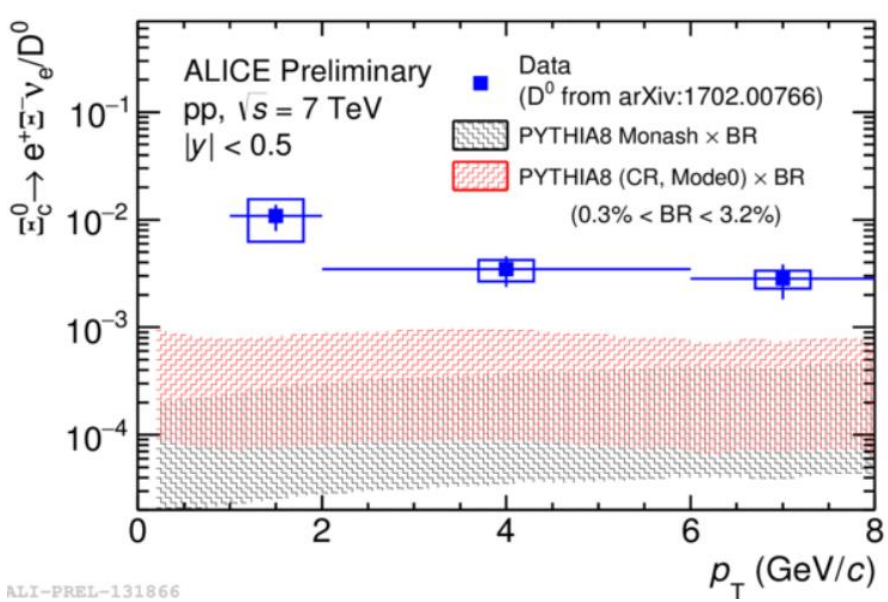
koAlice 2020. 1. 5

Jaehyeon Do

Charmed baryon

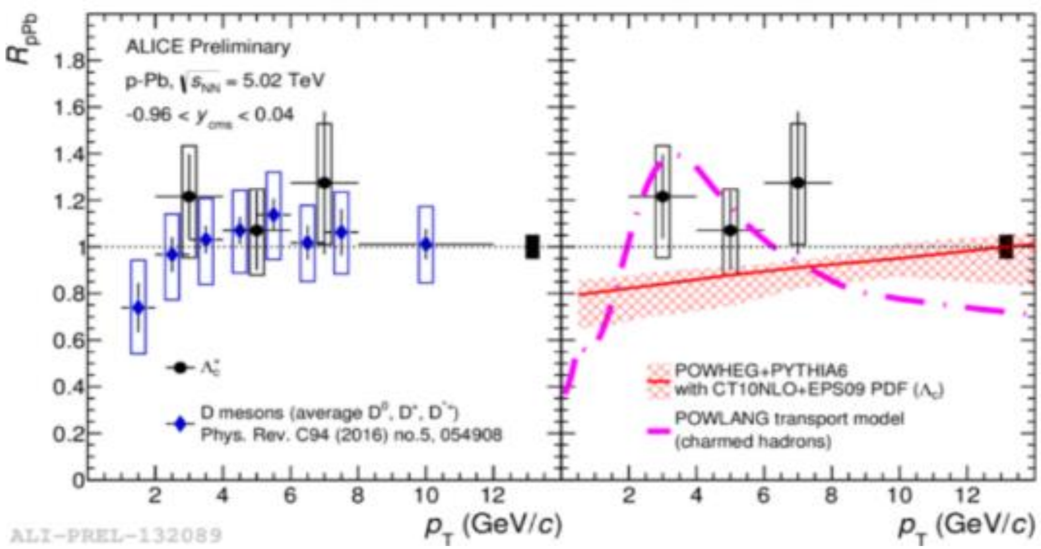
- Fragmentation in to charm baryons are well studied in e+e collisions
  - Fragmentation would same in pp (or pPb, PbPb) system?
  - Multiple parton interaction (MPI) and color reconnection (CR) could increase the baryon to meson ratio
  - Recent analysis reported charm baryon enhancement from model prediction, even with CR





Charmed baryon

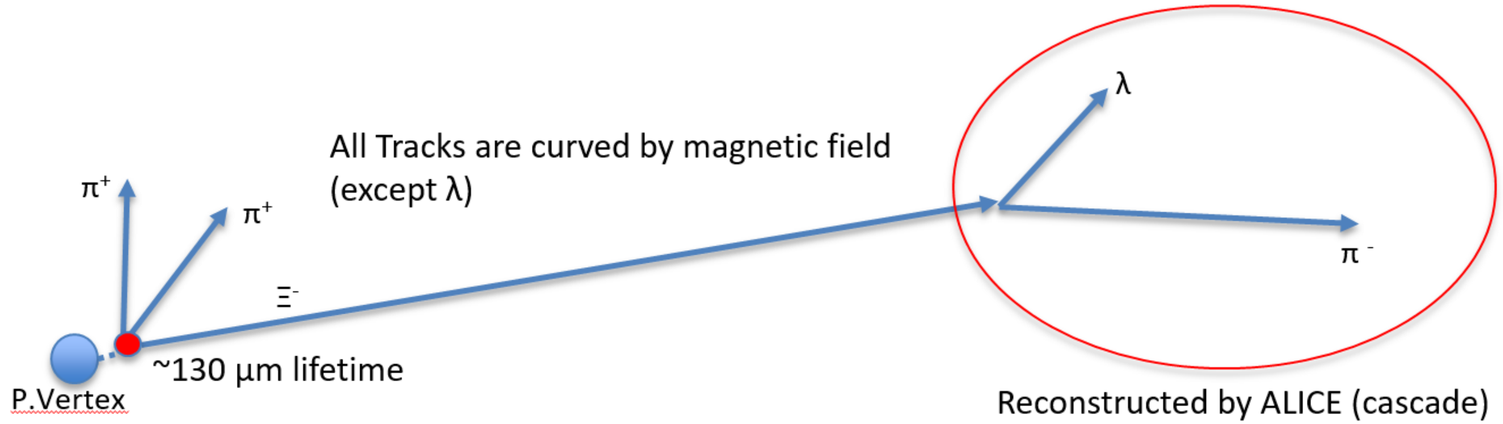
- pPb, PbPb collisions are further affected by cold nuclear matter effect and final state effect
  - pp charmed baryon measurement would be reference of bigger system (pPb, PbPb)
  - Strangeness enhancement?
  - Recombination could enhance charmed baryon yield?



Ξ_c^+(csu, 2467MeV) Decay Modes

$\Sigma(1385)^+ K^- \pi^+$	[b,g]	<0.3	90%	678
$\Sigma^+ K^- \pi^+$	[g]	0.94 ± 0.11		811
$\Sigma^+ \overline{K}^*(892)^0$	[b,g]	0.81 ± 0.15		658
$\Sigma^0 K^- \pi^+ \pi^+$	[g]	0.29 ± 0.16		735
$\Xi^0 \pi^+$	[g]	0.55 ± 0.16		877
$\Xi^- \pi^+ \pi^+$	[g]	DEFINED AS 1		851
$\Xi(1530)^0 \pi^+$	[b,g]	<0.1	90%	750
$\Xi^0 \pi^+ \pi^0$	[g]	2.34 ± 0.68		856
$\Xi^0 \pi^+ \pi^+ \pi^-$	[g]	1.74 ± 0.50		818
$\Xi^0 e^+ \nu_e$	[g]	$2.3 \begin{smallmatrix}+0.7\\-0.9\end{smallmatrix}$		884
$\Omega^- K^+ \pi^+$	[g]	0.07 ± 0.04		399
Cabibbo-suppressed decays				
$p K^- \pi^+$	[g]	0.21 ± 0.03		944
$p \overline{K}^*(892)^0$	[b,g]	0.12 ± 0.02		828
$\Sigma^+ K^+ K^-$	[g]	0.15 ± 0.07		580
$\Sigma^+ \phi$	[b,g]	<0.11	90%	549
$\Xi(1690)^0 K^+$, $\Xi(1690)^0 \to \Sigma^+ K^-$	[g]	<0.05	90%	501

Motivation



- Ξ^-, π^+, π^+ vs K^-, π^+, P
- Pros :
  - Larger branching ratio (x5)
  - Resonance channel provide further constraints on signal selection (Mass window cut)
- Cons :
  - Has more 5 daughter particles (Harder to reconstruct, introduce little more combinatorics)

