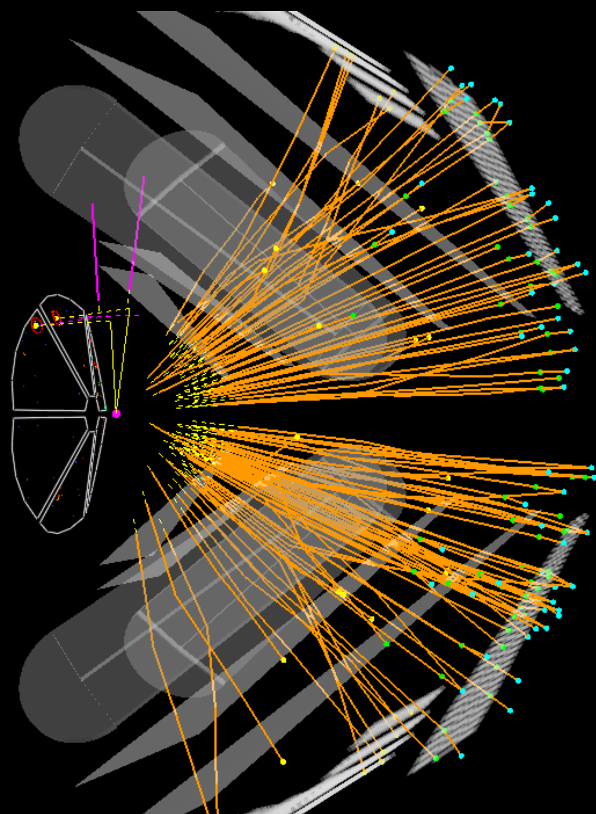
Λ Polarization in Au+Au collisions at $\sqrt{s_{NN}} = 2.4\ GeV$

Measured with



HADES

TECHNISCHE UNIVERSITÄT DARMSTADT

Frederic Kornas

for the HADES collaboration

17.01.2019

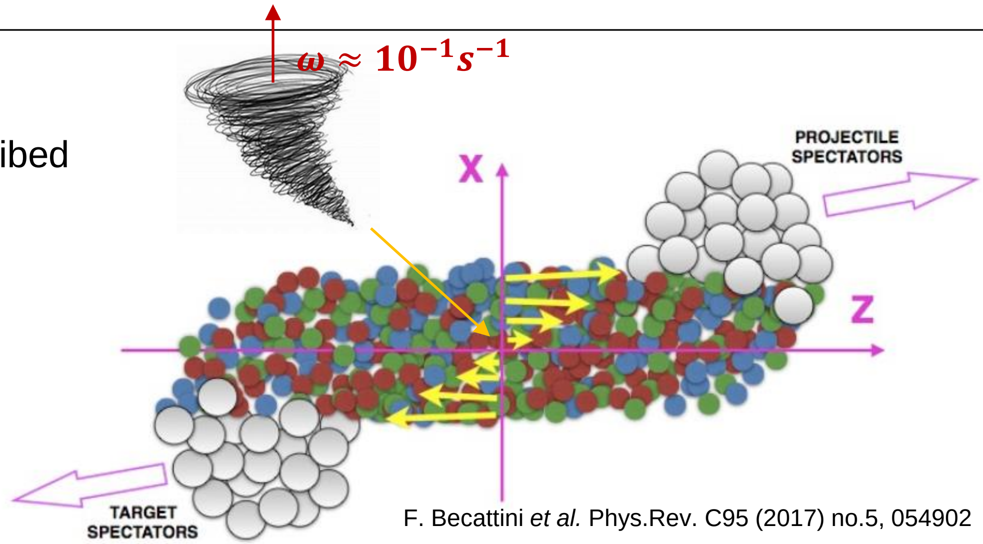
Hirschegg 2019

Polarization measurement

TECHNISCHE UNIVERSITÄT DARMSTADT

Global Polarization Measurement:

- System created in HICs successfully described by relativistic hydrodynamics.
- In peripheral collisions: $|L| \sim 10^5 \hbar$
- What is the effect on fluid/transport?



F. Becattini *et al.* Phys.Rev. C95 (2017) no.5, 054902

Vorticity: $\vec{\omega} = \frac{1}{2}\vec{\nabla} \times \vec{v}$

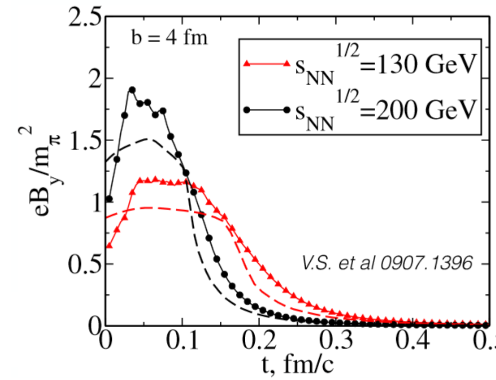
- Vorticity could be very high $\boldsymbol{\omega} \approx \mathbf{10^{21} s^{-1}}$

How to measure the vorticity?

- **Large orbital momentum ⇒ Polarization of the particle spins**

⟶Two contributions:

1. Spin-orbit coupling (same for q and $\bar{q}$)
2. Electromagnetic coupling (opposite for for q and $\bar{q}$)



Magnetic field effect on photon production, V.Skokov, Western Michigan University,2014

HADES

Polarization measurement

TECHNISCHE UNIVERSITÄT DARMSTADT

STAR Collaboration (Abelev *et al.*) Phys.Rev. C76 (2007) 024915, Erratum: Phys.Rev. C95 (2017) no.3, 039906

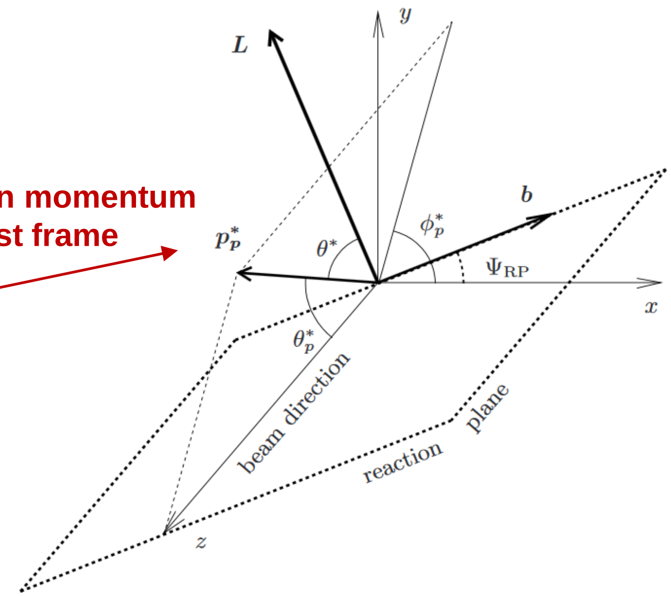
How to measure the particle spin?

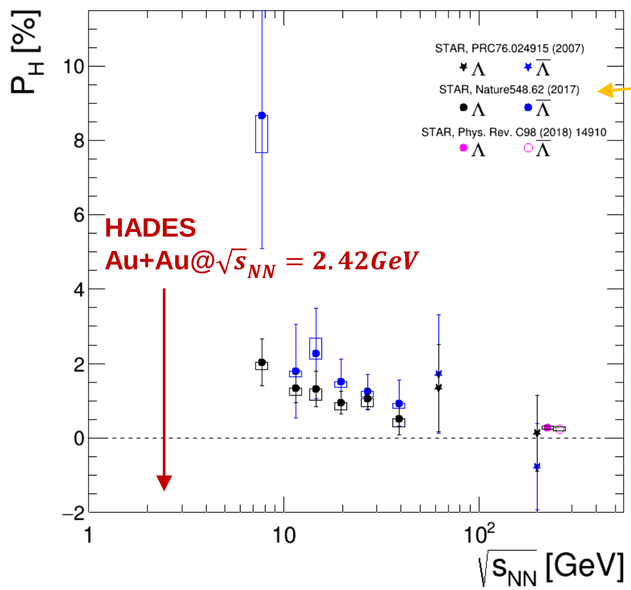
- Spin measurement for most of the hadrons very difficult
  $\longrightarrow$ Concentrate on **self-analyzing weak decays**
- Good candidate:

$$\Lambda \rightarrow p + \pi^-$$

- ***Proton is predominantly emitted in spin direction!***
- ***Spin measurement $\longrightarrow$ Momentum measurement***

