



# Inclusive $\Sigma^+(1385)$ production in p+p 3.5 GeV

**Konrad Sumara**

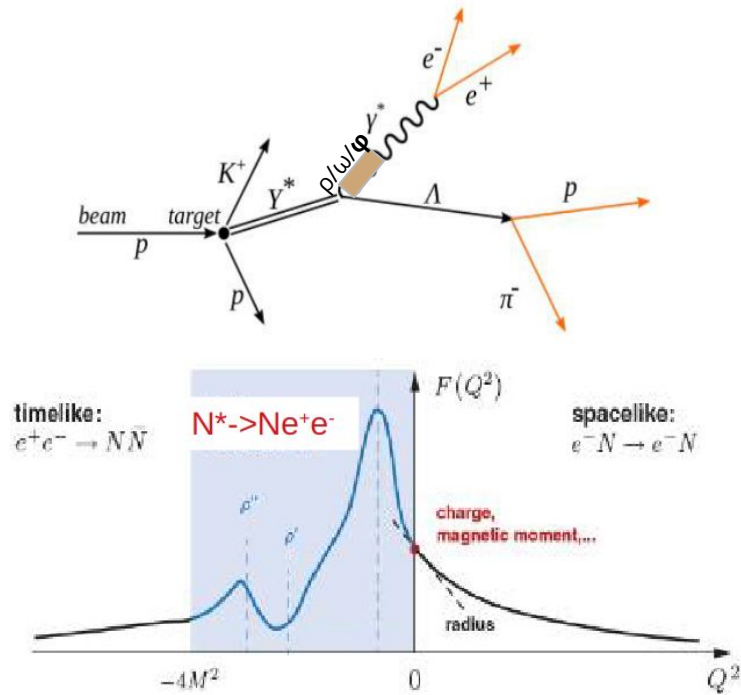
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Institute of Physics

# Agenda

1. Motivation
2. Introduction to  $\Sigma^+(1385)$  analysis
3. HADES Experiment
4. Machine Learning methods and metrics introduction
5.  $\Lambda(1115)$  distribution reconstruction and background reduction
6. Reconstruction of  $\Sigma^+(1385)$  and background subtraction
7. Analysis of  $\Sigma^+(1385)$  signal distributions
8. Short presentation of  $\Lambda(1520)$  decay analysis by Krzysztof Nowakowski
9. Conclusions and outlook

# Hyperon radiative and Dalitz decay

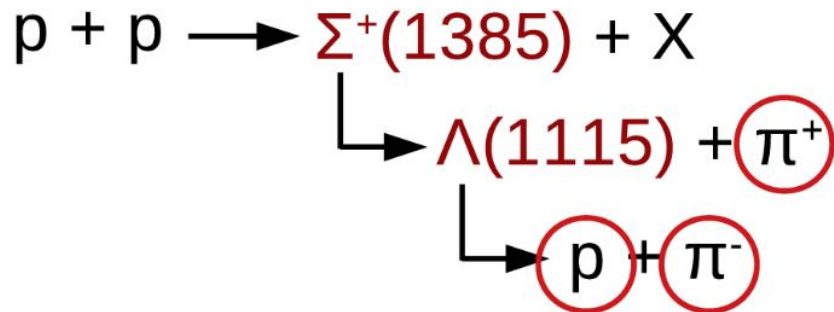
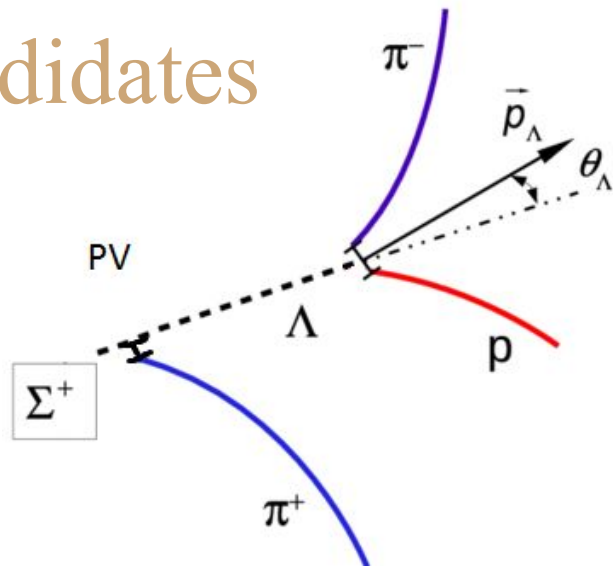
- One of physics goals of pp 4.5 GeV proposal:
  - Provide insight into photon-hyperon coupling, including applicability of Vector Meson Dominance model.
  - Dalitz decays of  $\Lambda(1520)/\Sigma(1385) \rightarrow \Lambda e^+e^-$  allow for first measurement of hyperon Form Factors in time-like region.
  - Production cross-sections of  $\Lambda(1520)/\Sigma(1385)$  are not yet measured in pp and pA reactions at HADES energies.
  - Hadronic decays of  $\Lambda(1520) \rightarrow \Lambda\pi^+\pi^-$  and  $\Sigma(1385) \rightarrow \Lambda\pi^+\pi^-$  (large branching ratios) can be used for normalization for Dalitz decay studies.



Expected dependence of FF for nucleon resonances ( $N^*$ )

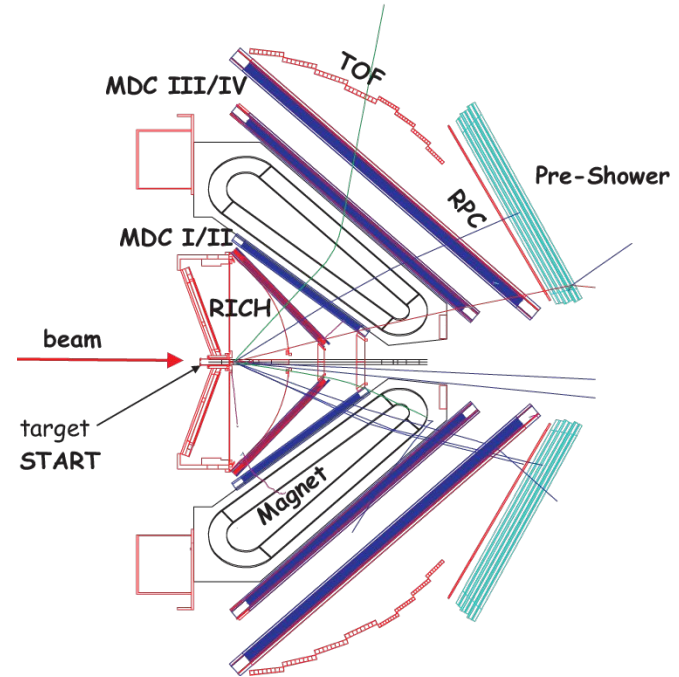
# Selection of $\Sigma^+(1385)$ candidates