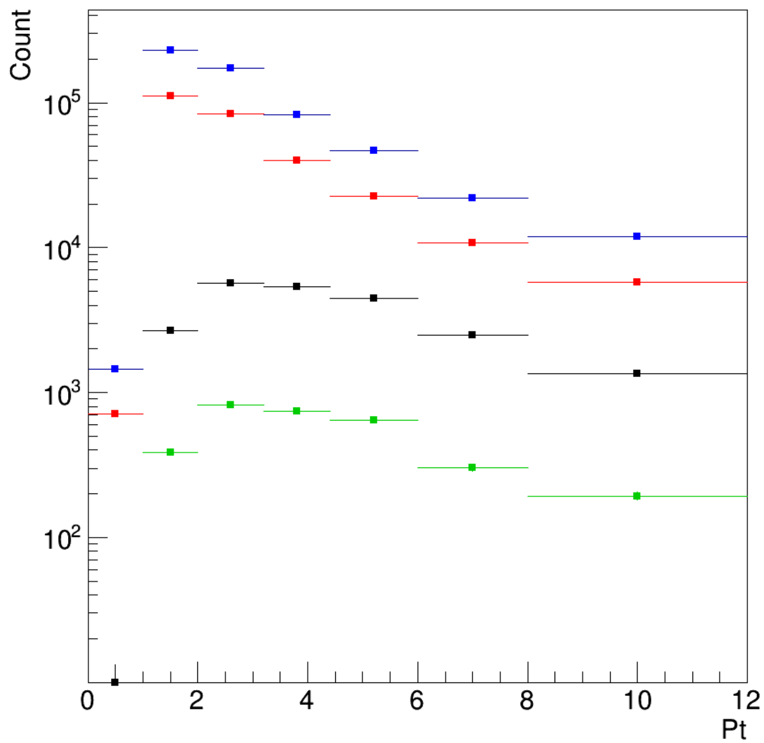
Data Analysis

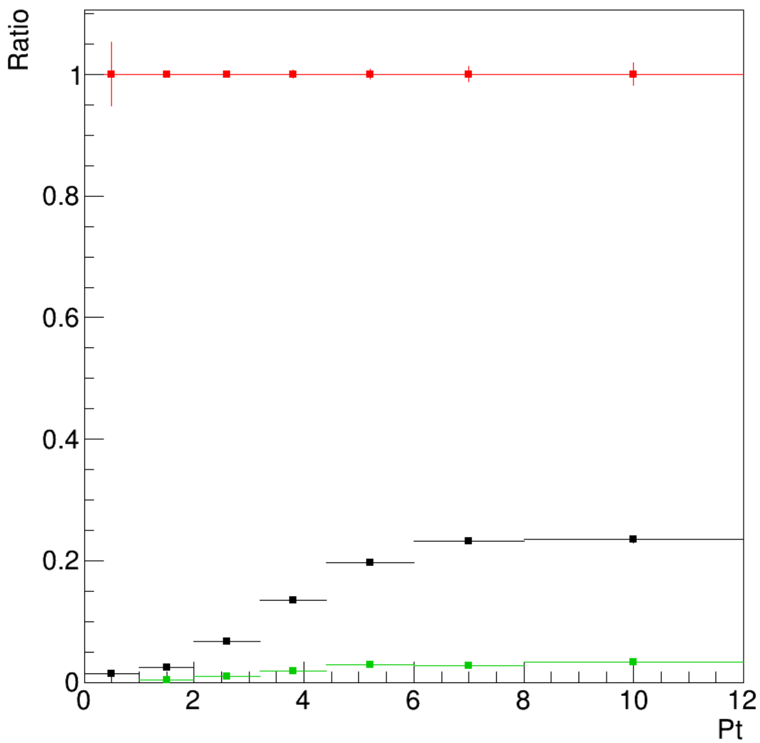
- DataSet : LHC16l (pp 13TeV)
- DataSet : LHC19g6a2, LHC19g6b2, LHC19g6c2 (pp 13TeV, MC)
  - 3M events were selected
  - Ξ_c^+, Ξ_c^0 emebedded (Heavy flavor enhanced event)
  - Interested physics Ξ_c^+ decayed into $\Xi^- + \pi^+ + \pi^+$
  - $\Xi_c^+ \rightarrow \Xi^- + \pi^+ + \pi^+$(~90%)
  - $\Xi_c^+ \rightarrow \Xi^* + \pi^+ \rightarrow \Xi^- + \pi^+ + \pi^+$ (~ 10%)

- Loose trackcut applied
  - Mass window cut on cascade (12MeV)
  - 4 sigma TPC PID cut for Pions
  - 500μm PiPi DCAcut
  - Minimum Ncluster_TPC (80)
  - Minimum Ncluster_ITS (3)

- Ξ_c^+ Signals are tagged by truth information

Ξ_c^+ Generated Spectrum





- ①
- ①&②
- ①&②&③
- ①&②&③&④

① : Ξ_c^+ Generated $|y| < 0.8$

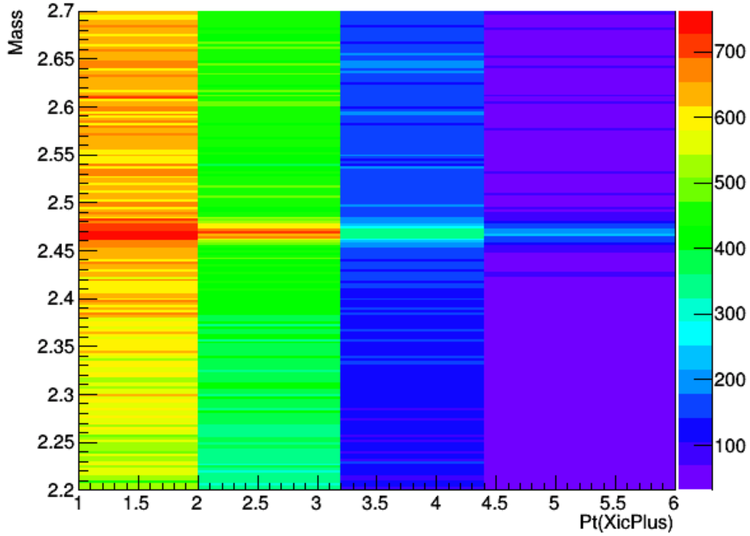
② : $\Xi_c^+ \rightarrow \Xi^- + \pi^+ + \pi^+$

③ : Ξ_c^+ All Daughter are found

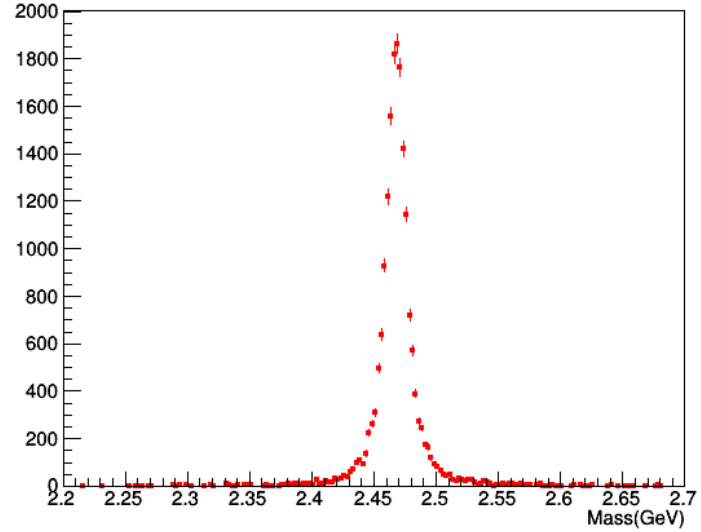
④ : Ξ_c^+ Cut passed

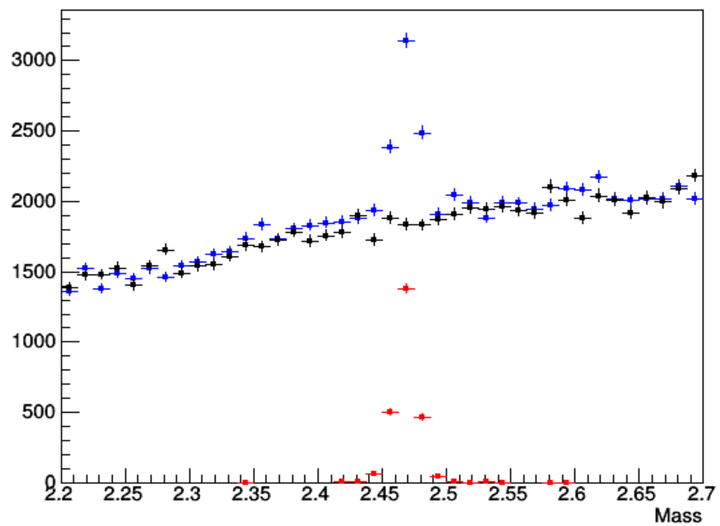
Ξ_c^+ Reconstructed Mass (Pt : 1-5GeV)

