Particle Identification in the NA48 Experiment Using Neural Networks

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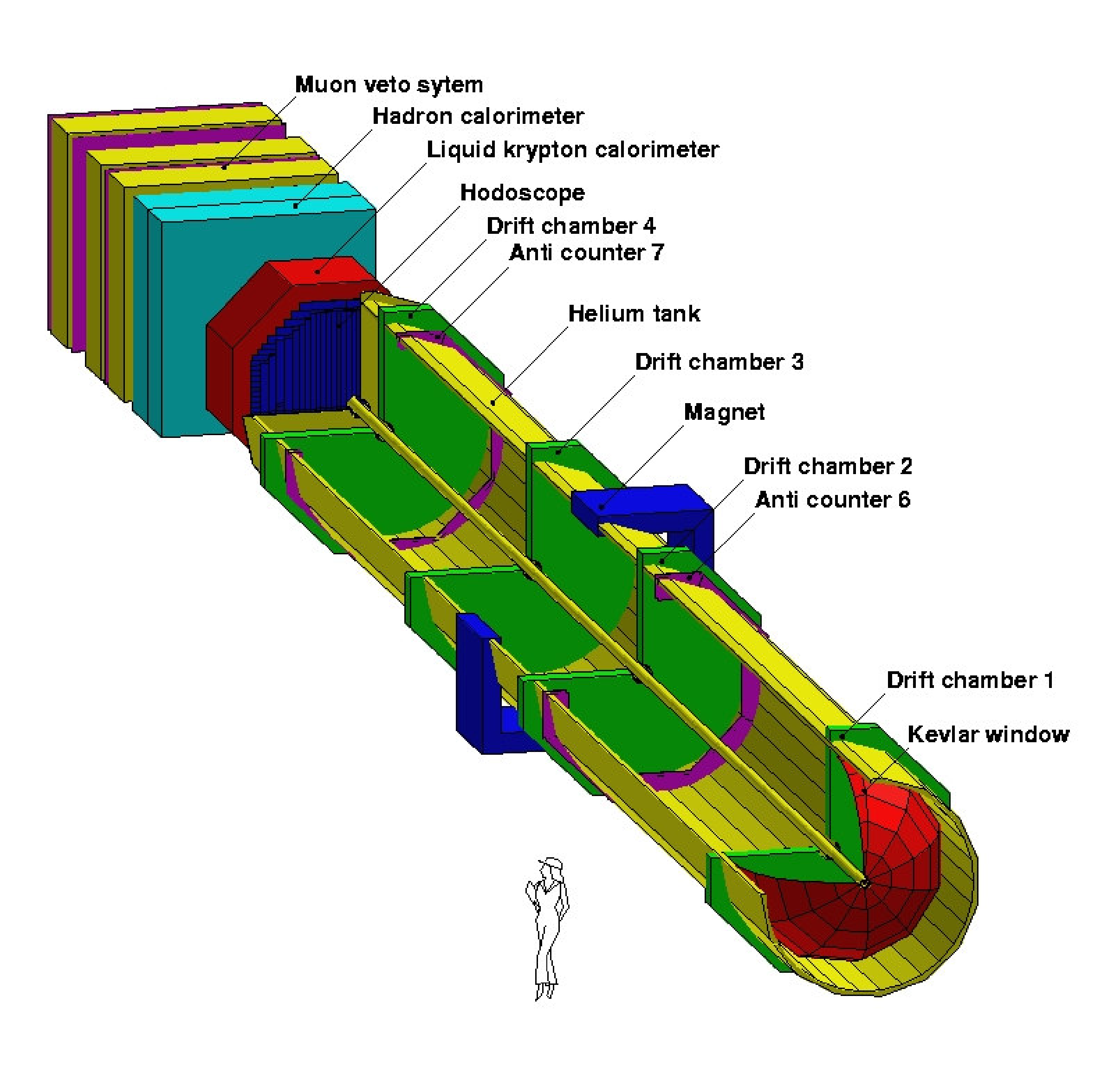
Introduction