- Reconstruction of  $\Lambda(1115)$  and reduction of background utilizing neural networks.
- Reconstruction of  $\Lambda\pi^+$  signal
- Search for  $\Sigma^+(1385)$  and background subtraction.
- Analysis of  $\Sigma^+(1385)$  signal distributions:
  - Invariant mass
  - Transverse momentum
  - Rapidity



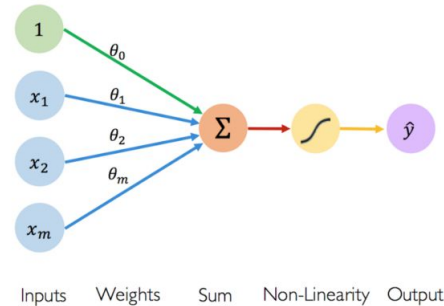
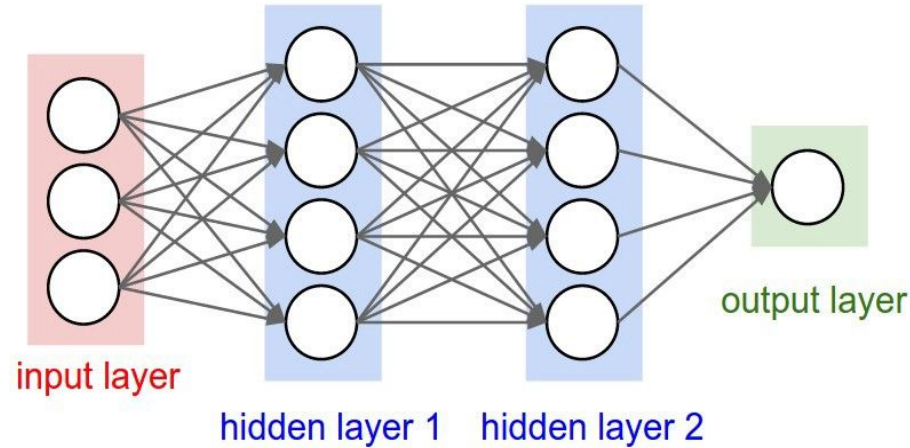
# HADES experiment in pp 3.5 GeV

- **High Acceptance Di-Electron Spectrometer (HADES)** operating on a beam from the SIS18 synchrotron at the GSI research facility.
- The experiment uses a stationary target.
- Specialized in the detection of dileptons (e.g. electron-positron pair) and hadrons during heavy-ion collisions in the 1-4 GeV energy range.
- High angular acceptance:  $18^\circ - 80^\circ$  (now upgraded +  $3^\circ - 7^\circ$  with Forward Detector → details in Gabriela Perez talk) in polar angle and almost complete in azimuthal angle.



# Artificial Neural Networks

- **Artificial Neural Networks** - machine learning methods inspired by structure of biological neural networks present in human and animal brains.:
  - Training information presented in the form of examples.
  - Information gathered during **training** stores in the form of **strength (weights) of connection between neurons** in the network.
- **Multilayer Perceptron (MLP)** - most commonly used class of feedforward artificial neural networks.

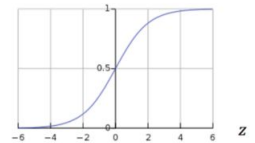


## Activation Functions

$$\hat{y} = g(\theta_0 + \mathbf{X}^T \boldsymbol{\theta})$$

- Example: sigmoid function

$$g(z) = \sigma(z) = \frac{1}{1 + e^{-z}}$$



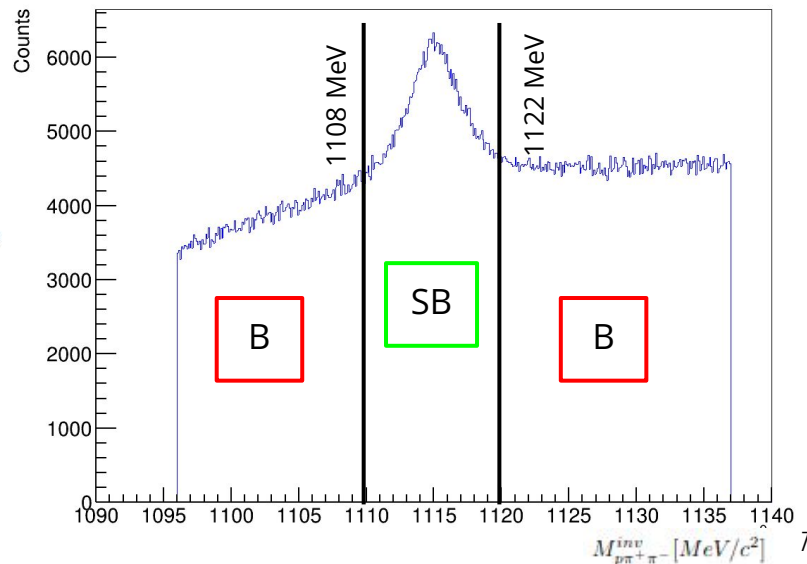
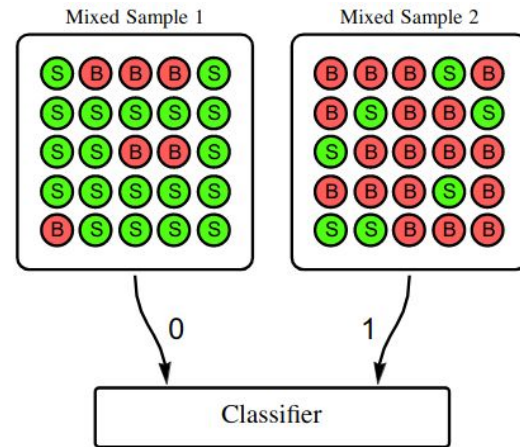
# Classification without labels

- **Neymann-Pearson Lemma:** the optimal classifier is the ratio of probabilities of the event being signal and background respectively, or any classifier that is monotonically related to it.