Inclusive(MC)



Ξ_c^+ Pure Signal(MC)





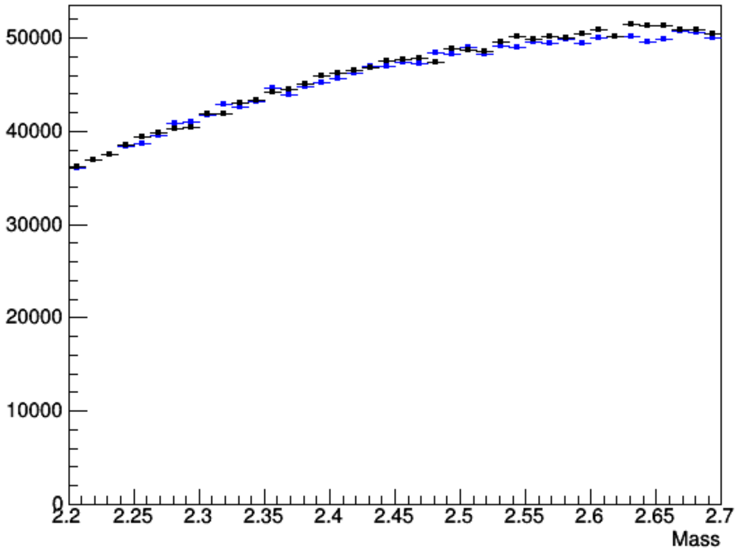
Inclusive

Signal Tagged

Wrong sign background

Ξ_c^+ Reconstructed Mass (Pt : 1-5GeV)

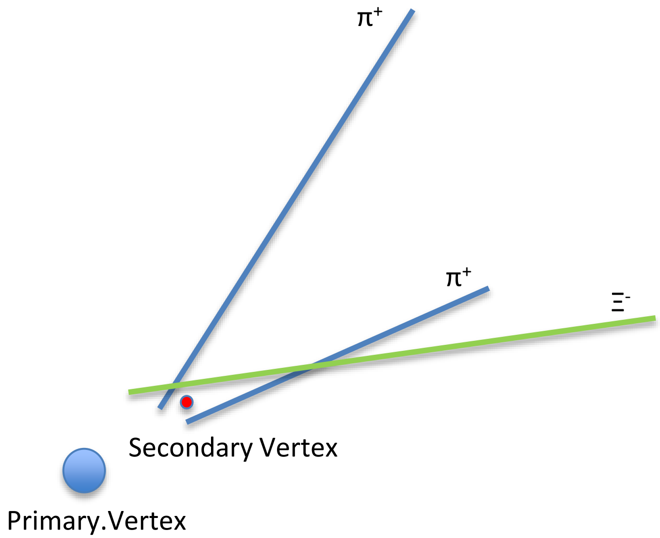
Data (Almost Background)

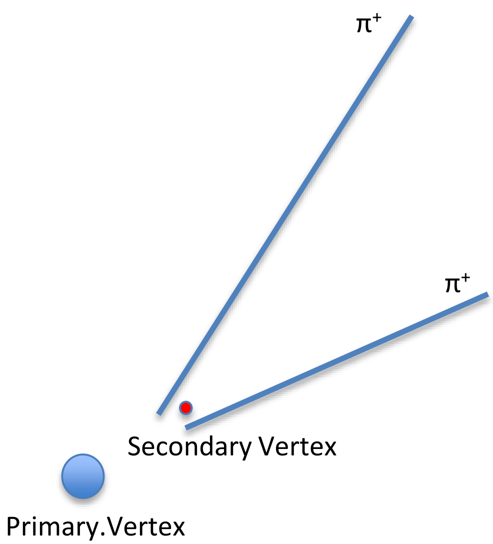


Inclusive

Wrong sign background

Secondary Vertex

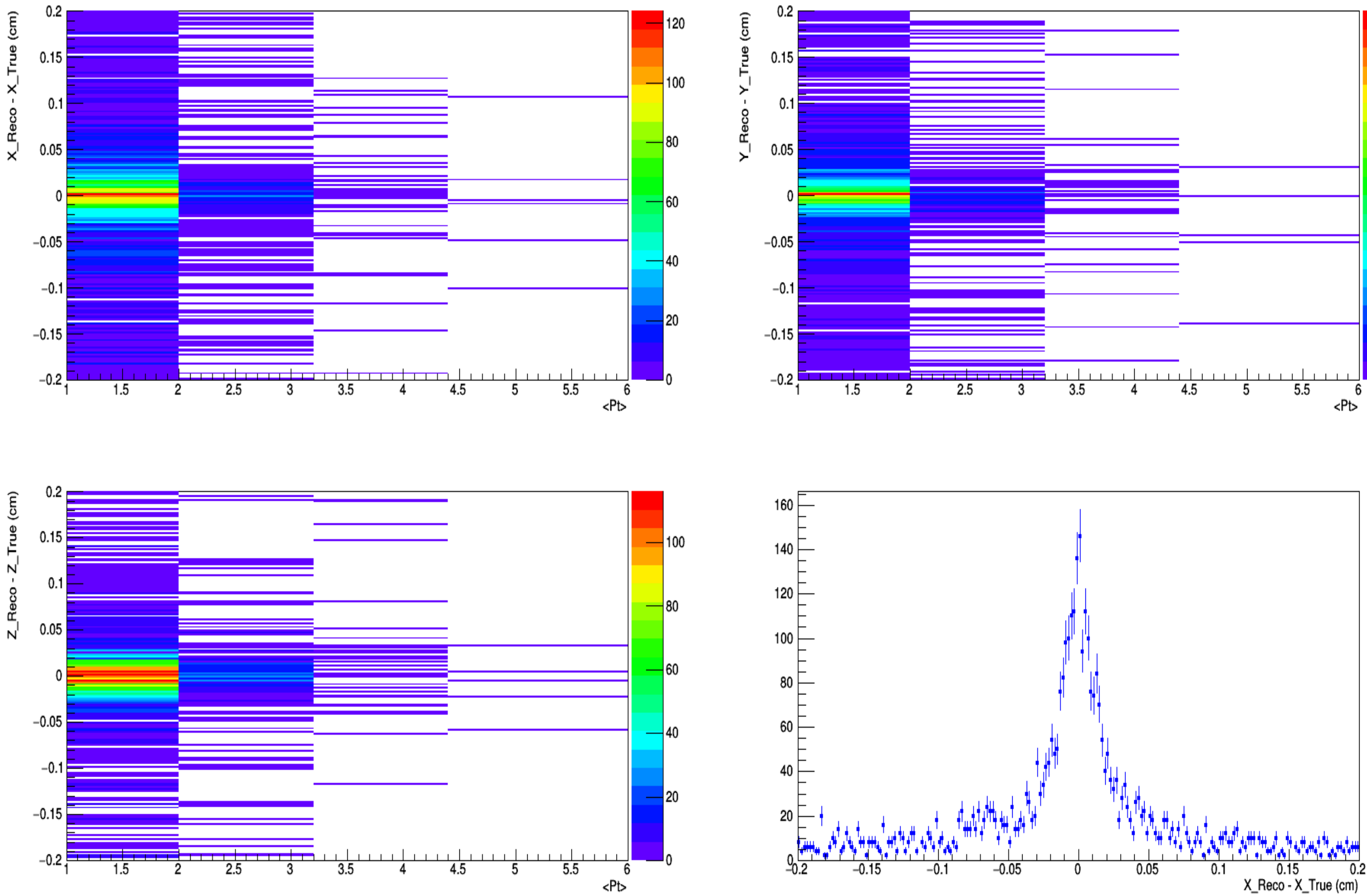




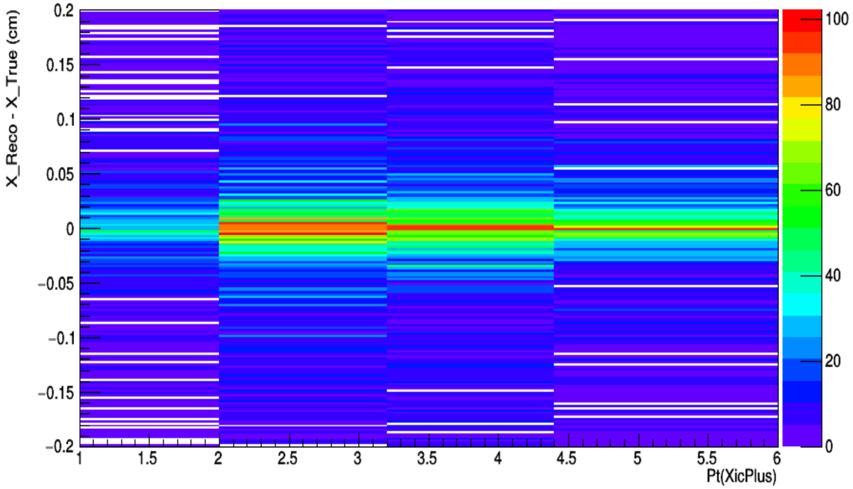
- AliVertexerTracks is used for searching vertex
  - Algorithm : 1 (Default)
  - Tracks are approximated as straight line