- NA 48 detector is designed for measurement of the CP-violation parameters in the K^0 – decays –successfully carried out.
- Investigation of rare $K^0{}_s$ and neutral Hyperons decays – 2002
- Search for CP-violation and measurement of the parameters of rare charged Kaon decays – 2003
- A clear particle identification is required in order to suppress the background
  - In K – decays – μ, π and e
  - Identification of muons do not cause any problems
- We need as good as possible e/π - separation

NA48 detector



Introduction

❖2003 Program for a precision measurement of Charged Kaon Decays Parameters

- Direct CP – violation in $K^{\pm} \to \pi^{\pm}\pi^{\pm}\pi^{\mp}$, $K^{\pm} \to \pi^{0}\pi^{0}\pi^{\pm}$
- Ke4 - $K^{\pm} \to \pi^{\pm}\pi^{\mp}e^{\pm}\nu\,(\overline{\nu})$
- Scattering lengths a_0^0, a_0^2
- Radiative decays $K^{\pm} \to \pi^{\pm}\gamma\gamma$, $K^{\pm} \to \pi^{\pm}\gamma\gamma\gamma$, $K^{\pm} \to \pi^{\pm}\pi^{0}\gamma$

Introduction

- Significant background in K_{e4} comes from $K_{3\pi}$

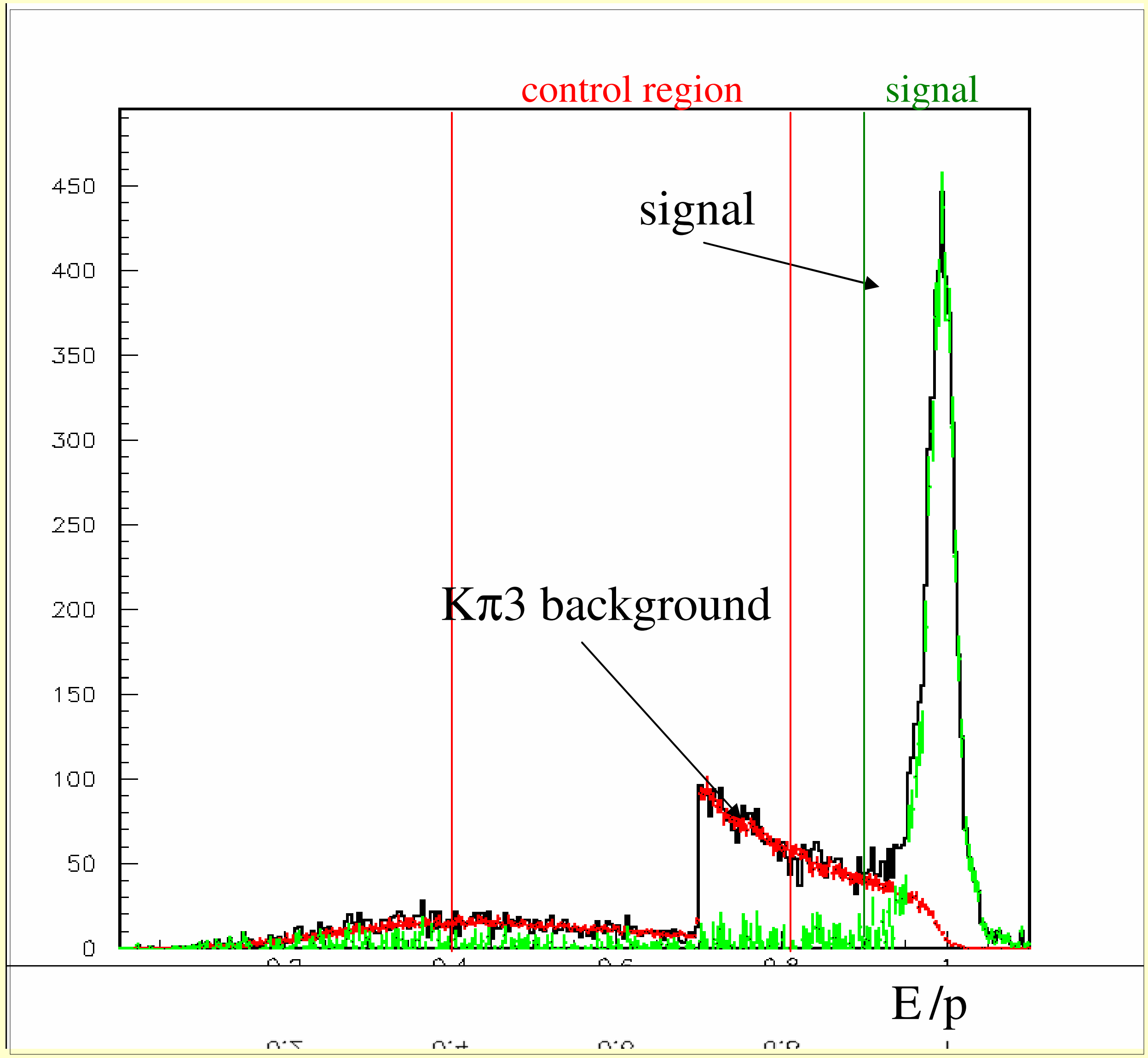
$K^+ \to \pi^+\pi^+\pi^-$ decay	Background in K^c_{e4}
π with $0.9 < E_{cal}/p < 1.1$	4%
$K^+ \to \pi^+\pi^+\pi^- \to \delta ray > eGeV$	$\leq 0.1\%$
$K^+ \to \pi^+\pi^+\pi^- \to e\nu_e (Br = 1.2 \cdot 10^{-4})$	$\leq 0.1\%$
$K^+ \to \pi^+\pi^+\pi^- \to \mu\nu_\mu \to e\nu_e$	$\leq 0.1\%$