Proton momentum in the Λ rest frame





All Au+Au

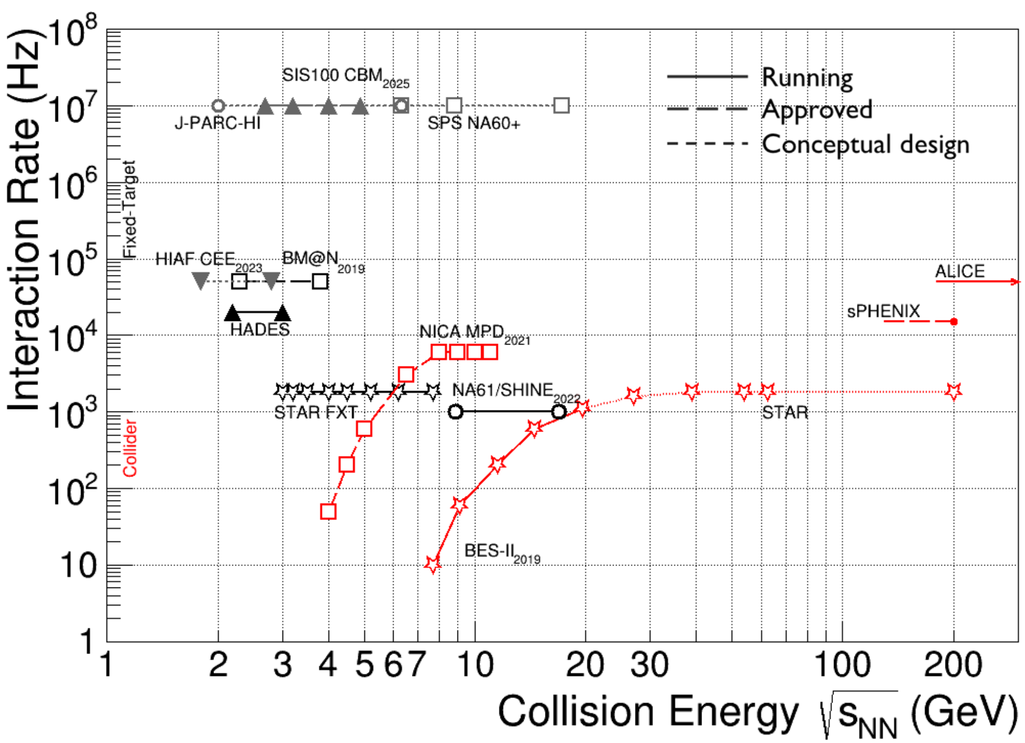
Polarization can be measured:

$$P_\Lambda = \frac{8}{\pi\alpha_\Lambda}\frac{\langle \sin(\Psi_{EP} - \phi_p^*)\rangle}{R_{EP}}$$

- Decay parameter $\alpha_\Lambda = 0.642 \pm 0.013$
- Orientation with respect to the event plane Ψ_{EP}
- Azimuthal angle of the proton in the Λ frame ϕ_p^*

High Acceptance DiElectron Spectrometer

TECHNISCHE UNIVERSITÄT DARMSTADT

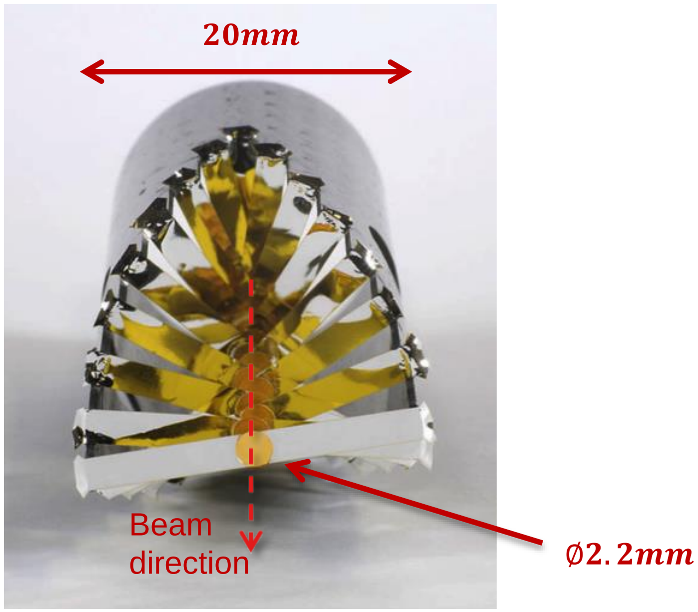


CBM Collab. EPJA 53 3 (2017) 60
TG, NPA-D-18-00411 (2018)

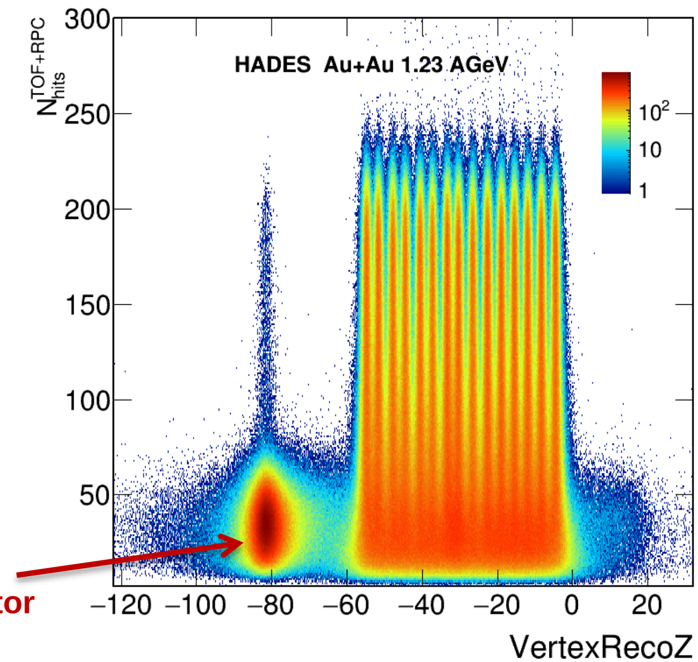
- **High acceptance:**
  - Full azimuthal coverage, $18-85°$ polar angle
- **Efficient track reconstruction:**
  - Low mass tracking with drift chambers
  - $0.14-0.3Tm$ toroidal field
- **Precise:**
  - Mass resolution few %
- **Fast:**
  - Interaction rate up to $50kHz$ trigger rate

HADES

Au+Au run at $\sqrt{s_{NN}} = 2.4 GeV$



- Beam: $1.5 \cdot 10^6$ Au ions per second
→ LVL1 trigger rates of up to $8kHz$
- Overall: $7 \cdot 10^9$ events recorded
- LVL1 trigger on 40% most central collisions
- Min. bias events scaled down (factor 8)

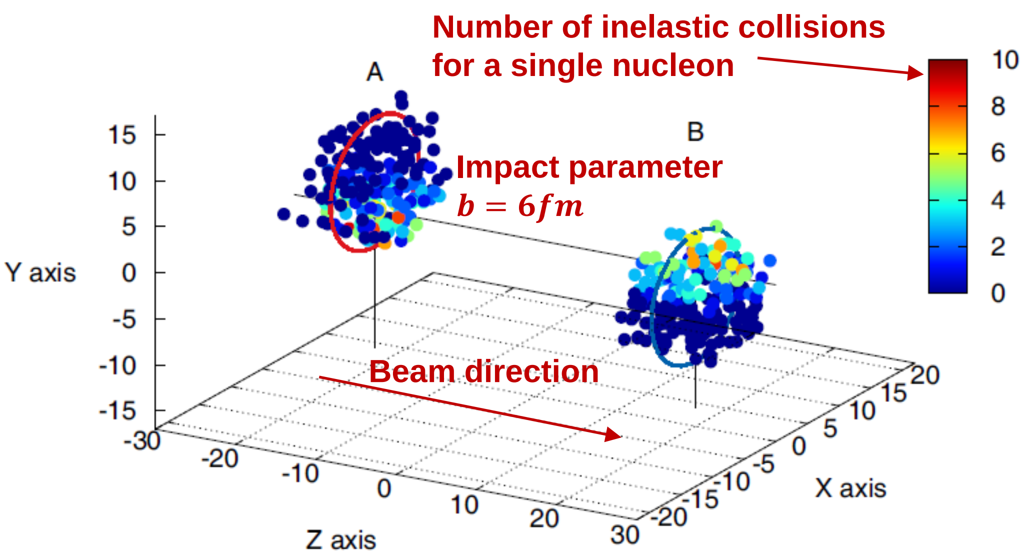


- 15 segmented Au target (very low material budget)
- $\Delta z = 3.6mm$
- 2.0% interaction probability

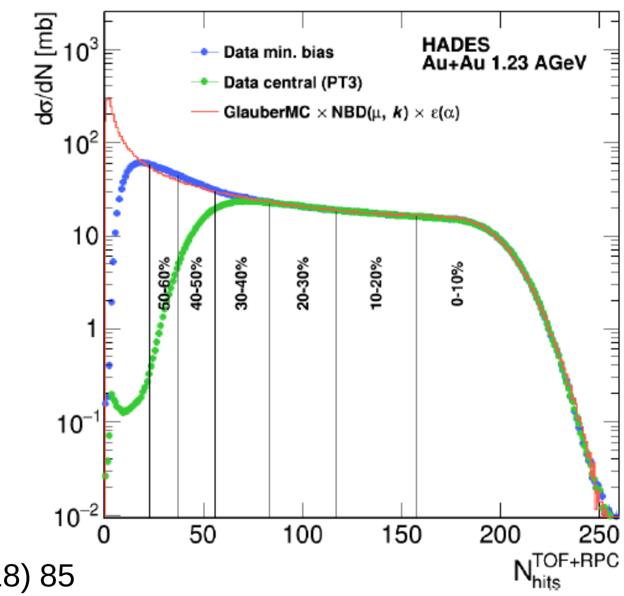
Centrality Estimation

TECHNISCHE UNIVERSITÄT DARMSTADT

Offline centrality selection based on hit or track multiplicity



- Task: relate observable quantities to the centrality of the collision
- Assumption: $\langle N_{part} \rangle \propto \langle N_{produced} \rangle$