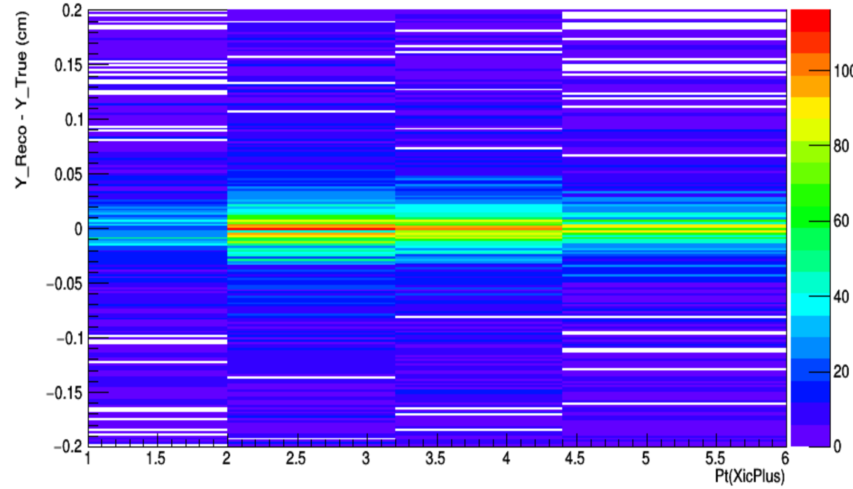
- Cascade has much worse vertex resolution
  - Not causing too much problem since AliVertexer take into account track resolution

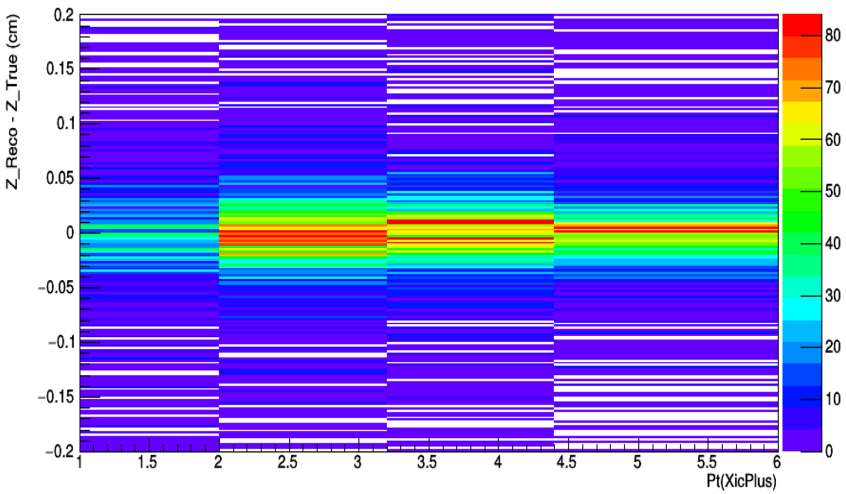
Two Track Vertex Residual (Pt : 1-5GeV)

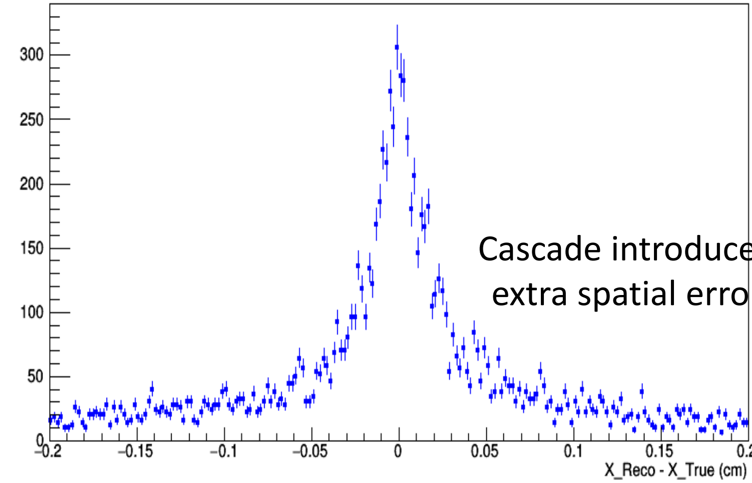


Three Track Vertex Residual(Pt : 1-5GeV)