- Optimal classifier for distinguishing between M1 and M2 ( $L_{M1/M2}$ ) can be expressed through classifier  $L_{S/B}$ :

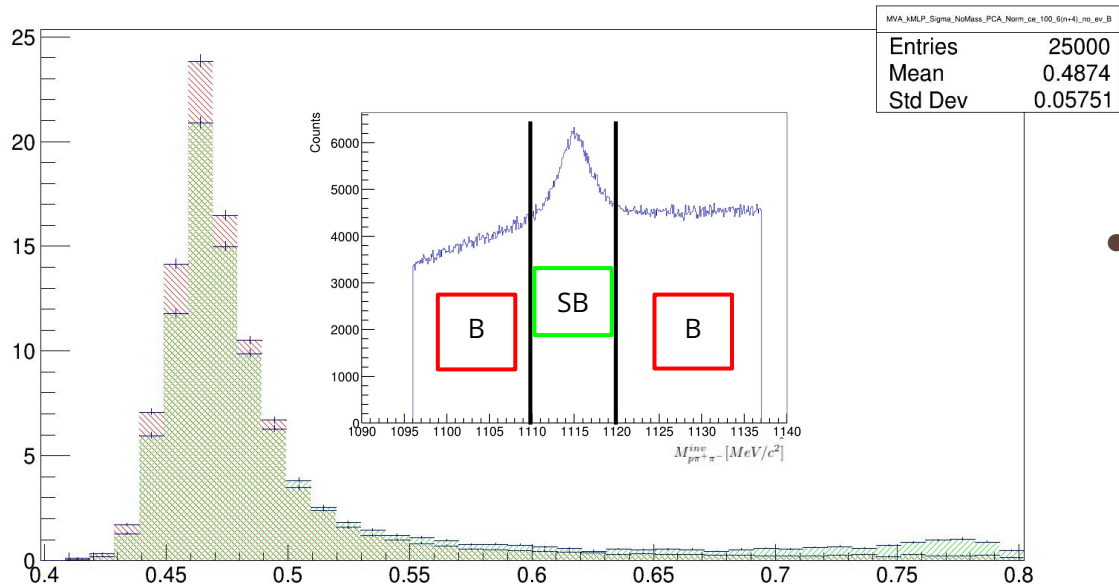
$$L_{M1/M2} = \frac{p_{M1}}{p_{M2}} = \frac{f_1 p_S + (1 - f_1) p_B}{f_2 p_S + (1 - f_2) p_B} = \frac{f_1 L_{S/B} + (1 - f_1)}{f_2 L_{S/B} + (1 - f_2)},$$

- Which is a monotonically increasing rescaling of the likelihood  $L_{S/B}$  as long as  $f_1 > f_2$ .
- **Therefore,  $L_{S/B}$  and  $L_{M1/M2}$  define the same classifier.**



# Classification

## Neural Network output

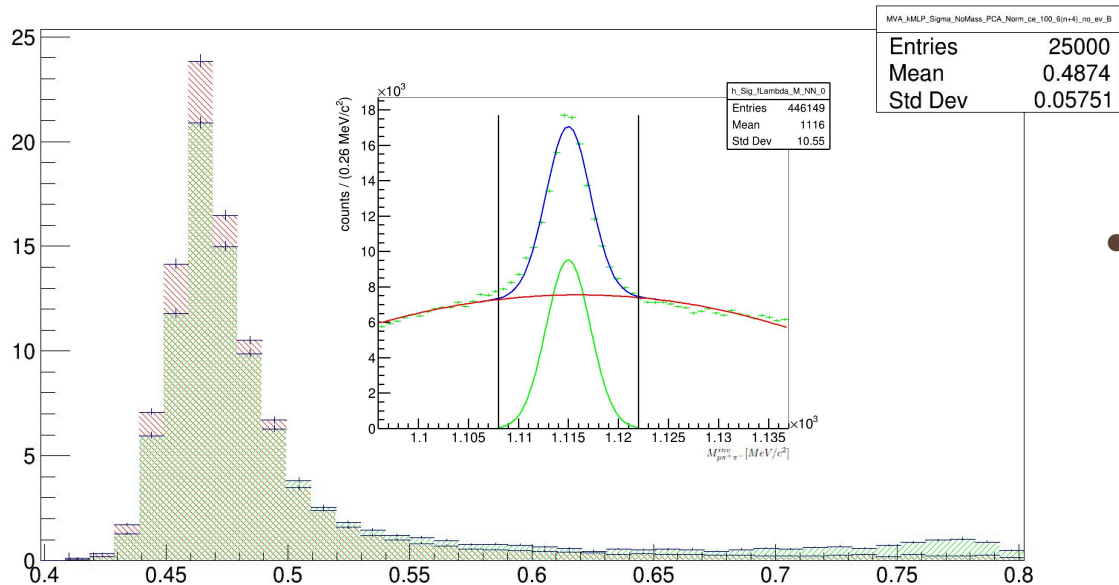


- Classifier produced by training a Multilayer Perceptron type network on two sets of data, each containing 50 000 events:
  - (Green) - Signal + Background Dataset
  - (Red) - Background Dataset
- Training of Neural Network and classification performed sequentially in 4 steps → Improved Signal/Background ratio improves classification efficiency in each subsequent iteration



# Classification

## Neural Network output



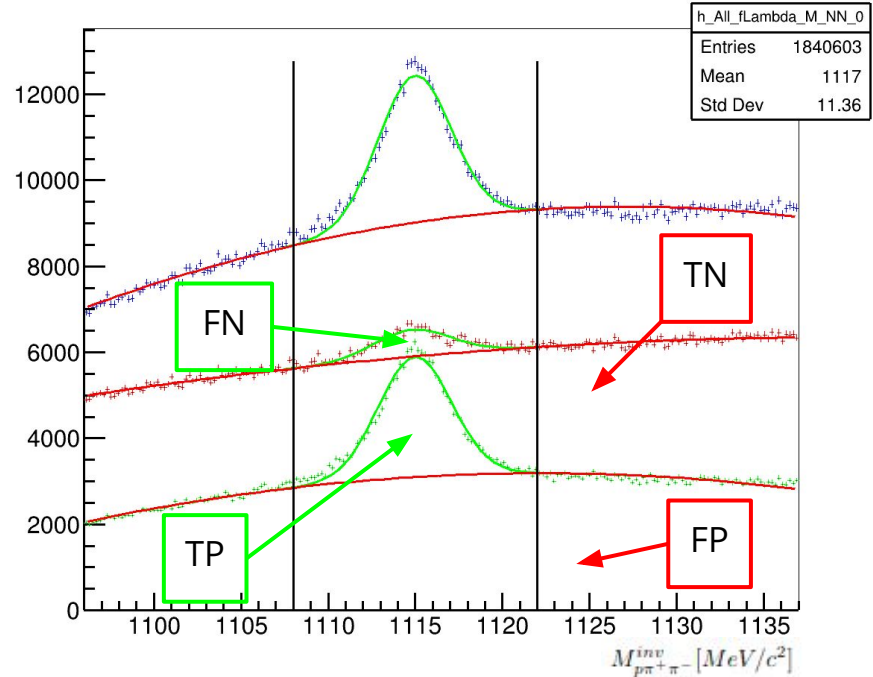
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# Confusion matrix