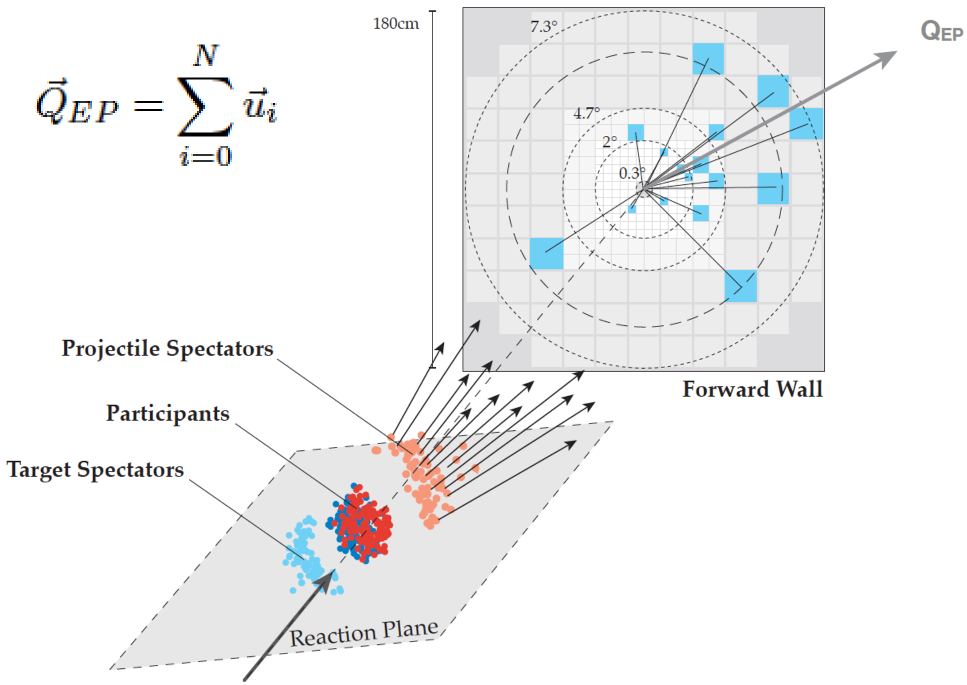


- Centrality determination using Glauber
- Distributions agree with transport model calculations (*processed by GEANT*)

For more Details see:
Eur. Phys. J. A54 (2018) 85

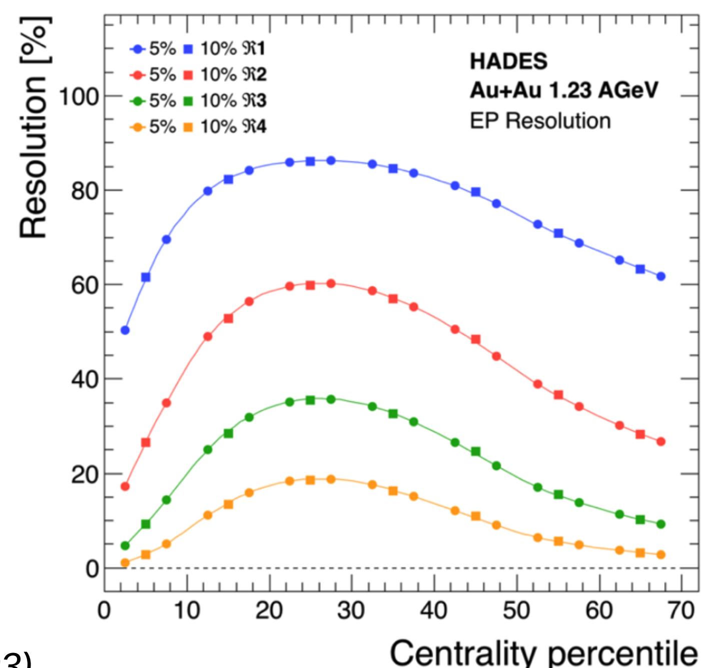
Event Plane Reconstruction

$$\vec{Q}_{EP} = \sum_{i=0}^{N} \vec{u}_i$$



Event Plane Reconstruction:

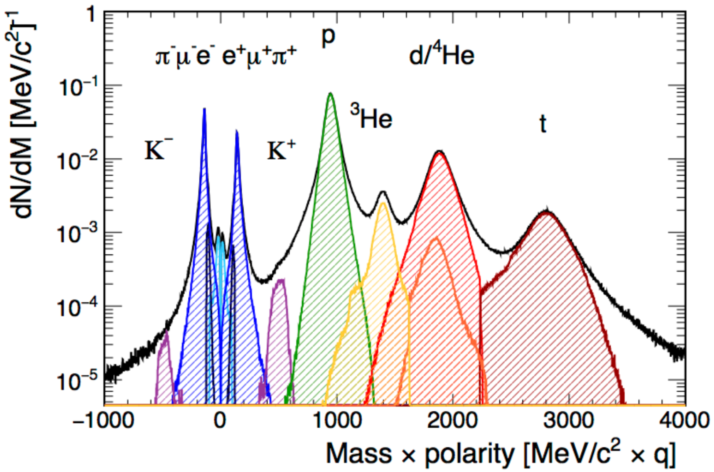
- Based on hits of charged projectile spectators in the Forward Wall



Event Plane Resolution:

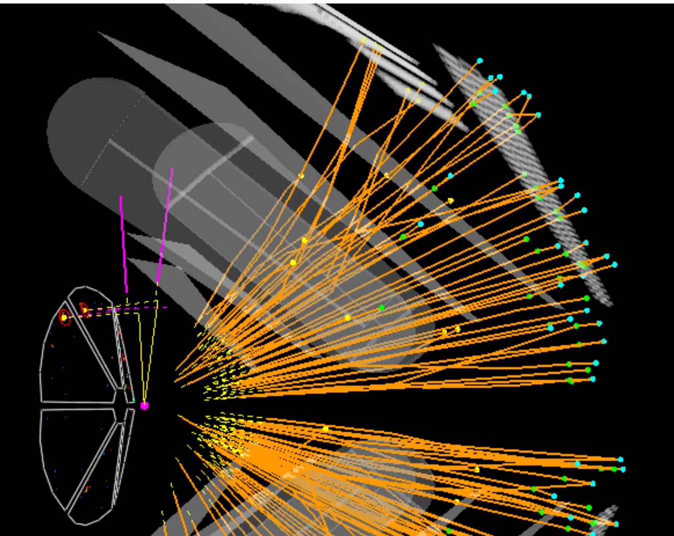
- Determination of Full Resolution from Sub-Event Resolution *(distribution randomly divided into 2 sub-samples)*
- *Based on method by J.-Y. Ollitrault (arXiv:nucl-ex/9711003)*

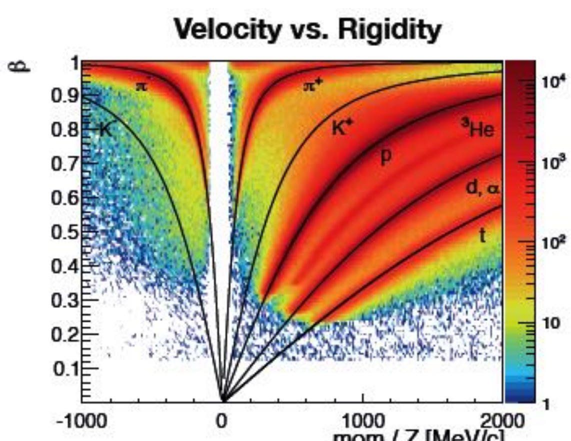
Particle Identification

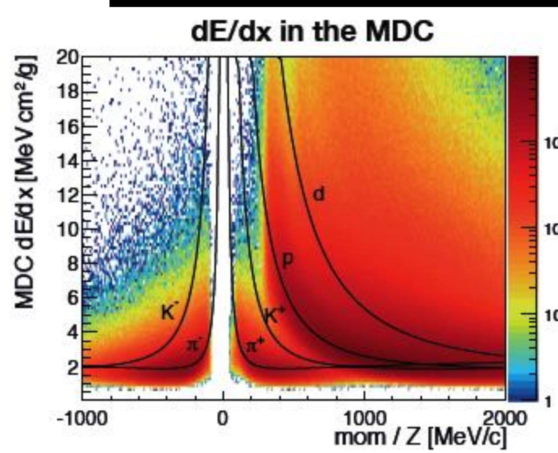


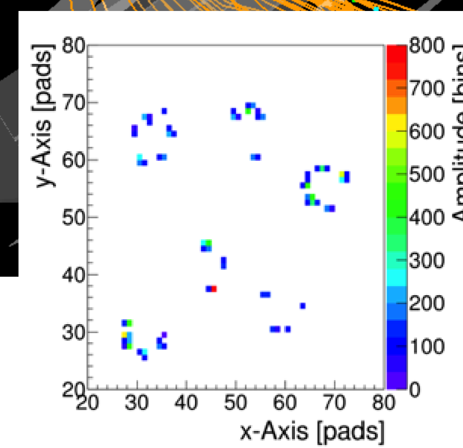
Observables:

- Velocity
- Momentum
- Energie Loss
- RICH information

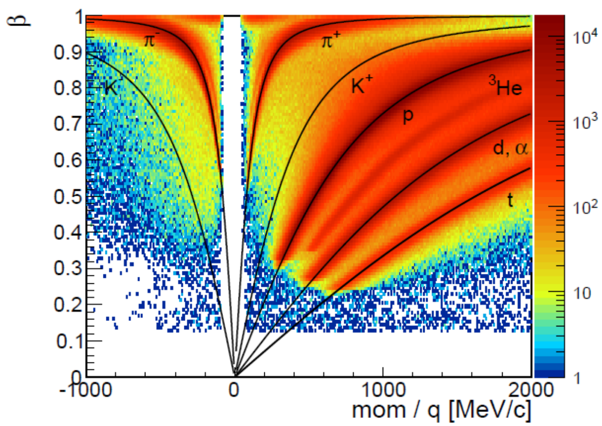


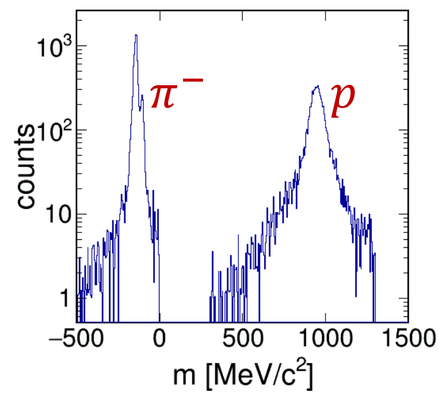


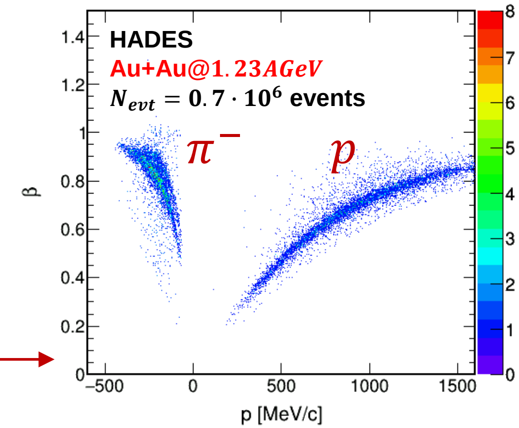




Particle Identification

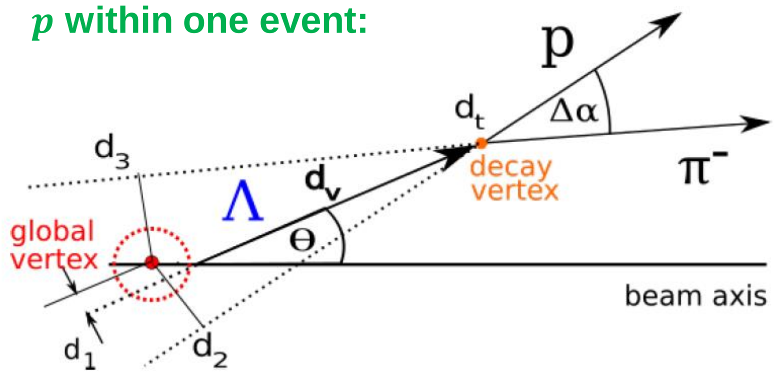






Create all possible combinations of π^- and p within one event:

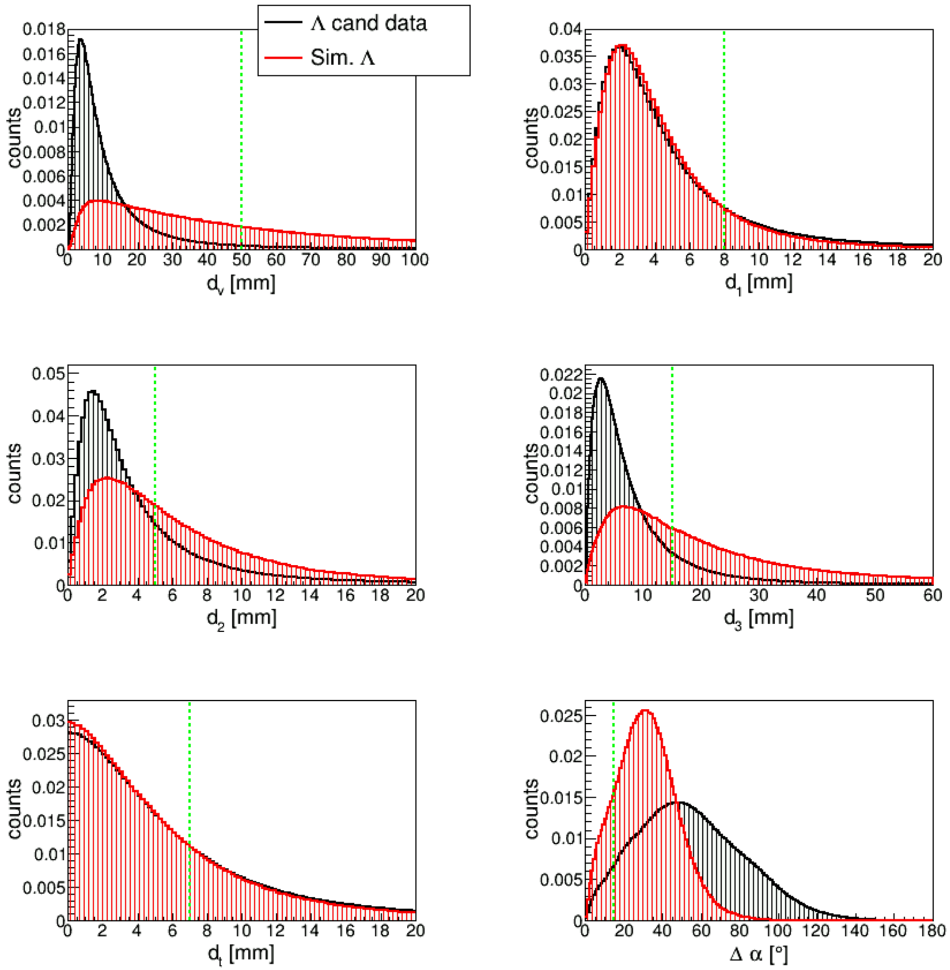
Decay channel:
$\Lambda \rightarrow p + \pi^-$



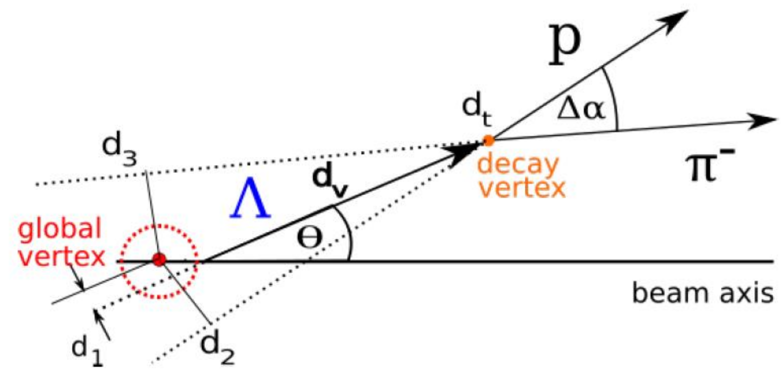
Decay topology

- d_1: Λ has to come from the primary vertex
- d_2, d_3: p and π^- are most likely not pointing to the global vertex
- d_t: common crossing point for p and π^- track
- d_v: Λ distance before it decays ($c\tau \sim 8cm$)
- $\Delta\alpha$: Opening angle, added to account for efficiency loss of closed pairs

Decay Topology



- **Simulations: Thermal Λs embedded into UrQMD (1Λ per event)**
- **Total distribution (Background)**



- **Enough statistics very crutial for the polarization analysis**
- **Employ neural network in order to gain more statistics!**

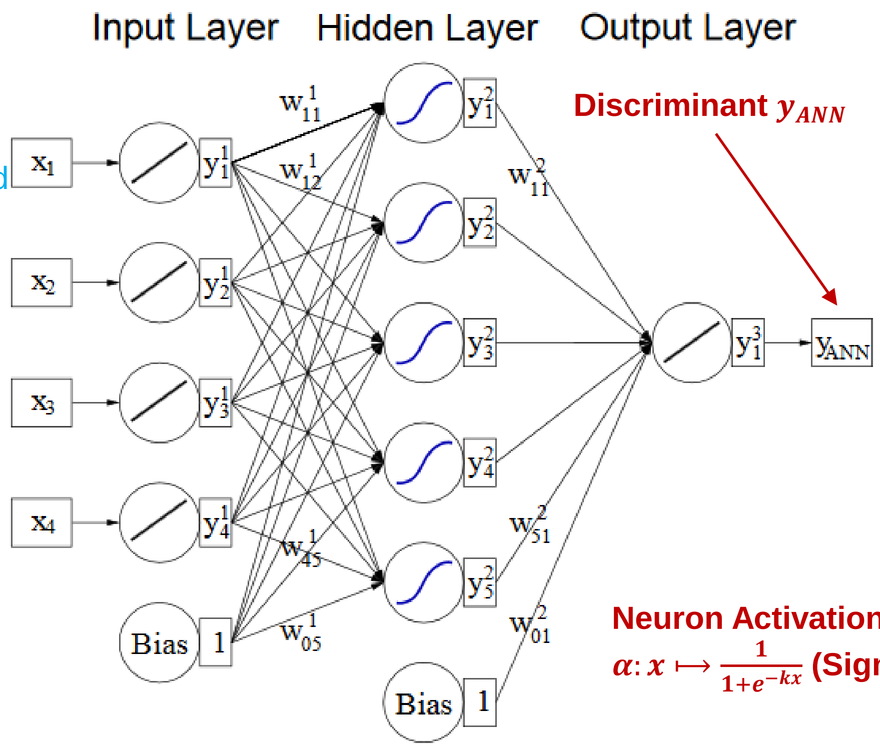
Neural Network

Toolkit for Multivariate Data Analysis (TMVA) included in ROOT

Topology Parameters

Signal:
Thermal Λs embedded into UrQMD

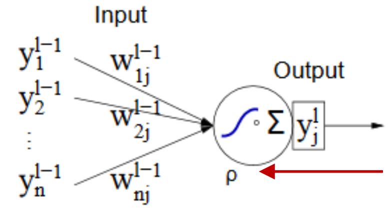
Background:
Mixed-Event –
π^- from one event and
p from another event



Discriminant y_{ANN}

Training:
Convergence of the weights for maximal descrimination between signal and background!