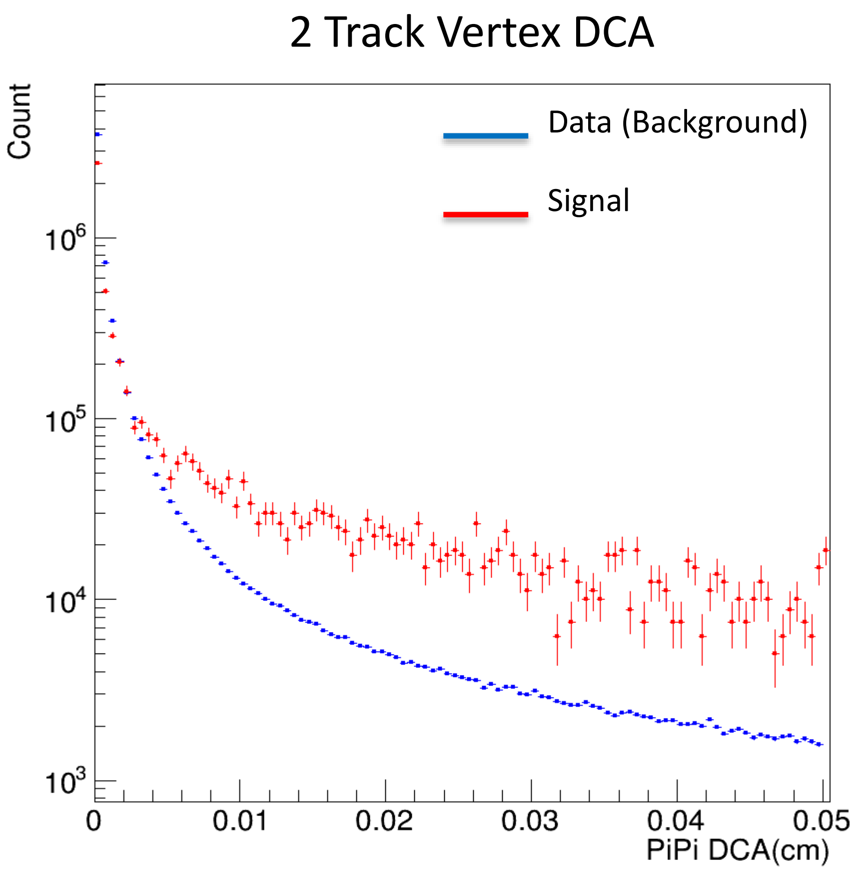


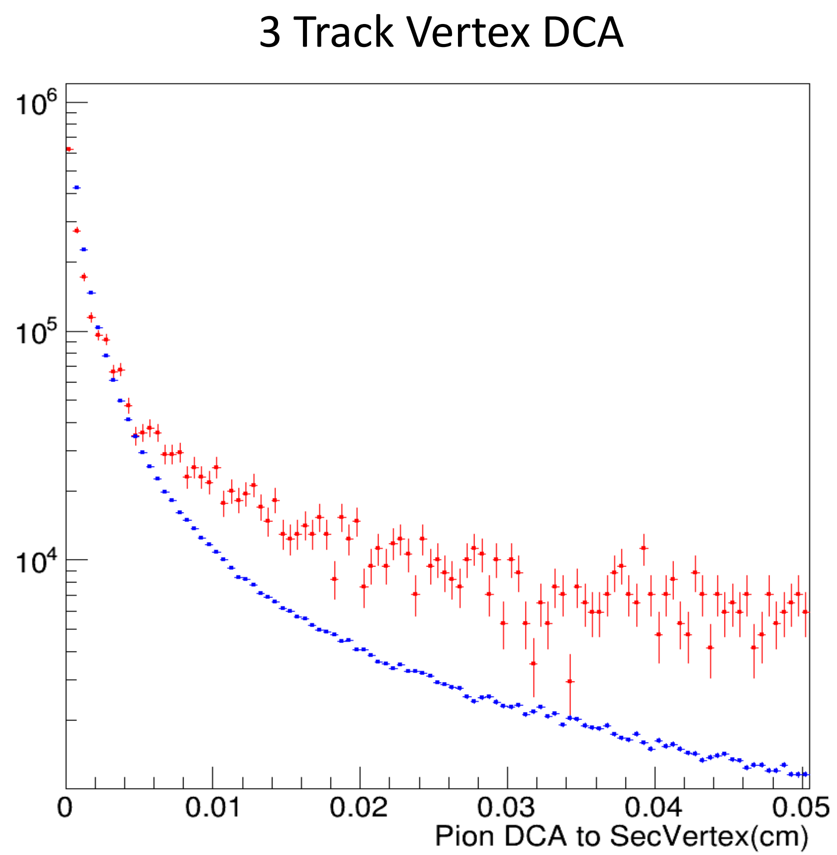




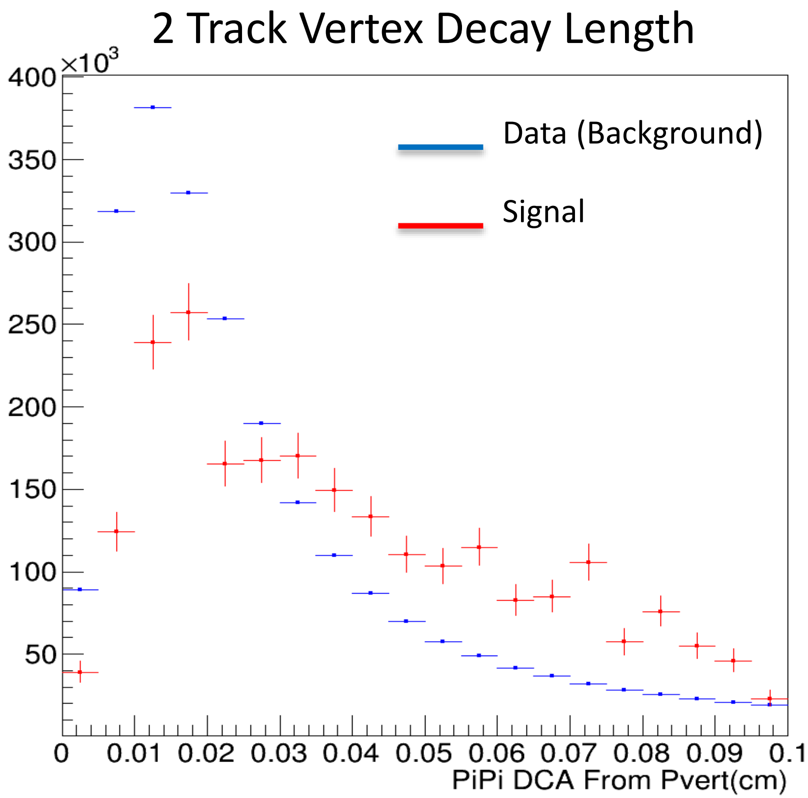
Cascade introduced extra spatial error

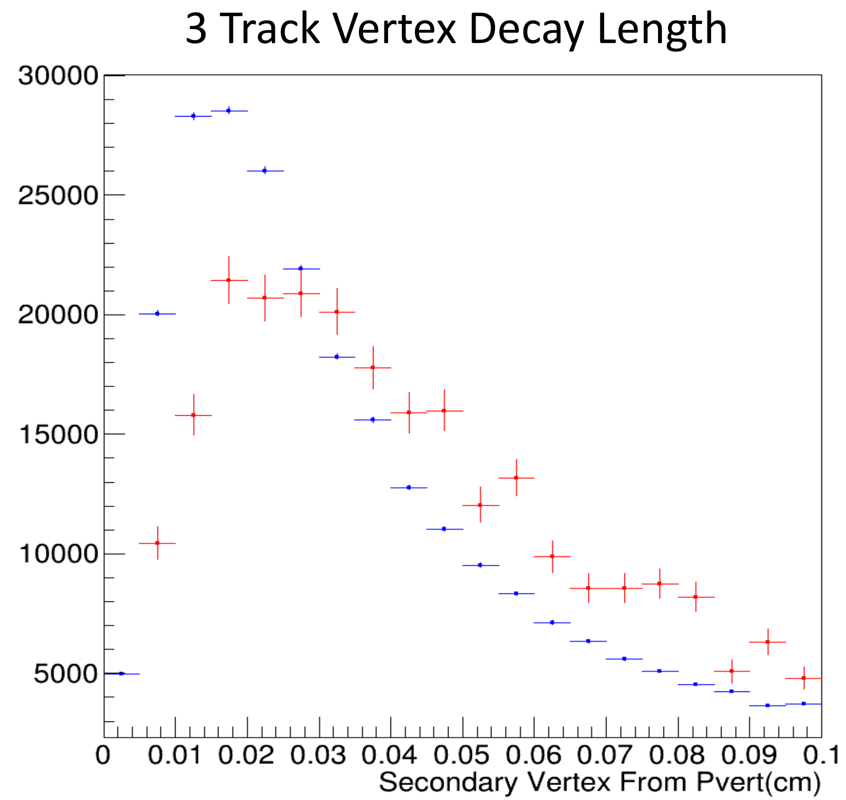
Secondary Vertex Pion DCA(Pt : 1-5GeV)





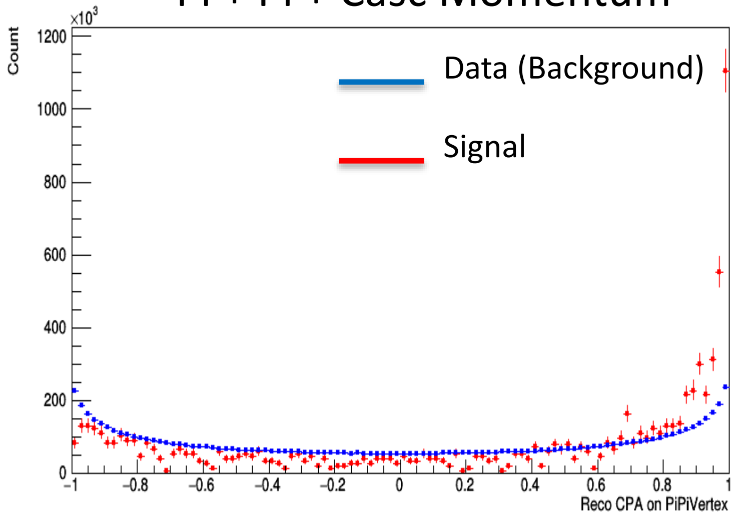
Decay Length(Pt : 1-5GeV)