- Goal - to reach good enough e/π separation
- $K^+ \to \pi^+\pi^+\pi^- < 0.1$ %
- Definitions:
  - Probability to identify a π as an e : $\epsilon^{\pi \to e}$
  - Probability to identify an e as an e : ϵ^{e}_{eff}
  - i.e. relatively to E/p < 0.9 cut $\epsilon^{\pi \to e} \sim 2.5 \cdot 10^{-2}$

Introduction

K3π Background

- The standart way to separate e and π is to use **E/p**
  - E – energy deposited by particle in the EM calorimeter
  - **p** – particle momentum
- cut at **E/p** > 0.9 for e
- cut at **E/p**< 0.8 for π



Sensitive Variables

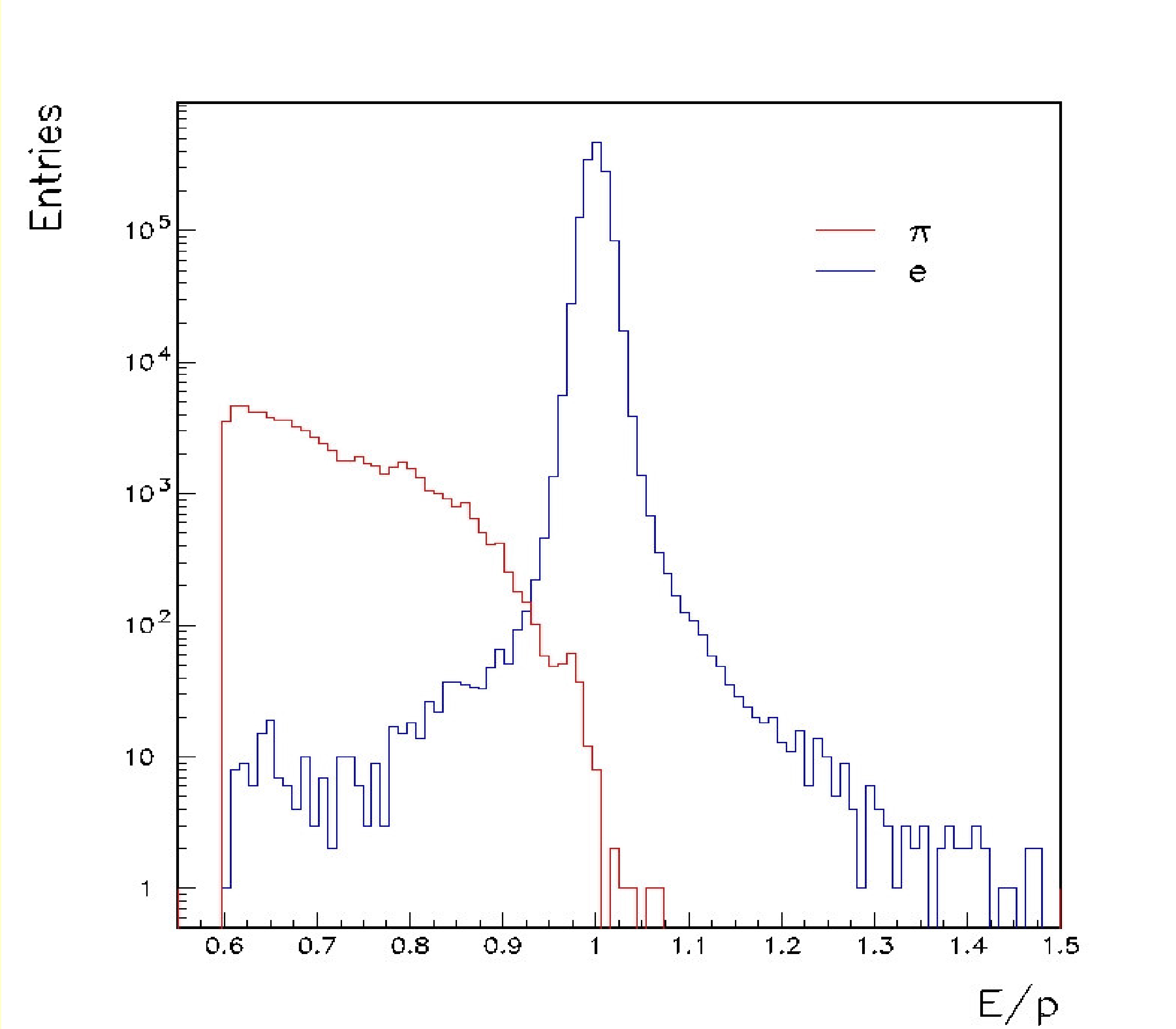
- Difference in development of e.m. and hadron showers
- Lateral development
- EM calorimeter gives information for lateral development
- From Liquid Kripton Calorimeter (LKr)

  - E/p
  - E_{max}/E_{all}, RMSX, RMSY
  - Distance between the track entry point and the associated shower
  - Effective radius of the shower