- **Confusion matrix**, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm.
- Possible combinations in binary classification:

		Actual Value (as confirmed by experiment)	
		positives	negatives
Predicted Value (predicted by the test)	positives	<b>TP</b> True Positive	<b>FP</b> False Positive
	negatives	<b>FN</b> False Negative	<b>TN</b> True Negative

**Lambda invariant mass  
(example cut on NN output)**



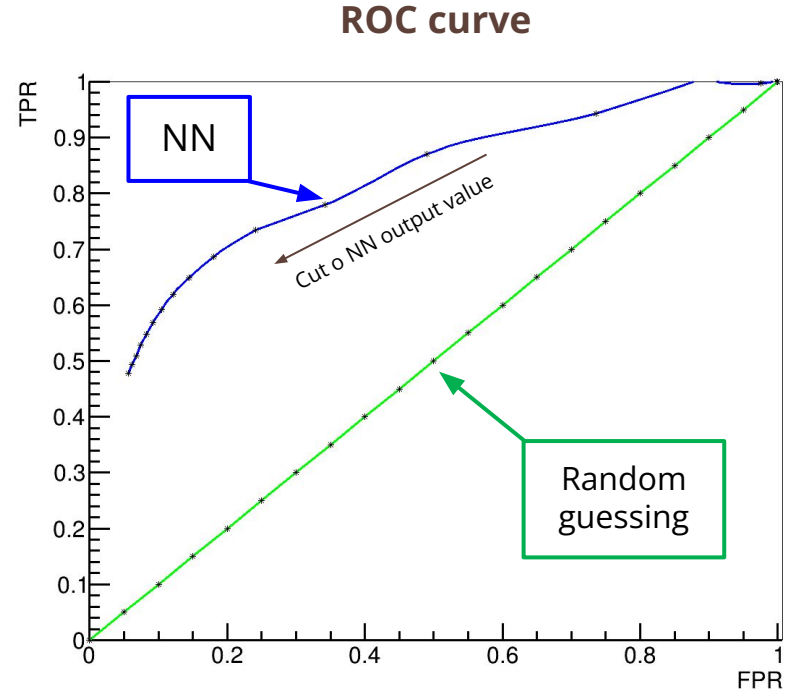
# ROC curve

- A **Receiver Operating Characteristic curve**, or **ROC curve**, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.
- The ROC curve is created by plotting the **true positive rate (TPR)** against the **false positive rate (FPR)** at various threshold settings.
- True Positive Rate (signal efficiency):

$$\text{TPR} = \frac{\text{TP}}{\text{P}} = \frac{\text{TP}}{\text{TP} + \text{FN}} = 1 - \text{FNR}$$

- False Positive Rate (misidentified background):

$$\text{FPR} = \frac{\text{FP}}{\text{N}} = \frac{\text{FP}}{\text{FP} + \text{TN}} = 1 - \text{TNR}$$



# How to find best operating point?

- In statistical analysis of binary classification, the **F-score** or **F-measure** is a measure of a test's accuracy. It is calculated from the precision and recall of the test.
- **Precision** is the number of correctly identified positive results divided by the number of all positive results, including those not identified correctly.

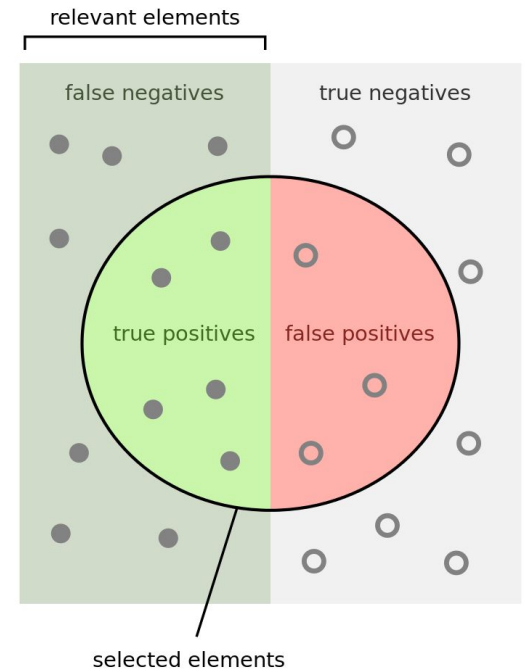
$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

- **Recall** is the number of correctly identified positive results divided by the number of all samples that should have been identified as positive.

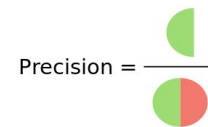
$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

- The **F<sub>1</sub>** score is the harmonic mean of the **precision** and **recall**. The more generic **F<sub>β</sub>** score applies additional weights, valuing recall **β** times more than precision.

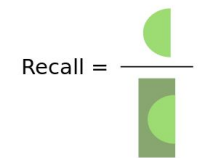
$$F_{\beta} = (1 + \beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$



How many selected items are relevant?