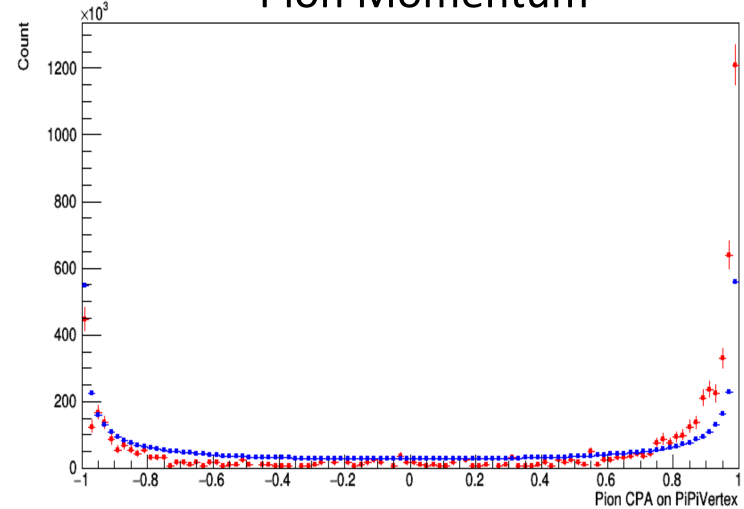


Cosine Pointing Angle at 2 Track Vertex

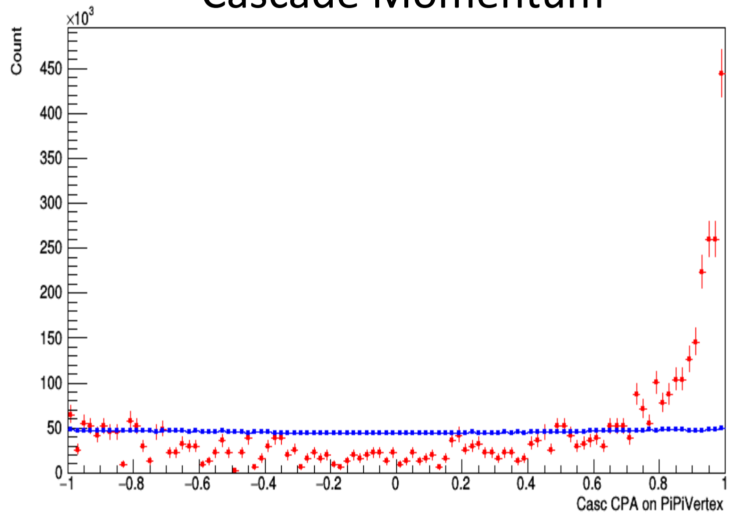
Pi + Pi + Casc Momentum

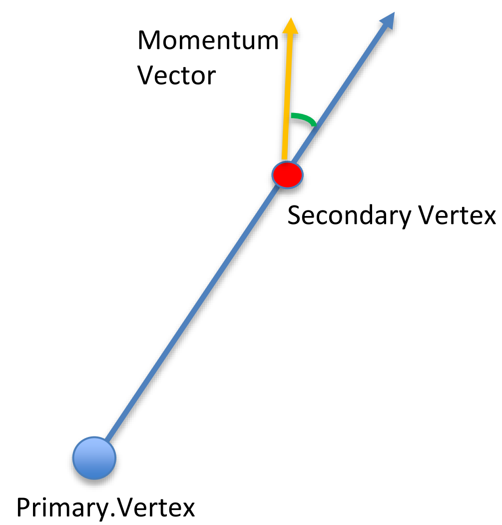


Pion Momentum



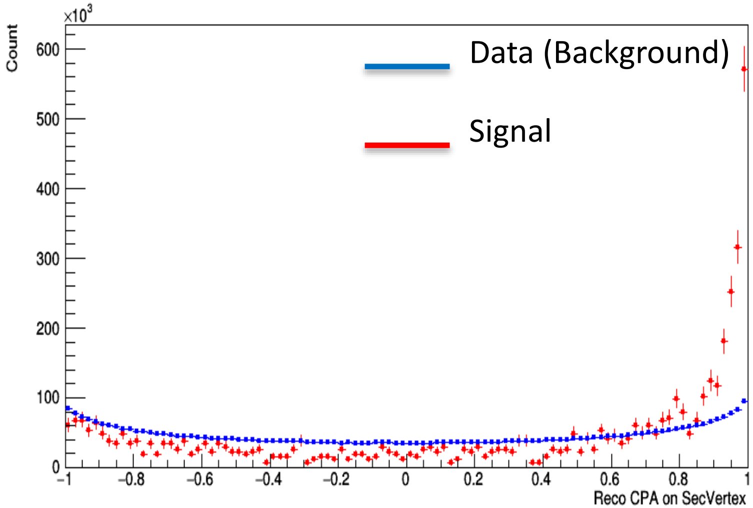
Cascade Momentum



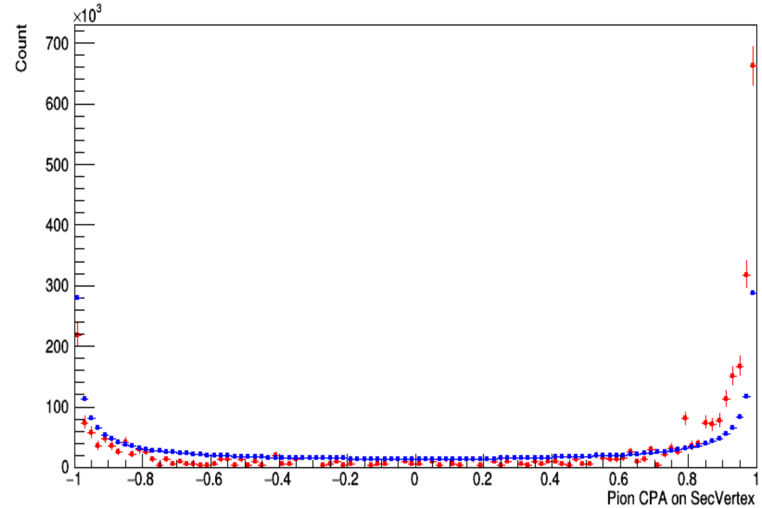


Cosine Pointing Angle at 3 Track Vertex

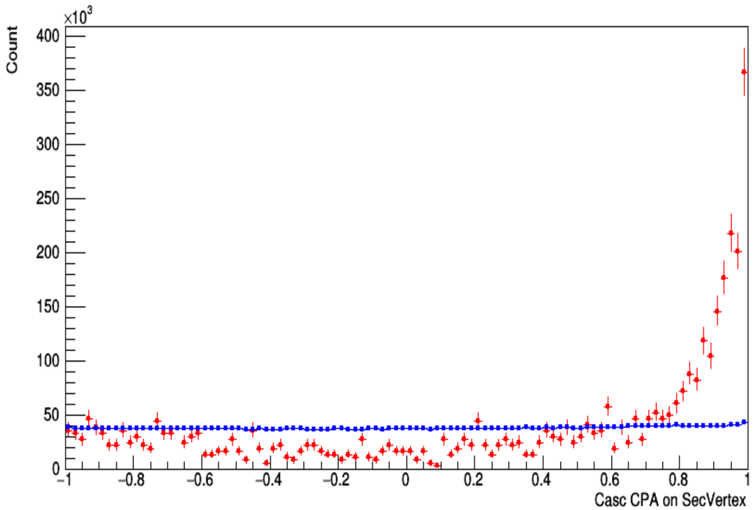
Pi + Pi + Casc Momentum

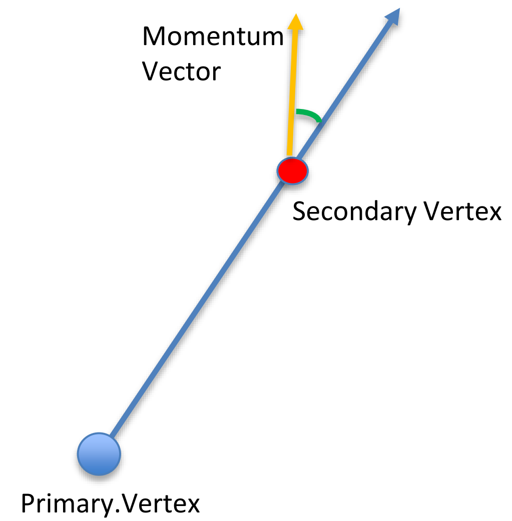


Pion Momentum



Cascade Momentum

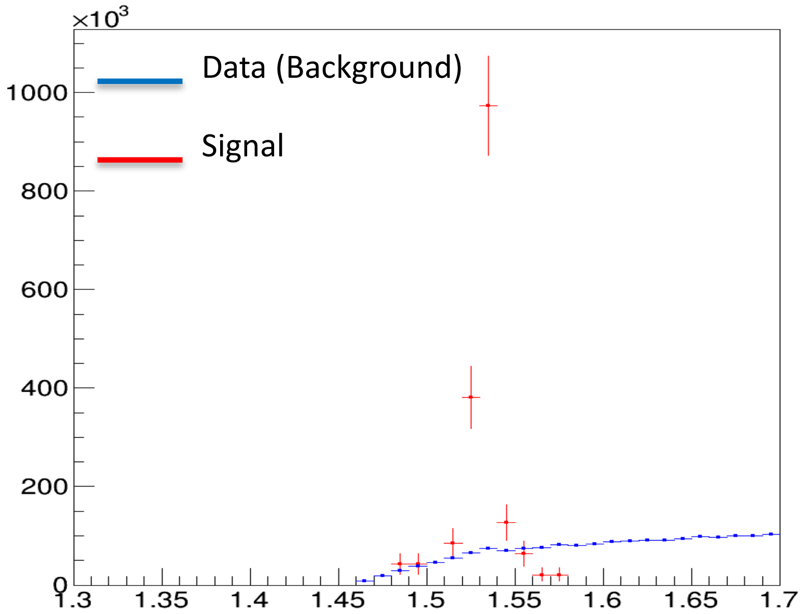


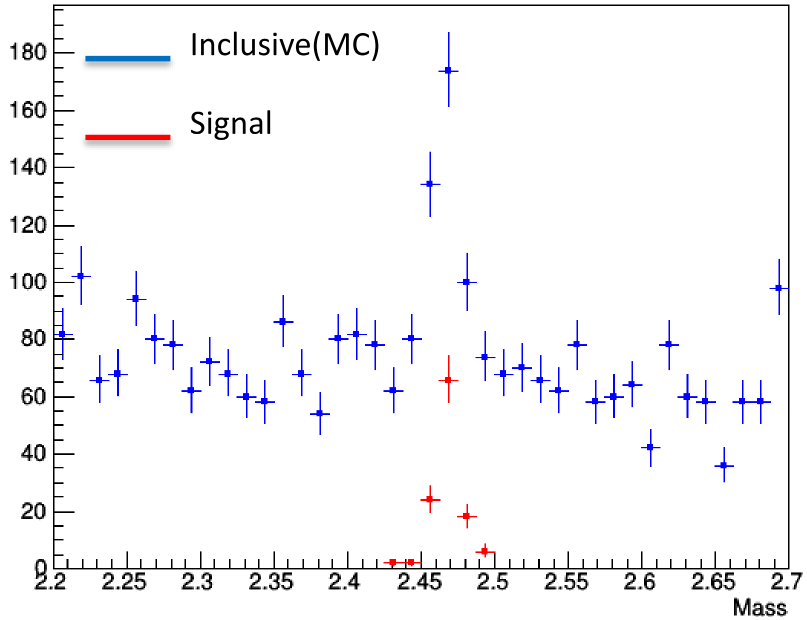


Resonance channel decay

- Ξ (1530) Can be reconstructed by paring π^+ and Ξ^- , we can apply additional mass cut (12MeV for now)
  - Expected further enhancement on S/B ratio