Sensitive variables - E/p

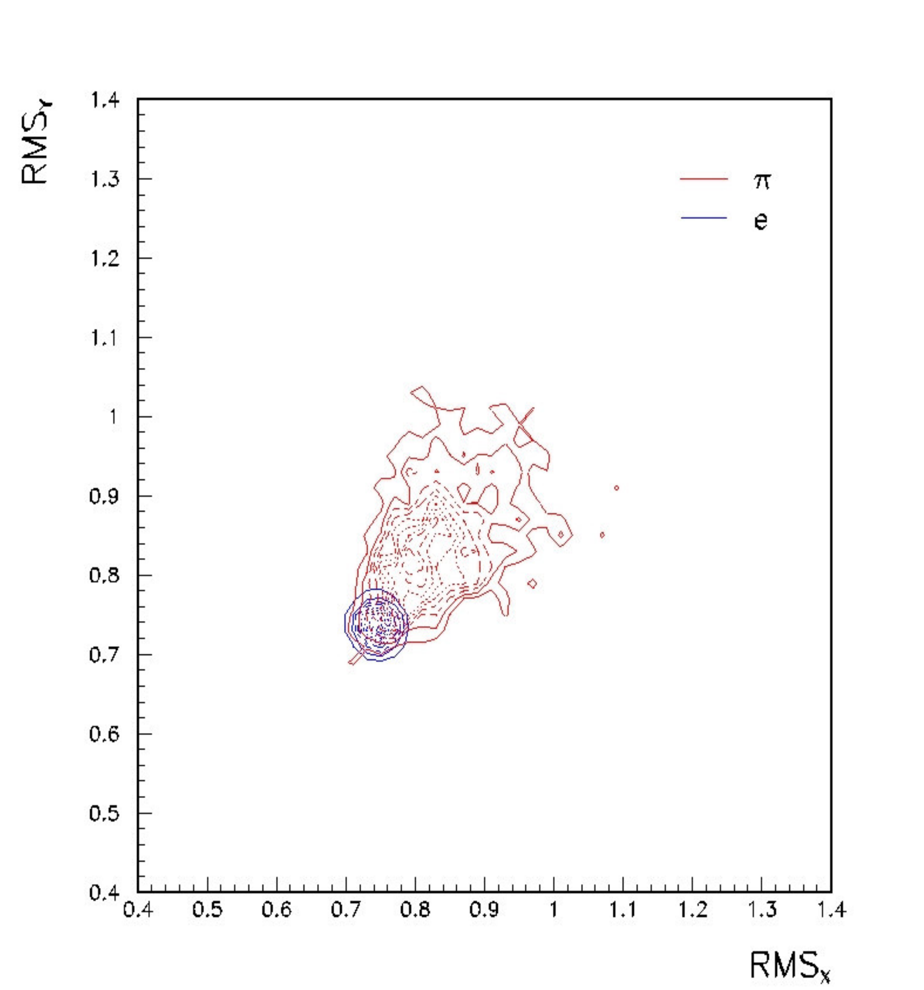
E/p distribution

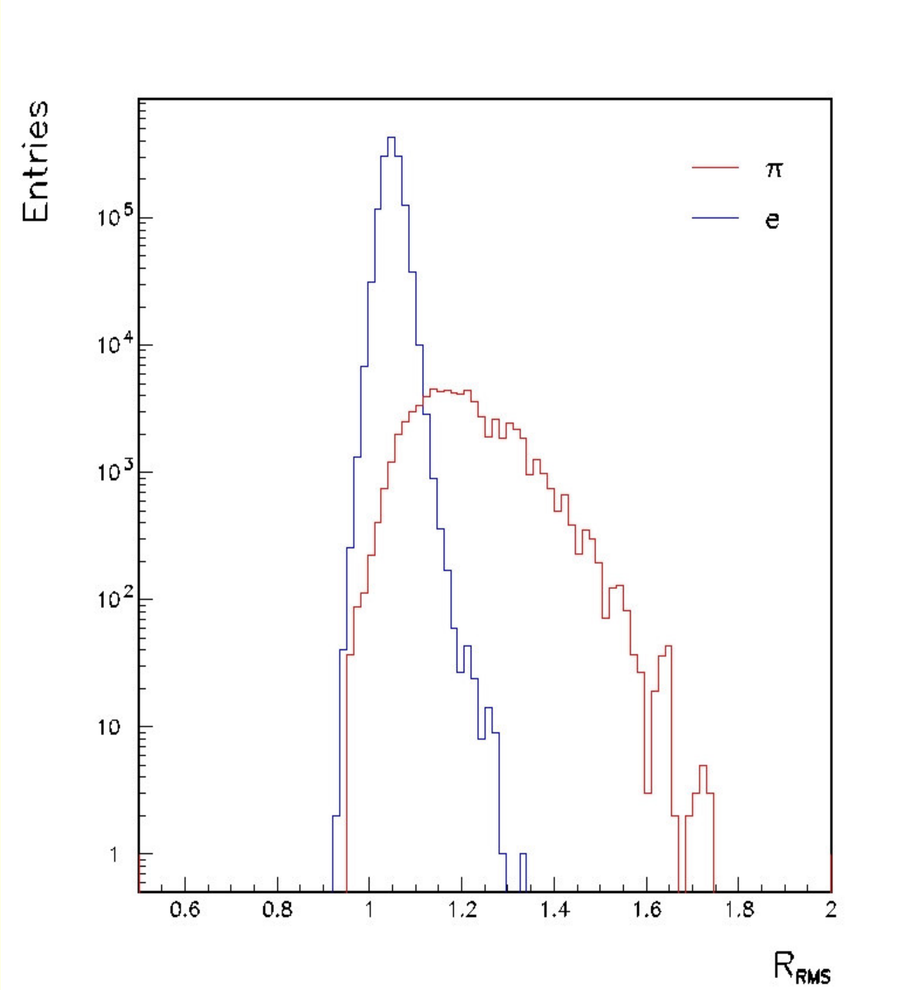
- MC simulation
- A correct simulation of the energy deposed by pions in the EM calorimeter - problem for big E/p
- It is better to use experimental events