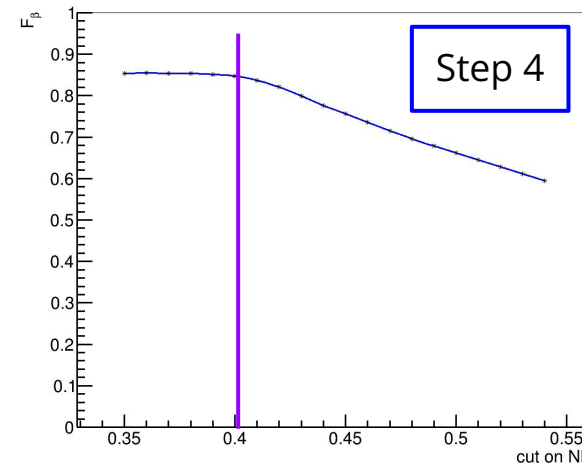
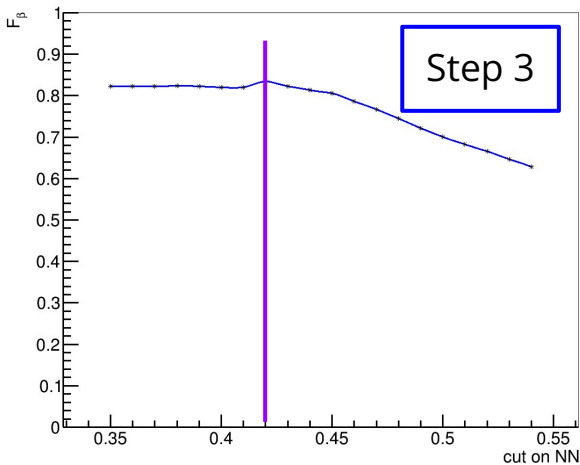
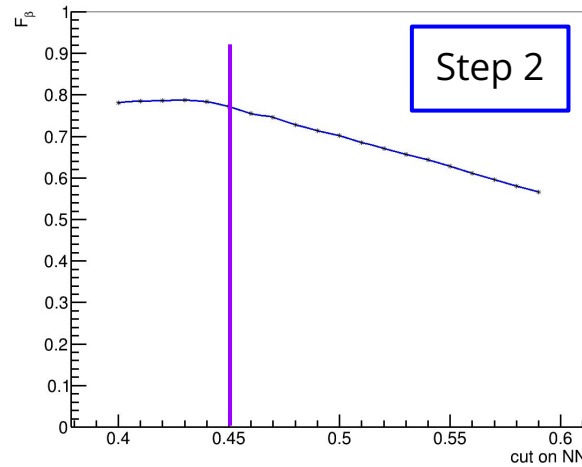
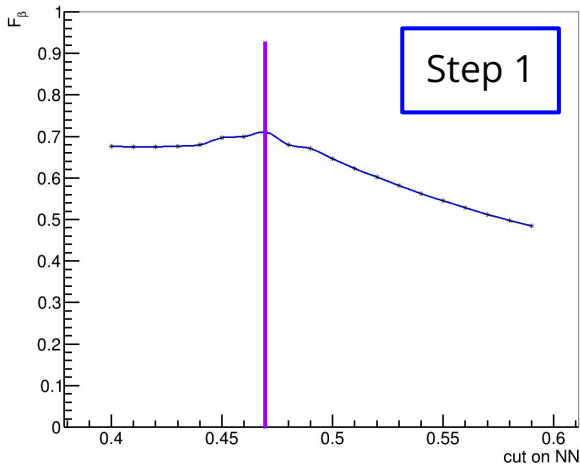
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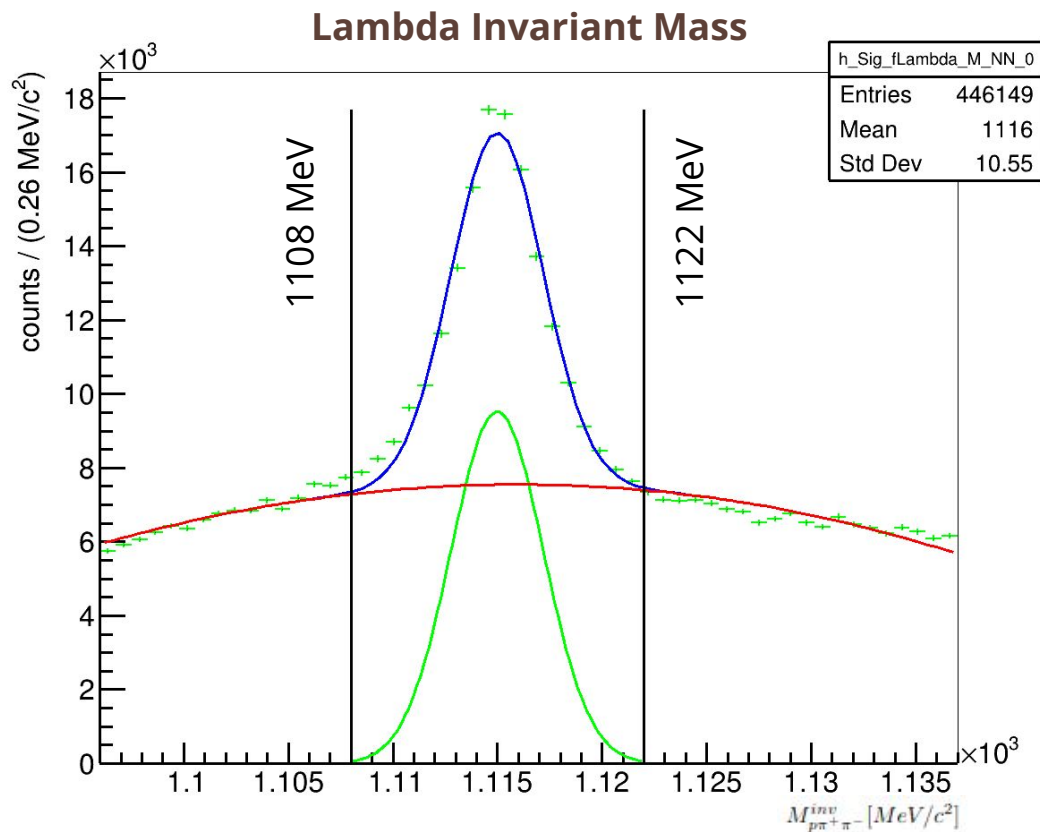
# $F_{3.5}$ score

$$F_{\beta} = (1 + \beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$

- $F_{3.5}$  score plots for each step of the analysis.
- In each step  $F_{3.5}$  score at selected cut value has a bit higher value than in previous step  $\rightarrow$  in each step classification is a bit more efficient than in previous one.



# Background subtraction



- Events from outside signal range were used as sideband to approximate background underneath the Gaussian signal distribution.
- Rescaling was applied based on integrals from a polynomial function fitted to data (red line).