Example:



Neuron Response Function

$$\rho = \alpha \circ \kappa$$

Neuron Activation Function:
$\alpha: x \longmapsto \frac{1}{1+e^{-kx}}$ **(Sigmoid)**

Synapse Function:
$$\kappa: \left(y_{ij}^{l-1} \middle| w_{ij}^{l-1}\right) \longmapsto w_{0j}^{l-1} + \sum_{i=1}^{n} w_{ij}^{l-1} y_i^{l-1}$$

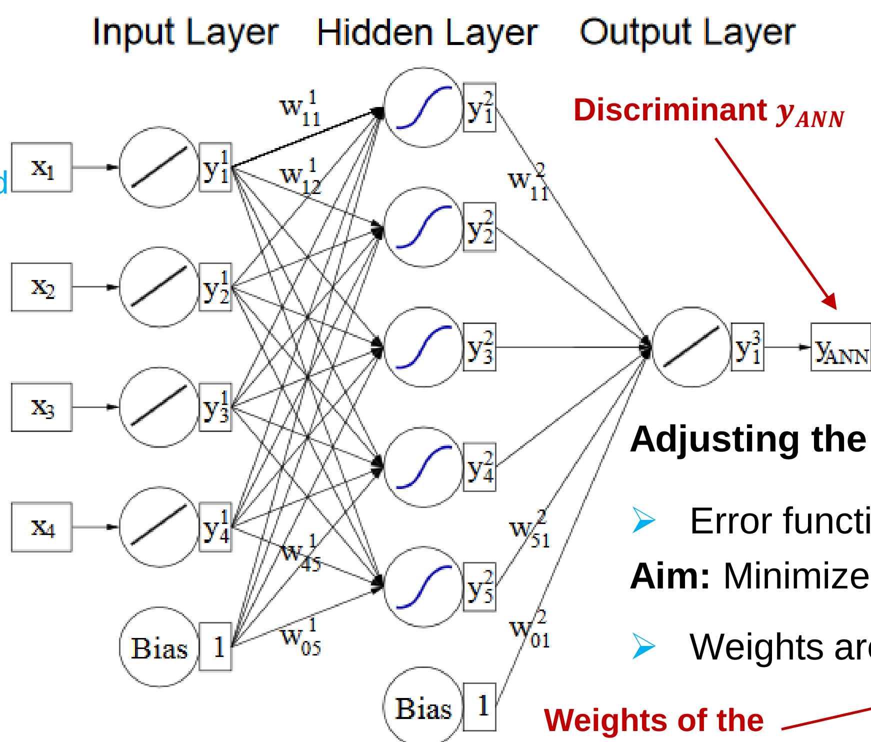
Neural Network

Toolkit for Multivariate Data Analysis (TMVA) included in ROOT

Topology Parameters

Signal:
Thermal Λs embedded into UrQMD

Background:
Mixed-Event –
π^- from one event and
p from another event



Discriminant y_{ANN}

Training:
Convergence of the weights for maximal descrimination between signal and background!

Network returns Discriminant y_{ANN}:
0 – Background
1 – Signal (in ideal case)

Adjusting the weights: Back-Propagation

Number of training events

- Error function: $E(\boldsymbol{x}_1, \dots, \boldsymbol{x}_N) = \sum_{a=1}^{N} \frac{1}{2} \left(y_{ANN,a}(\vec{w}) - \hat{y}_a \right)^2$

Aim: Minimize the error function!

- Weights are updated: $\boldsymbol{w}^{k+1} = \boldsymbol{w}^k - \eta \nabla_{\boldsymbol{w}} E$

Weights of the next training cycle

Weights of the current training cycle

Learning rate

Max. gradient in w-space

Neural Network

TECHNISCHE UNIVERSITÄT DARMSTADT

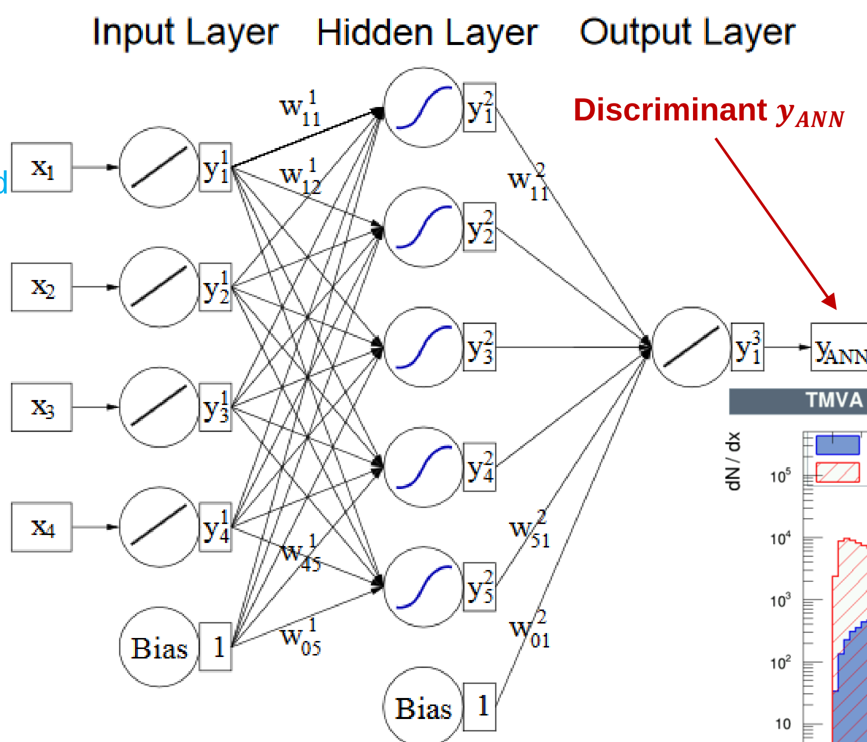
Toolkit for Multivariate Data Analysis (TMVA) included in ROOT

Topology Parameters

Signal:
Thermal Λs embedded into UrQMD

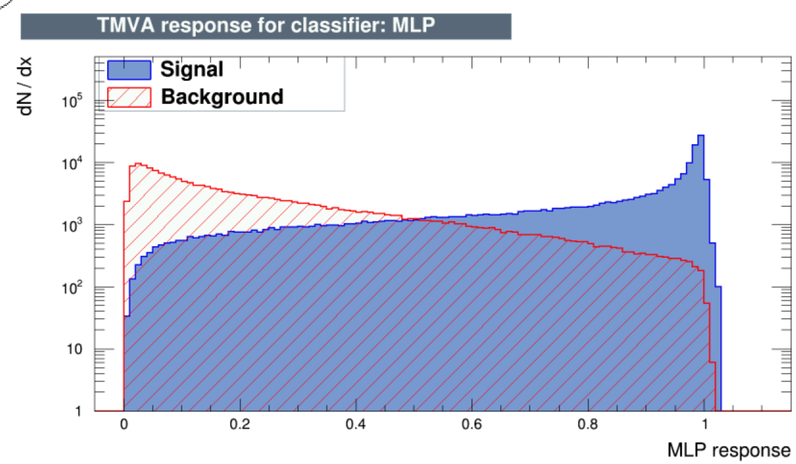
Background:
Mixed-Event –
π^- from one event and
p from another event

Discriminant y_{ANN}



Training:
Convergence of the weights for maximal descrimination between signal and background!

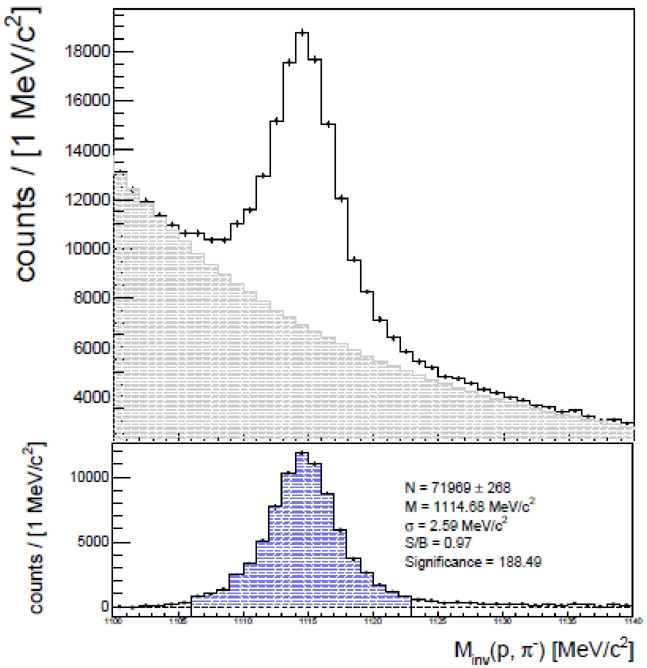
Network returns Discriminant y_{ANN}:
0 – Background
1 – Signal (in ideal case)