- Data has about 10% Resonance channel compared to total Ξ^-, π^+, π^+ decay mode





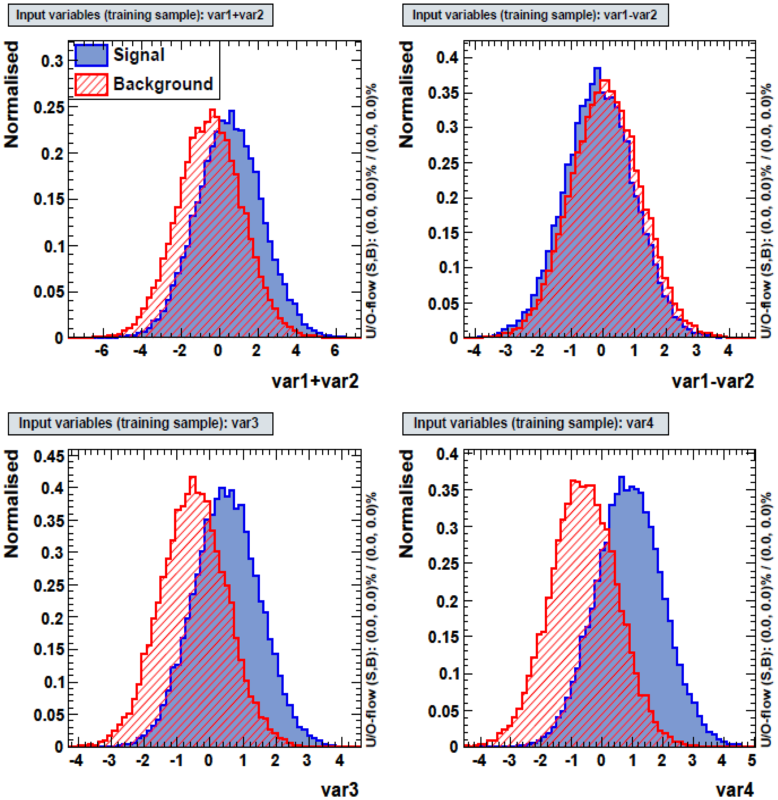
TMVA (Toolkit for Multivariate Data Analysis)

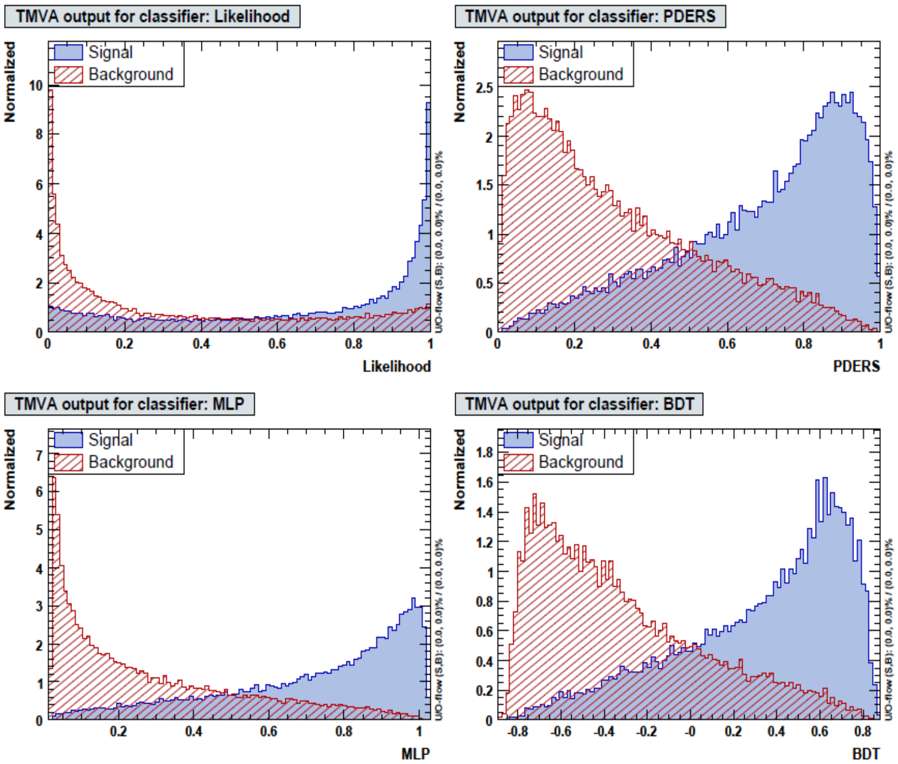
- Root Implemented multi variable analysis tool (TMVA) which provide wide range of choice for optimizing cut
  - Rectangular cut optimization
  - Likely hood estimation
  - Bagged/Boosted Decision Tree
  - Artificial neural network
  - Support Vector machine
  - ….

- User Manual
  https://root.cern.ch/download/doc/tmva/TMVAUsersGuide.pdf
- Jamie’s talk & Tutorial
  https://n-ext.inha.ac.kr/event/320/contributions/1780/attachments/1051/1134/Presentation.pdf

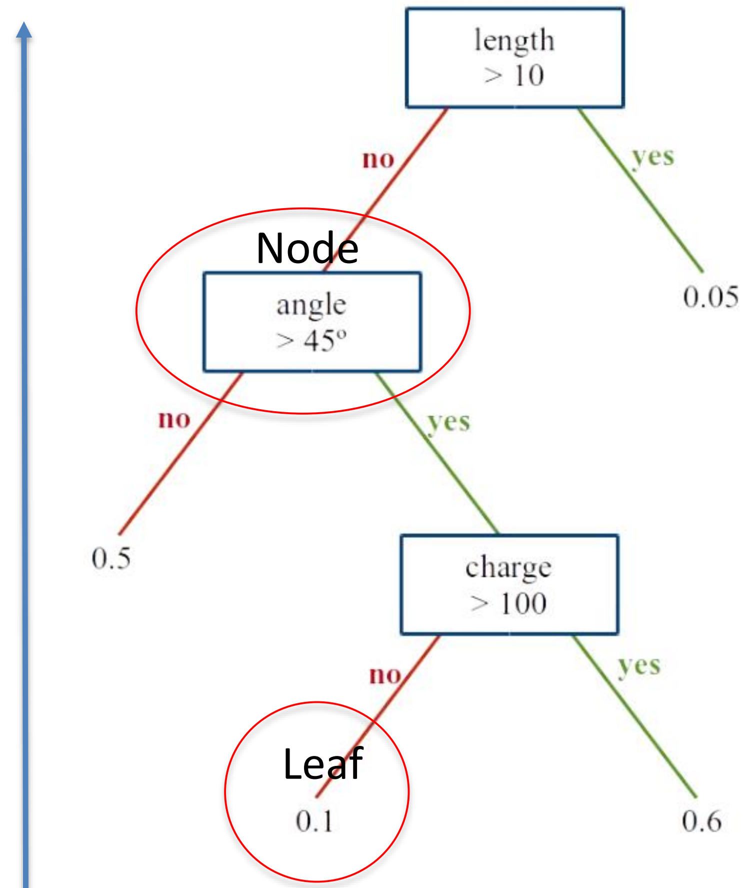
https://cernbox.cern.ch/index.php/s/RvIESWYQF1u5zNI