# Sigma Invariant Mass - Fitting

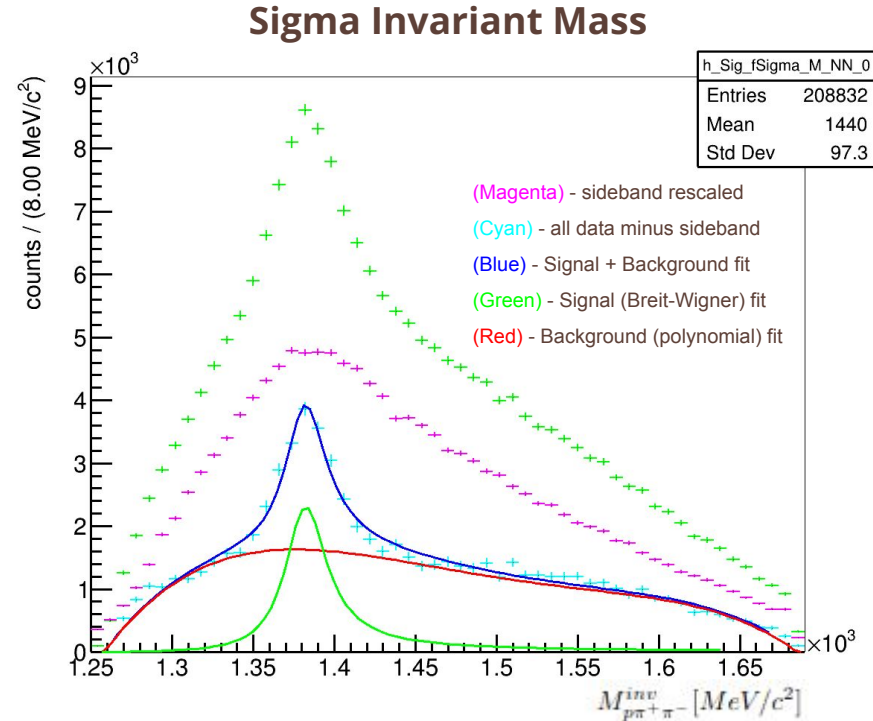
- Fitting of relativistic Breit-Wigner distribution on top of background (fifth degree polynomial), to the spectrum achieved by sideband subtraction (cyan spectrum in histogram), was performed.

$$\text{Breit-Wigner} \propto \frac{q^2}{q_0^2} \frac{m_0^2 \Gamma_0^2}{(m_0^2 - m^2)^2 + m_0^2 \Gamma^2},$$

$$\Gamma = \Gamma_0 \frac{m_0 q^3}{m q_0^3} F_1(q),$$

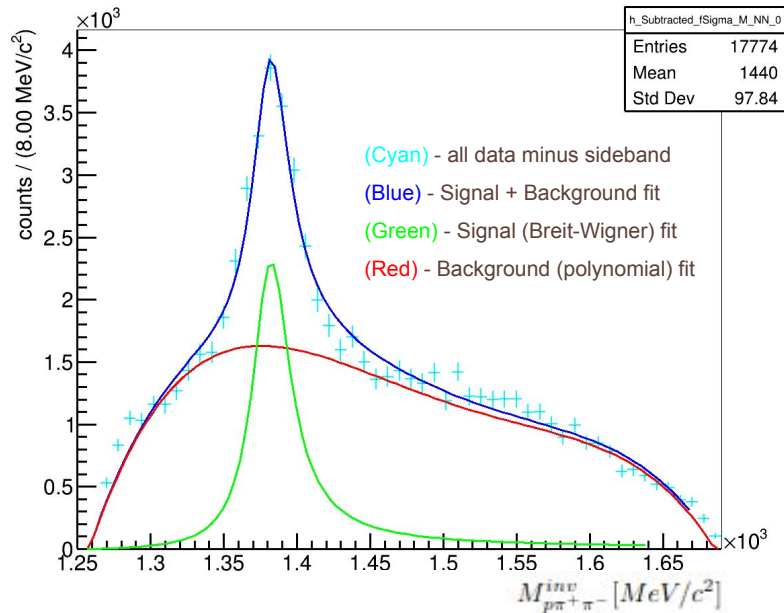
$$F_1(q) = \frac{1 + (q_0 R)^2}{1 + (q R)^2},$$

- $q$  - momentum
- $q_0$  - momentum that corresponds to the mass  $m_0$ ,
- $m$  - mass variable,
- $\Gamma_0$  - resonance width,
- $\Gamma$  - mass-dependent resonance width,
- $F_1(q)$  - Blatt-Weisskopf parameter
- $R = 1/197.327 \text{ MeV}^{-1}$  - centrifugal barrier parameter.



# Inclusive and exclusive comparizon

## Inclusive analysis



$$M_0 = 1382.96 \pm 0.59 \text{ MeV}/c^2$$

$$\Gamma_0 = 32.7 \pm 1.9 \text{ MeV}/c^2$$

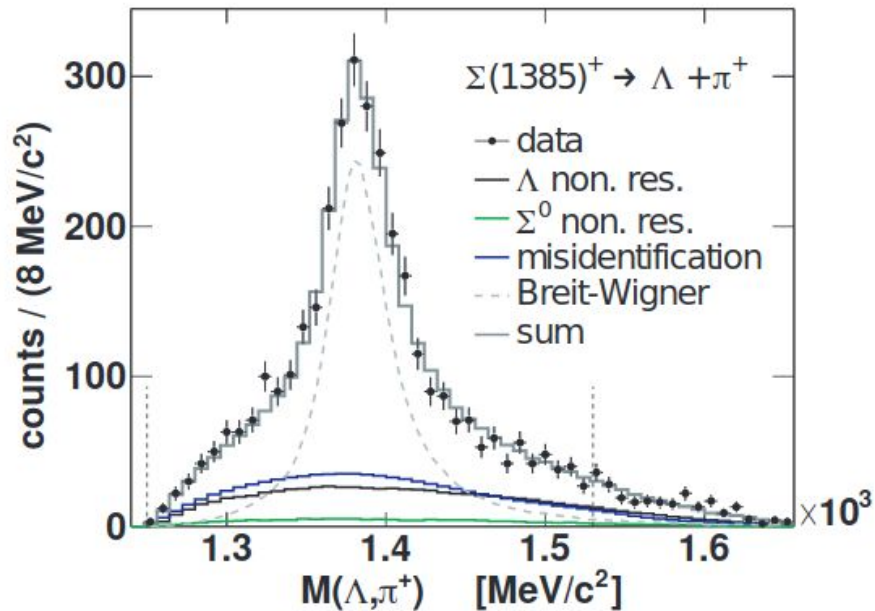
$$\text{Yield} = 15010 \pm 540 \text{ counts}$$