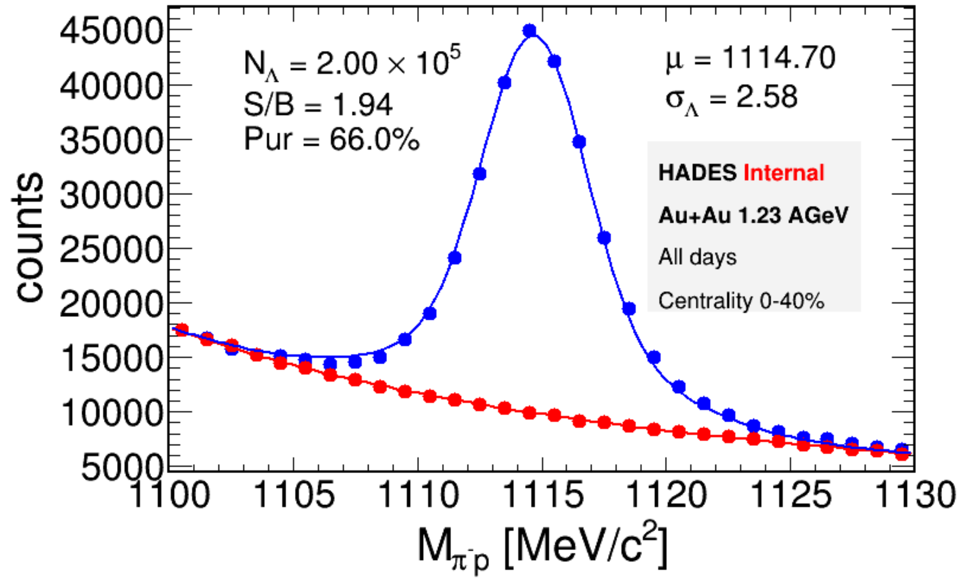
Invariant mass distribution

TECHNISCHE UNIVERSITÄT DARMSTADT

„Hard cut“ analysis:



MVA + Improved off-vertex tracking



Description of the distribution: **→ 8 free parameters**

$$f_{global}(M_{inv}) = \frac{1}{2\pi i}\int_{c-i\infty}^{c+i\infty} e^{s\cdot\log(s)+M_{inv}s}\,ds + G_1^{\mu,\sigma_1,A_1}(M_{inv}) + G_2^{\mu,\sigma_2,A_2}(M_{inv})$$

$$N_\Lambda^{old} = 0.7\cdot 10^5 \longrightarrow N_\Lambda^{new} = 2.0\cdot 10^5$$

⇒ Factor ~ 3 more Λs!

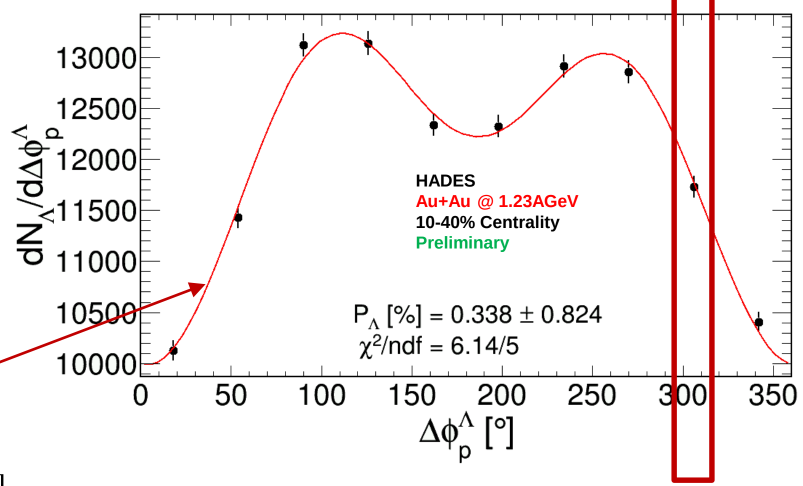
Λ Polarization: two approaches

	(1) Event plane method	(2) Invariant mass fit method
General procedure	➢ Get $\mathrm{dN/d}M_{inv}$ in a certain $\Delta\phi_p^*$-bin ➢ Get net amount of Λs in that bin ➢ Plot distribution of $N_\Lambda(\Delta\phi_p^*)$ ➢ Fit this distribution to get $\langle\sin(\Delta\phi_p^*)\rangle$ ➢ Calculate P_Λ	➢ Plot the distribution of $\langle sin(\Delta\phi_p^*)\rangle_{tot}$ as a function of M_{inv} ➢ Get S/B-ratio in each bin: $f(M_{inv})$ ➢ Make assumption for $\langle sin(\Delta\phi_p^*)\rangle_{BG}$ ➢ Fit the distribution to get $\langle sin(\Delta\phi_p^*)\rangle_{SG}$ ➢ Calculate P_Λ
Correction for R_{EP}	➢ Final result is corrected by $1/R_{EP}$ while $R_{EP}^{10-40\%}$ is used	➢ $1/R_{EP}^{10\%}$ in 10% centrality bins is weighted event-by-event when filling $\langle sin(\Delta\phi_p^*)\rangle_{tot}$
Advantage/ Drawback	➢ **D:** second decomposition in $\Delta\phi_p^*$-bins ➢ **A:** no background assumption	➢ **A:** direct extraction of $\langle sin(\Delta\phi_p^*)\rangle_{SG}$ ➢ **D:** background assumption needed

(1) Event plane method

Fit the distribution of the polarization angle $\Delta\phi_p^* = \Psi_{EP} - \phi_p^*$

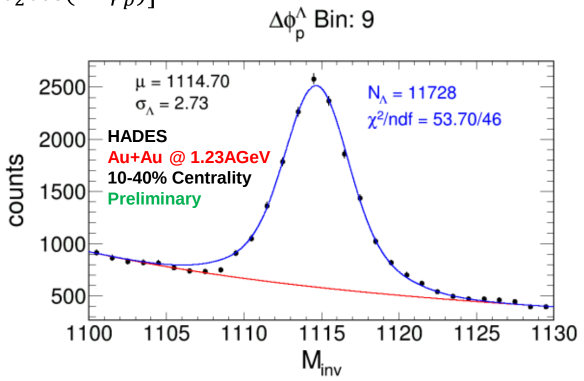
- Get distribution of M_{inv} in a certain $\Delta\phi_p^*$-bin
- Get net amount of Λs in that bin
- Plot distribution of $N_\Lambda(\Delta\phi_p^*)$
- Fit this distribution to get $\langle \sin(\Delta\phi_p^*) \rangle$
- Calculate P_Λ



$$\frac{dN}{d\Delta\phi_p^\Lambda} = N_0\left[1 + 2b_1\sin(\Delta\phi_p^*) + 2c_1\cos(\Delta\phi_p^*) + 2b_2\sin(2\Delta\phi_p^*) + 2c_2\cos(2\Delta\phi_p^*)\right]$$

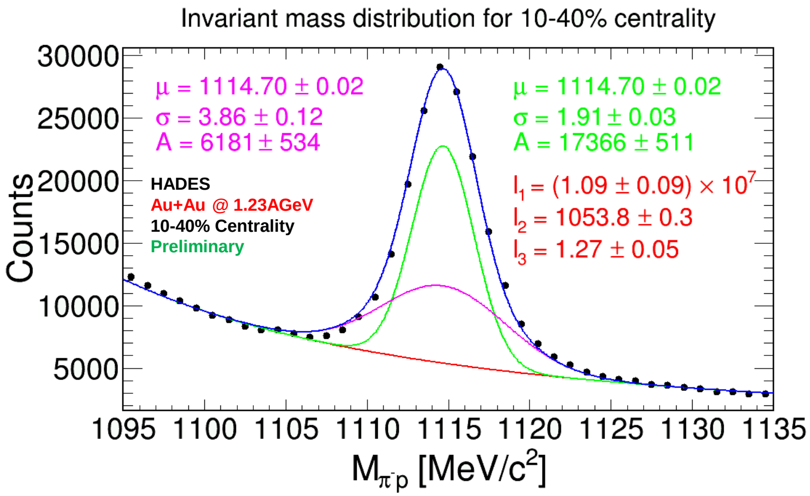
$$P_\Lambda = \frac{8}{\pi\alpha_\Lambda}\frac{b_1}{R_1}$$