TMVA (Toolkit for Multivariate Data Analysis)





Boosted Decision Tree (BDT)

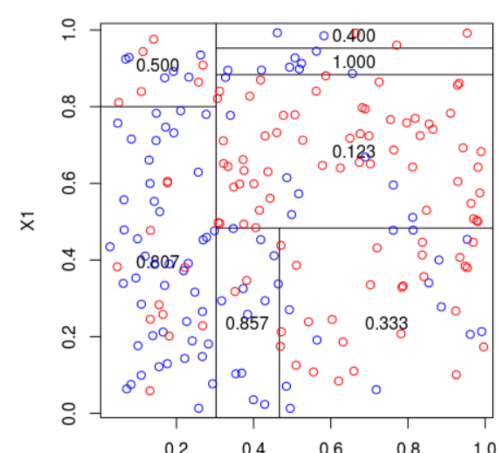


Depth : 2

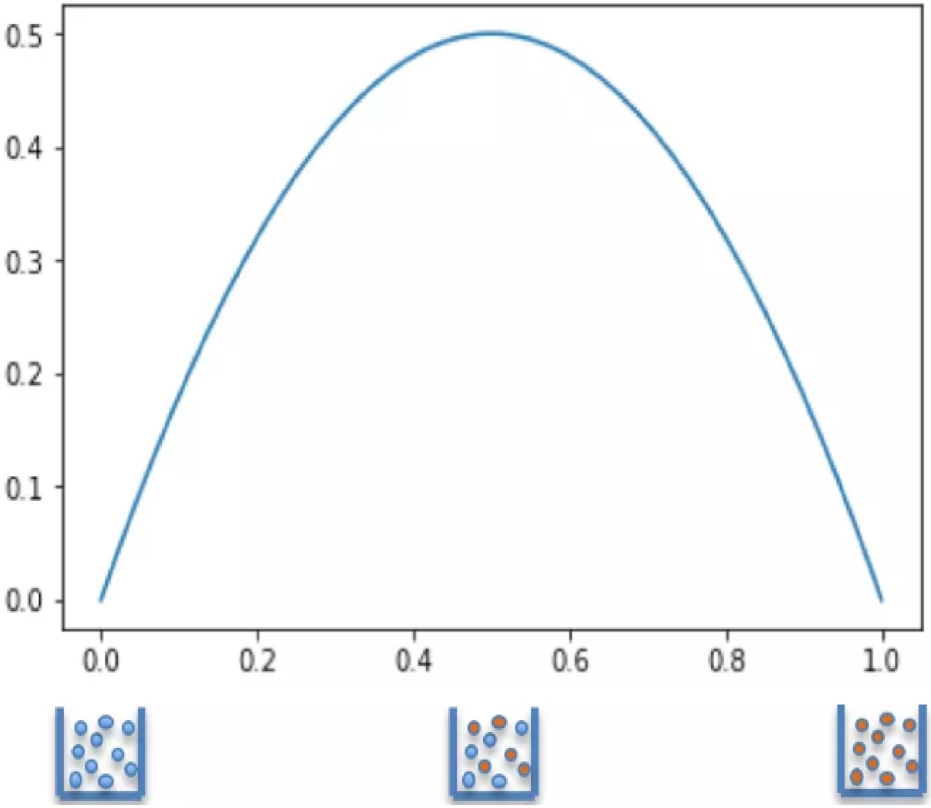
- Decision Tree is method that applying sequential cuts to classify objects (like tracks)

- Each ‘decision’(or cut) called node and at the end of nodes decision tree gives prediction called leaf

- Goal of training decision tree is optimize node(or cut) and prediction, try to minimize error (usually call loss)



Loss function : Gini Impurity



- Gini Impurity is one of most popular loss function for decision tree training (For finite class)
- Gini impurity shows how classified group mixed

$$\sum_{j=1}^{J} p_j(1-p_j)$$

- If classifier did perfect job, each sub-group contains same class (Signal or Background) make Impurity 0

Loss Function : Other option

- Decision Tree trained by greed searching
  - Trying to find variable and cut value that gives best result of classification (Minimum loss)
  - Repeat same procedure on the sub-group until hit limitation : Max_depth, Minimum number of sample event, No gain on loss

- Other loss function is also considerable in TMVA
  - Cross Entropy : $-\sum_{i=1}^{J} p_i \log_2 p_i$
  - Least square sum : Usually use when leaf has continuous value

What is Boosting?

- Boosting is making ensemble of weak Decision Trees rather than single strong tree, which makes prediction more stable and general

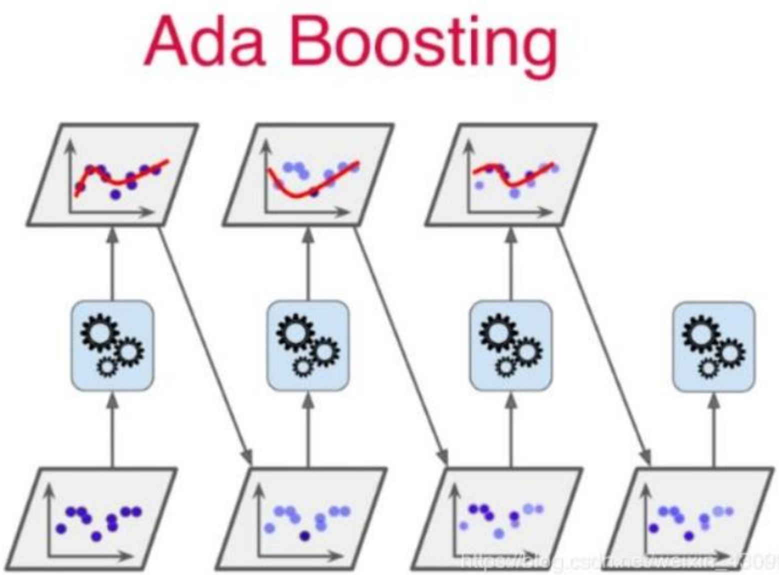
- Making final prediction by summing each weak prediction with weight, each weight decided to minimize loss of final prediction

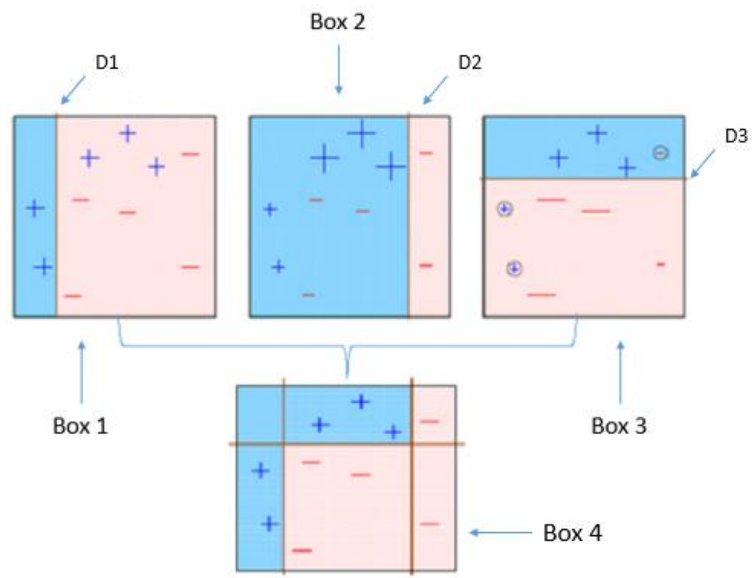
$$\underbrace{f(\mathbf{x})}_{\text{Strong classifier}} = \sum_{t=1}^{T} \overbrace{\alpha_t}^{\text{Weight}} \underbrace{h_t(\mathbf{x})}_{\text{Weak classifier}}$$

- Bagging making tree ensemble at same time by using fraction of dataset

Adaptive Boost (Ada Boost)

- One of common pick of Boosting method is adaptive boost
  - Each train step generate weak classifier (Decision tree) and modify weight of data (Each track in our case)
  - Weight of track increases when previous classifier failed to predict on that track
  - Repeat same procedure and generate different classifier
  - Make linear sum of prediction so we can get final answer





Next Step

- Code is still developing
  - Resonance Ξ(1530) reconstruction optimization
  - Tree output for BDT training
  - Add updating primary vertex

- Performance test for ITS upgrade