PDG (Particle Data Group):

$$M_0 = 1382.80 \pm 0.35 \text{ MeV}/c^2$$

$$\Gamma_0 = 36.0 \pm 0.7 \text{ MeV}/c^2$$

## Exclusive analysis



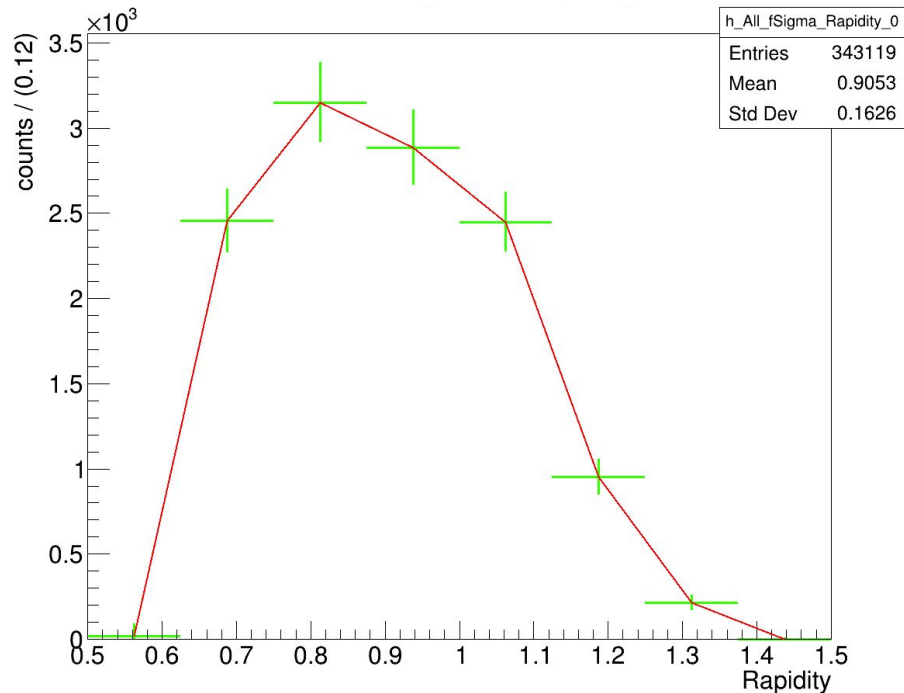
$$m_0 = 1383.2 \pm 0.9^{+0.1}_{-1.5} \text{ MeV}/c^2$$

$$\Gamma_0 = 40.2 \pm 2.1^{+1.2}_{-2.8} \text{ MeV}/c^2$$

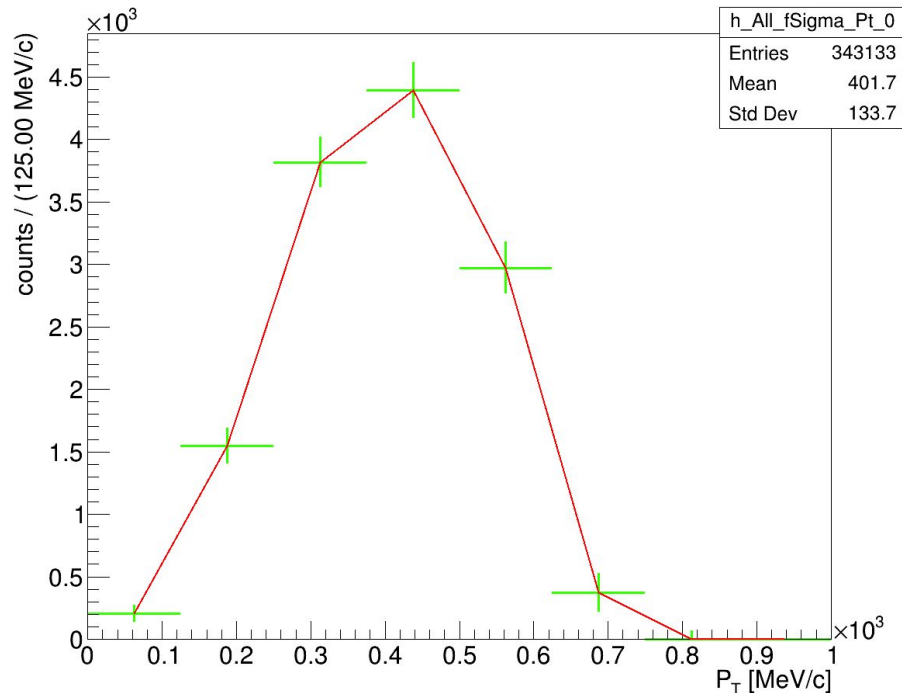


# Rapidity and Transverse Momentum

## Sigma 1385 Rapidity



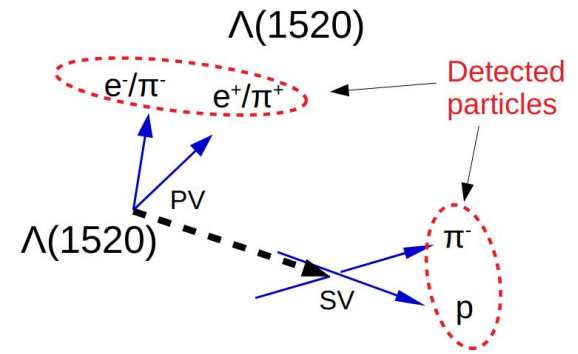
## Sigma 1385 Transverse Momentum



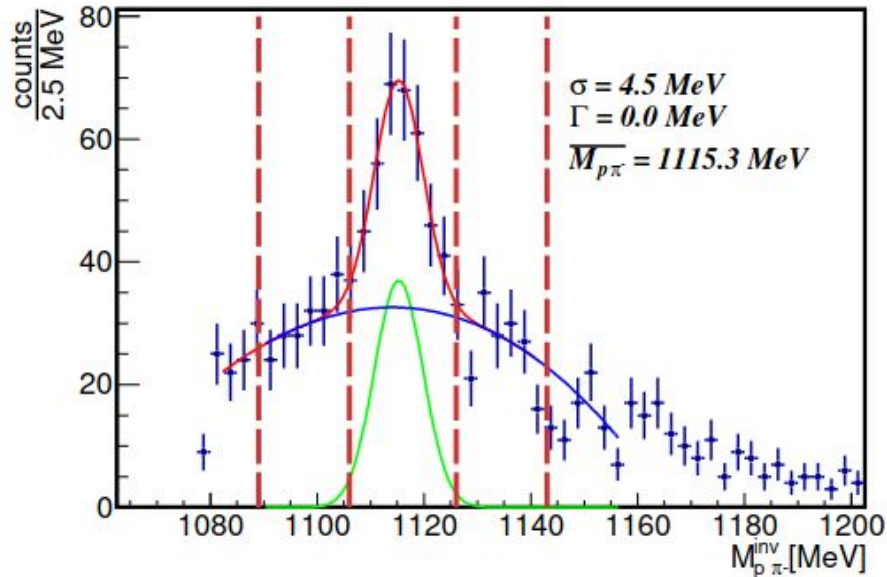
Not yet acceptance and efficiency corrected!