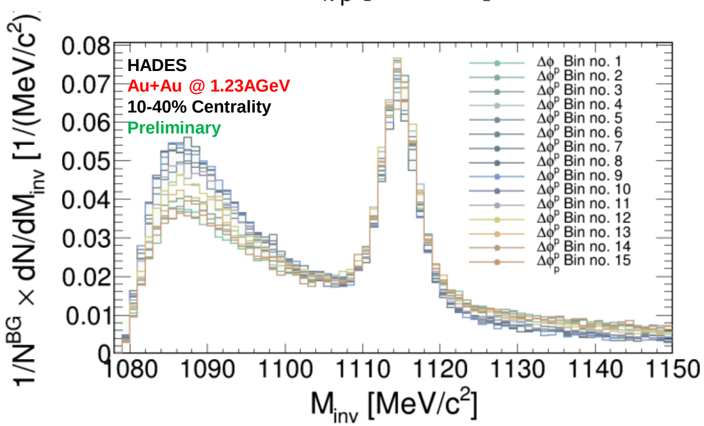
First order event plane resolution



$\Rightarrow P_\Lambda = 0.338 \pm 0.824\ (stat.)$

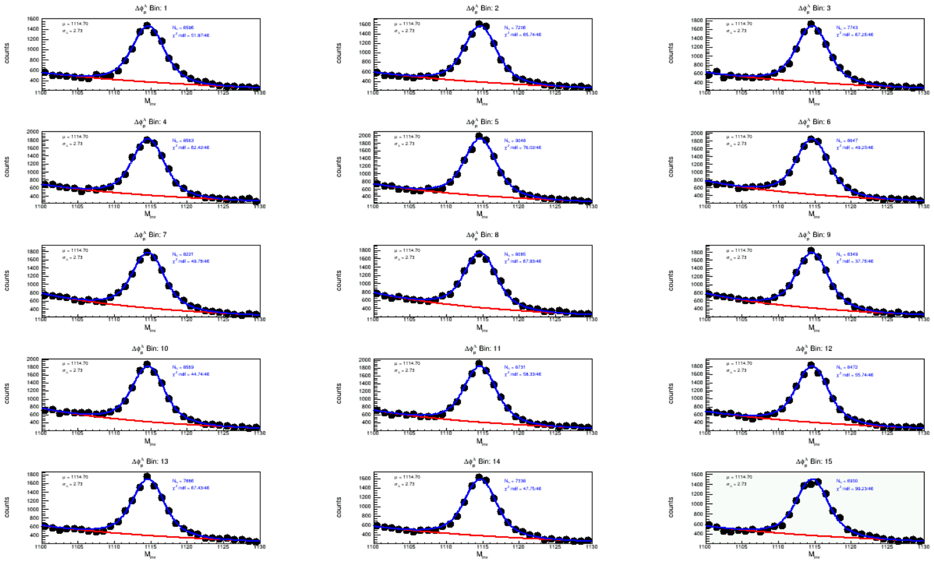
(1) Event plane method





- Fix: $\mu, \sigma_1, \sigma_2, A_1/A_2$ for the Λ peak
- Reduce number of fit parameters:

Global fit 8 par. → **Differential fit 4 par.**



- Background shape changes with polarization angle

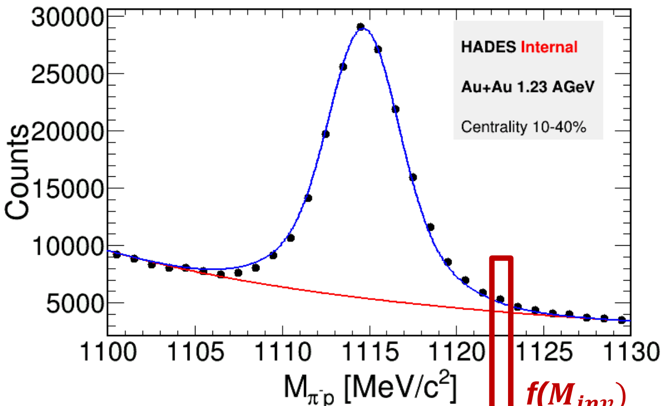
(2) Invariant mass fit method

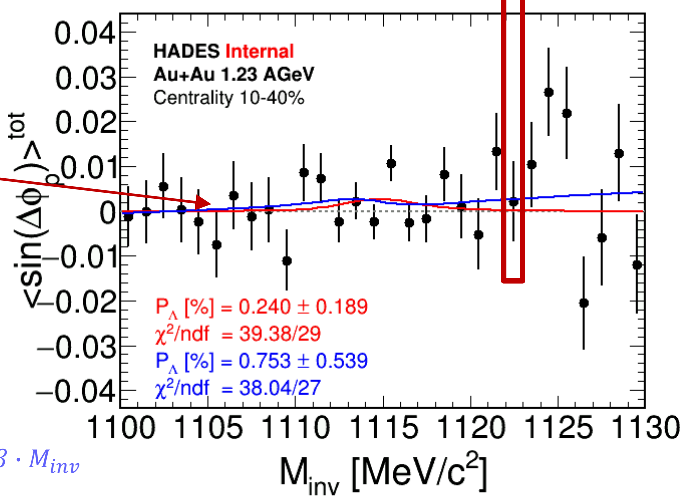
Fit the distribution of $\langle sin(\Delta\phi_p^*)\rangle$

- Plot the distribution of $\langle sin(\Delta\phi_p^*)\rangle_{tot}$ as a function of M_{inv}
- Get S/B-ratio in each bin: $f(M_{inv})$
- Make assumption for $\langle sin(\Delta\phi_p^*)\rangle_{BG}$
- Fit the distribution to get $\langle sin(\Delta\phi_p^*)\rangle_{SG}$
- Calculate P_Λ

$$\langle \sin(\Delta\phi_p^*)\rangle_{tot} = f(M_{inv})\langle \sin(\Delta\phi_p^*)\rangle_{SG} + (1 - f(M_{inv}))\langle \sin(\Delta\phi_p^*)\rangle_{BG}$$

$$P_\Lambda = \frac{8}{\pi\alpha_\Lambda}\langle \sin(\Delta\phi_p^*)\rangle_{SG}$$





$\langle \sin(\Delta\phi_p^*)\rangle_{BG} = 0$

$\langle \sin(\Delta\phi_p^*)\rangle_{BG} = \alpha + \beta \cdot M_{inv}$

$$\boldsymbol{P_\Lambda = 0.240 \pm 0.189(stat.)}$$

$$\boldsymbol{P_\Lambda = 0.753 \pm 0.539(stat.)}$$

Λ Polarization: Results

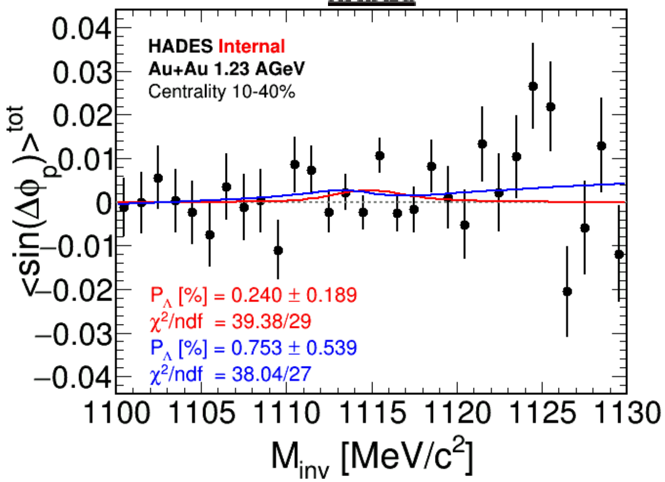
TECHNISCHE UNIVERSITÄT DARMSTADT

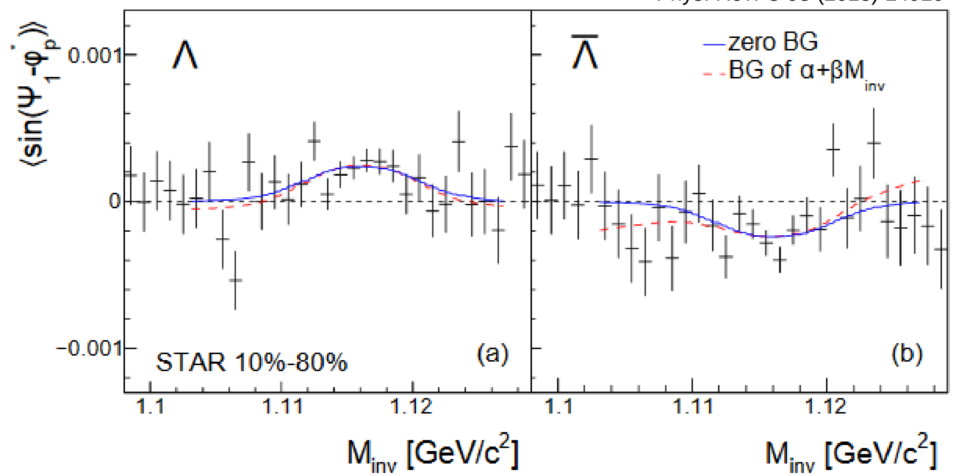
HADES

Comparison to STAR @ $\sqrt{s_{NN}} = 200GeV$:

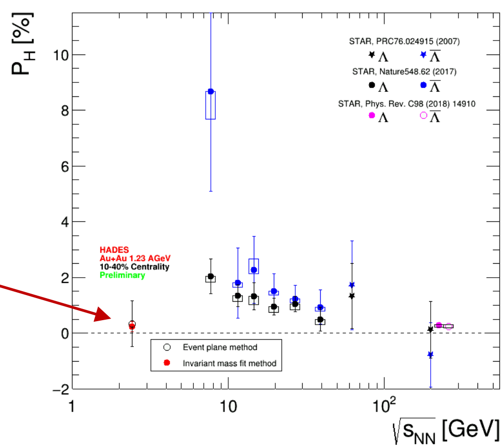
STAR

Phys. Rev. C **98** (2018) 14910





Results:
This analysis
(Preliminary)



$$P_\Lambda = 0.338 \pm 0.824\ (stat.)$$
$$P_\Lambda = 0.240 \pm 0.189 (stat.)$$
$$P_\Lambda = 0.753 \pm 0.539 (stat.)$$

(1) Event plane method

(2) Invariant mass fit method: $P_\Lambda^{BG} \equiv 0$

(2) Invariant mass fit method: $P_\Lambda^{BG} \equiv \alpha + \beta \cdot M_{inv}$

- **Both methods are consistent**
- **Results in well agreement with zero**

Summary and Outlook

Summary:

- Neural network to improve Λ identification and improved off-vertex tracking:

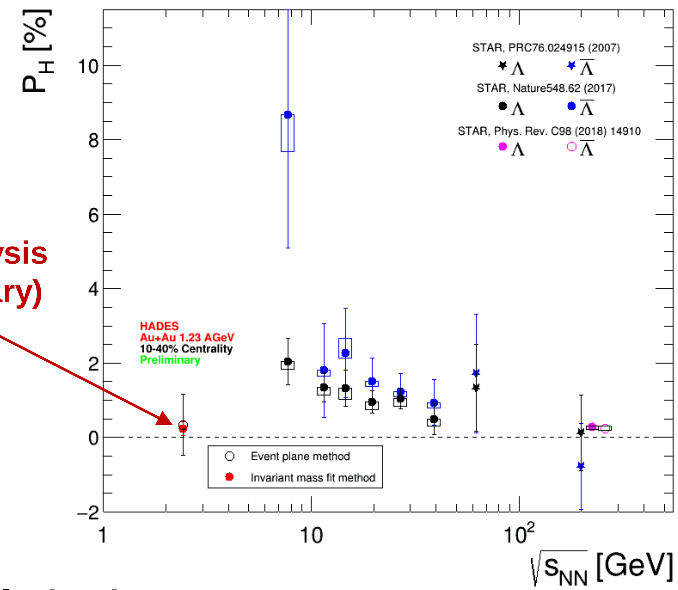
→ ~ 3 more Λs in comparison to previous analysis

- Polarization measurement:

→ 2 different methods applied: both in consistence

→ no polarization found at % level

Results:
This analysis
(Preliminary)



… but …

Outlook:

- **How does the finite detector acceptance influences the polarization measurement?**

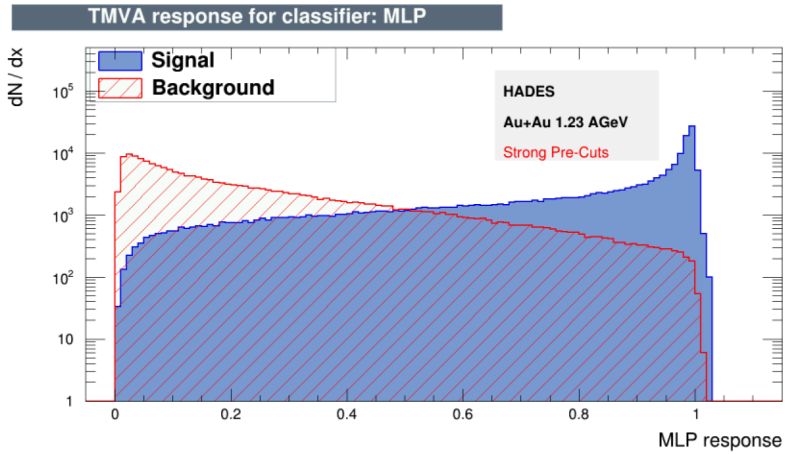
→ Use Pluto (Monte-Carlo simulation framework for HIC collisions and hadronic physics) to generate Λs:

1. Unpolarized: Guide them trough the HADES detector (GEANT) and apply analysis procedure (hopefully get $P_\Lambda = 0$)
2. Different degree of polarization: Do the same procedure → What do we measure as P_Λ?

Ongoing!

- Use minimum bias trigger and extend analysis to more peripheral events
- Estimate systematic errors

Backup



Topology Parameter	Cut Style	Strong Pre-Cuts	Loose Pre-Cuts	No Pre-Cuts
d_1	$<$	$8mm$	$10mm$	Clear ☺
d_2	$>$	$5mm$	$3mm$	
d_3	$>$	$15mm$	$10mm$	
d_v	$>$	$50mm$	$30mm$	
d_t	$<$	$7mm$	$8mm$	
$\Delta\alpha$	$>$	$15°$	$15°$	
N_Λ(sim)		$\mathbf{1.1 \cdot 10^6}$	$\mathbf{1.9 \cdot 10^6}$	$\mathbf{3.6 \cdot 10^6}$

- Choose discriminant such that the significance it at max.:

$$SIG = \frac{S}{\sqrt{S+B}}$$

- *Strong Pre-Cuts:*

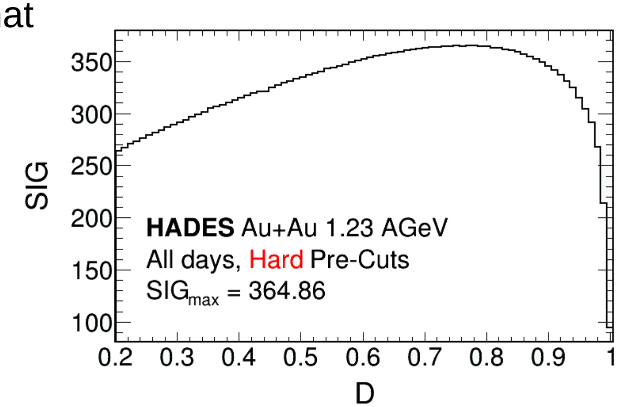
  $N_\Lambda(D > 0.79) = 2 \cdot 10^5$

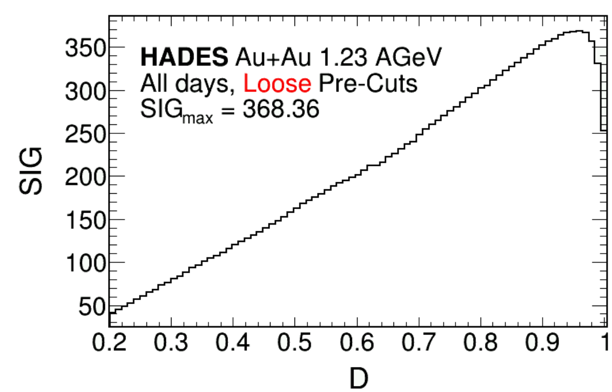
- *Loose Pre-Cuts:*

  $N_\Lambda(D > 0.96) = 2.25 \cdot 10^5$

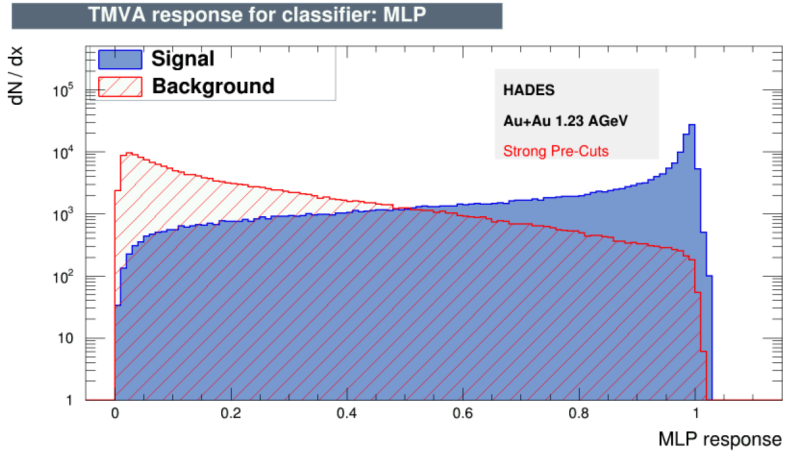
- *Analysis T.Scheib:*

  $N_\Lambda = 0.7 \cdot 10^5$





Backup

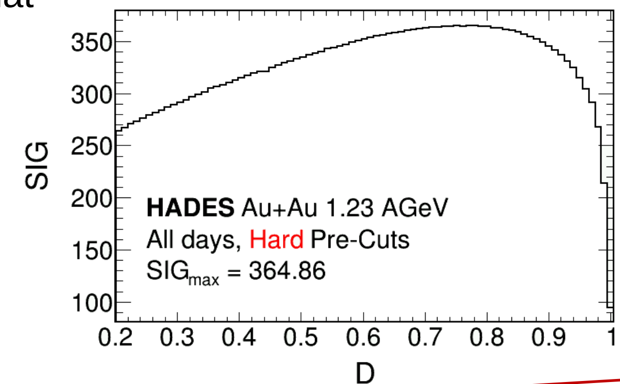


Topology Parameter	Cut Style	Strong Pre-Cuts	Loose Pre-Cuts	No Pre-Cuts
d_1	$<$	$8mm$	$10mm$	Clear ☺
d_2	$>$	$5mm$	$3mm$	
d_3	$>$	$15mm$	$10mm$	
d_v	$>$	$50mm$	$30mm$	
d_t	$<$	$7mm$	$8mm$	
$\Delta\alpha$	$>$	$15°$	$15°$	
N_Λ(sim)		$1.1 \cdot 10^6$	$1.9 \cdot 10^6$	$3.6 \cdot 10^6$

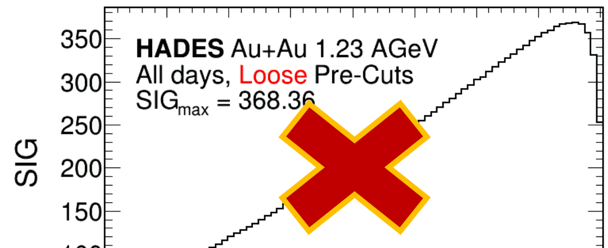
- Choose discriminant such that the significance it at max.:

$$SIG = \frac{S}{\sqrt{S+B}}$$

- *Strong Pre-Cuts:*
  $N_\Lambda(D > 0.79) = 2 \cdot 10^5$
- *Loose Pre-Cuts:*
  $N_\Lambda(D > 0.96) = 2.25 \cdot 10^5$
- *Analysis T.Scheib:*
  $N_\Lambda = 0.7 \cdot 10^5$



Strong Pre-Cut sample is used!



Not feasible, because for multi-differential analysis there is to much background, such that the Λ peak in the invariant mass spectrum cannot be fitted