# $\Lambda(1520)$ decay analysis

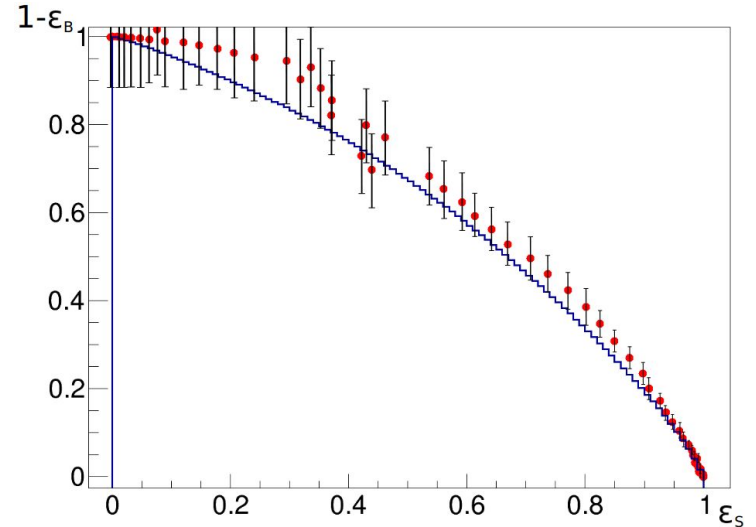
- $\Lambda(1520)$  decay analysis has been performed by Krzysztof Nowakowski in his PhD thesis:



$\Lambda(1116)$  reconstruction invariant mass

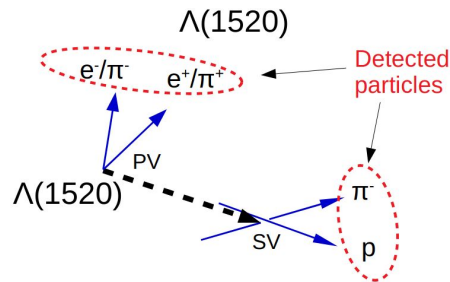


ROC curve

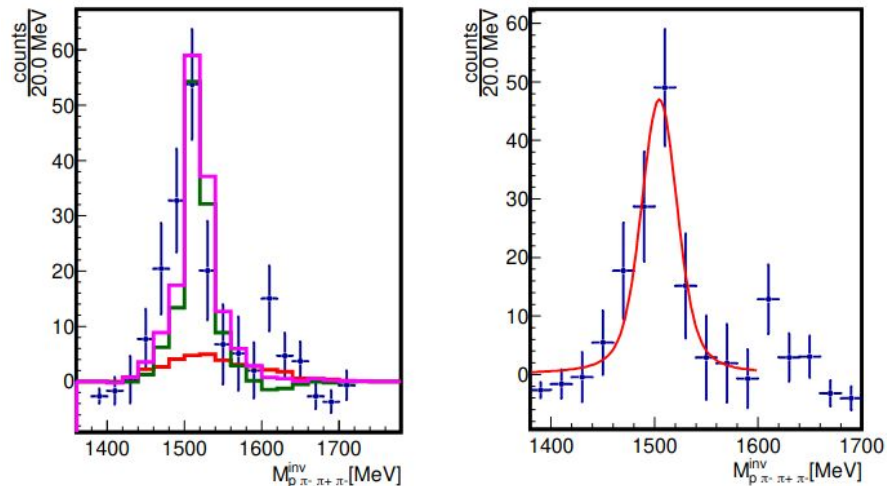


Krzysztof Nowakowski, PhD Thesis, “Measuring  $\Lambda(1520)$  production in proton-proton and proton-nucleus collisions with HADES detector”, 2022<sup>18</sup>

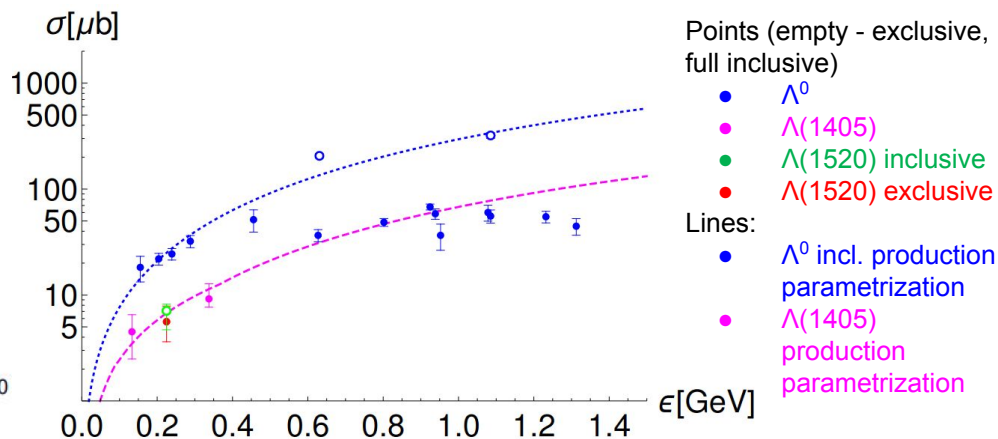
# $\Lambda(1520)$ decay analysis



$\Lambda(1520)$  reconstruction invariant mass



Cross section vs excess energy



$$\sigma_{pp \rightarrow \Lambda(1520)X} = 7.1 \pm 1.1_{-2.14}^{+0.0} \mu\text{b.}$$

	$M_{\Lambda(1520)}$ [MeV]	$\sigma_{\Lambda(1520)}$ [MeV]
PDG	$1519, 5 \pm 1$	not applicable
experiment	$1504.5 \pm 4.7$	$14.7 \pm 6.7$
simulation	$1515.6 \pm 2.1$	$11.3 \pm 3.6$

# Conclusions

- $\Sigma^+(1385)$  channel has been reconstructed and parameters of the distribution have been calculated:

$$M_0 = 1382.96 \pm 0.59 \text{ MeV}/c^2$$

$$\Gamma_0 = 32.7 \pm 1.9 \text{ MeV}/c^2$$

- Analysis technique utilizing machine learning methods has been developed and verified as effective for  $\Sigma^+(1385)$  and  $\Lambda(1520)$  analysis.

# Outlook

- Calculating value of cross-section for this channel.
- Performing analogous analysis for  $\Sigma^+(1385)$  and  $\Lambda(1520)$  channel reconstruction in **proton - proton 4.5 GeV** scattering.
- Expected increase of statistics by  $\sim 2$  orders of magnitude due to larger luminosity and cross-section in 4.5 GeV.