Sensitive variables - RMS

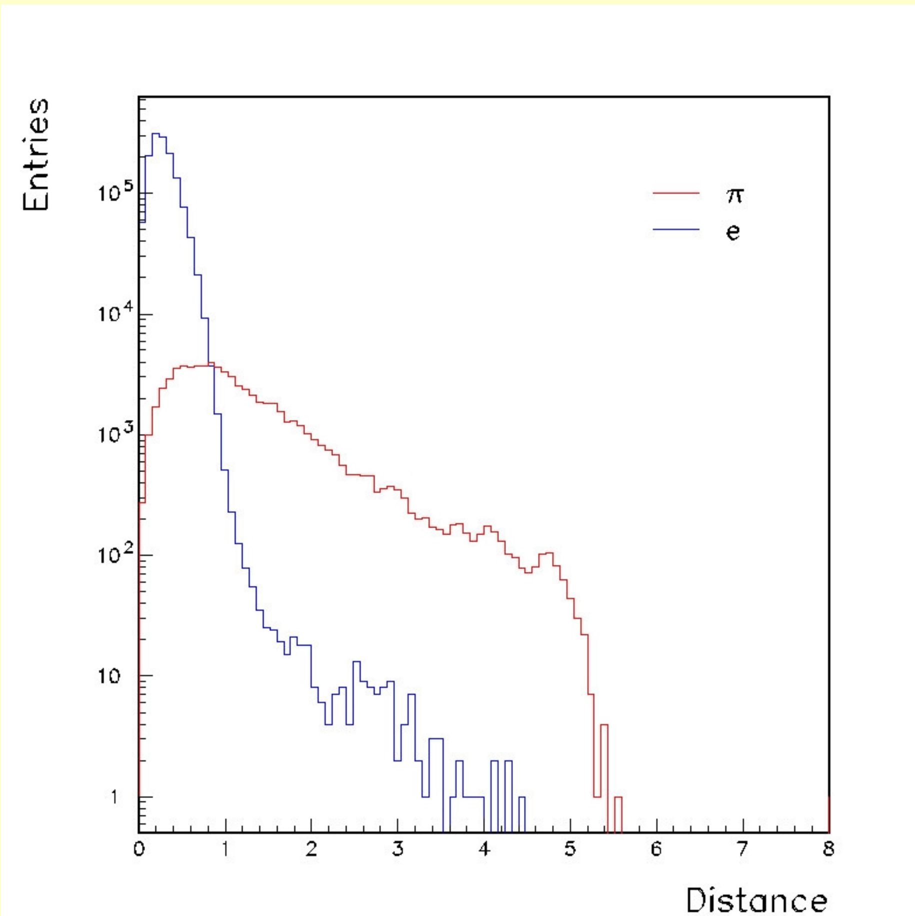
RMS of the electromagnetic cluster

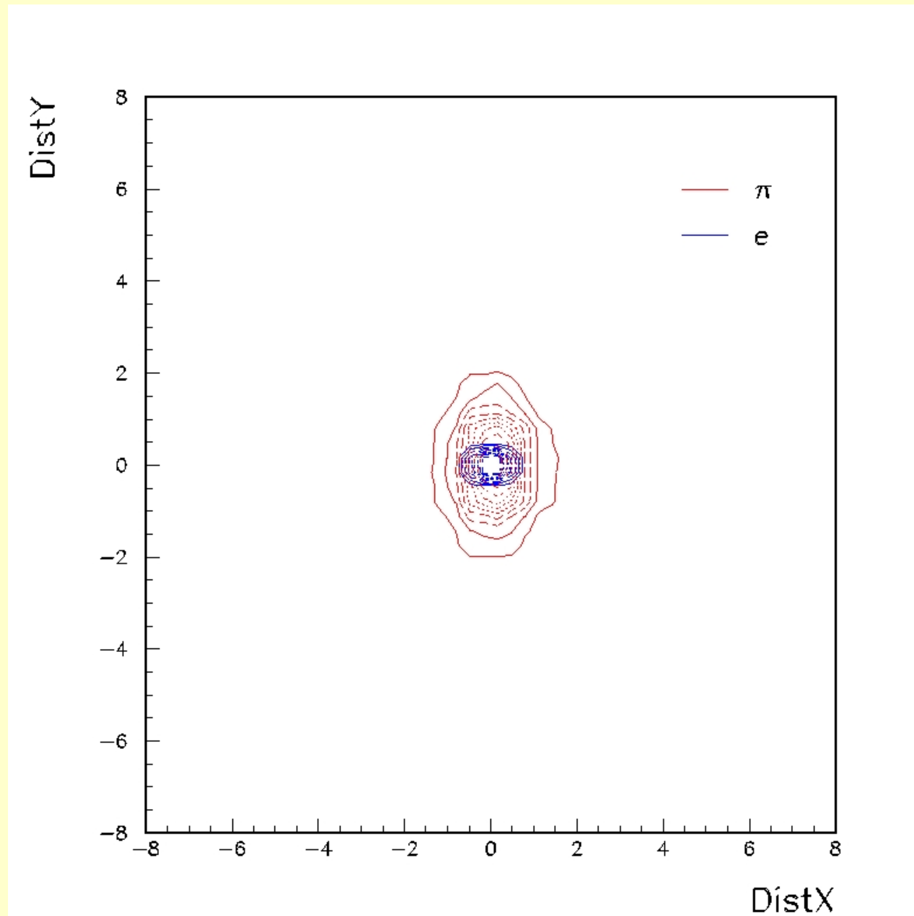




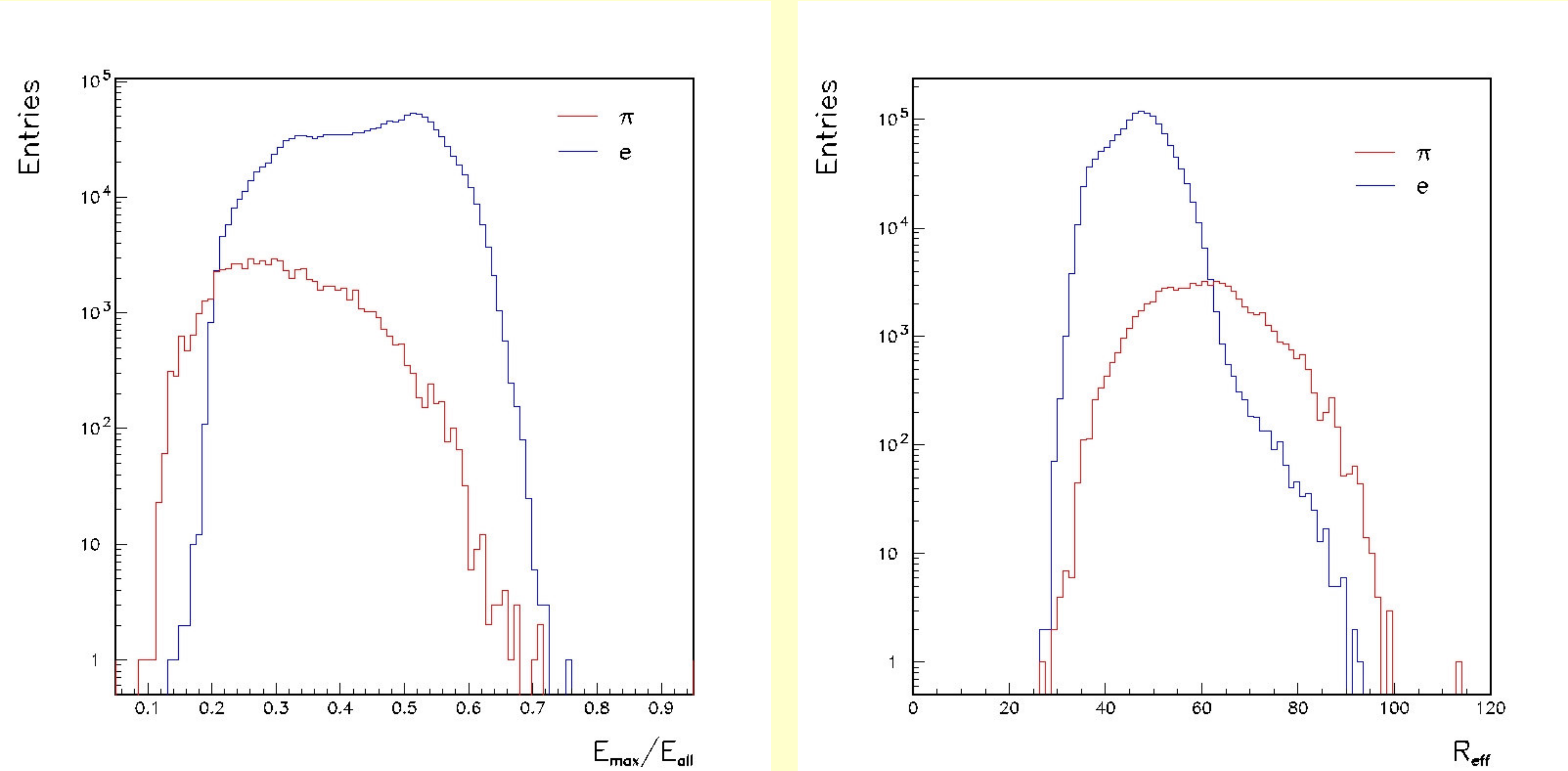
Distance

Distance between track entry point and center of the EM cluster





Sensitive variables - Emax/Eall, Reff



MC

- To test different possibilities we have used:
  - Simulated Ke3 decays – 1.3 M
  - Simulated single e and π – 800 K π and 200 K e
- Using different cuts we have obtained
  - Relatively to E/p < 0.9 cut $\varepsilon_{eff}^{\pi \to e} = 15.7 \times 10^{-2}$
  - Keeping ε_{eff}^{e} > 95 %
- Using Neural Network it is possible to reach e/π separation:
  - Relatively to E/p < 0.9 cut $\varepsilon_{eff}^{\pi \to e} < 2.0 \times 10^{-2}$
  - Keeping ε_{eff}^{e} > 98%
- The background from $K^{\pm} \to \pi^{\pm}\pi^{\pm}\pi^{\mp}$ ~ 0.1%

Neural Network

Powerful tool for:

- ❖Classification of particles and final states
- ❖Track reconstruction
- ❖Particle identification
- ❖Reconstruction of invariant masses
- ❖Energy reconstruction in calorimeters

Basic computing element - Neuron

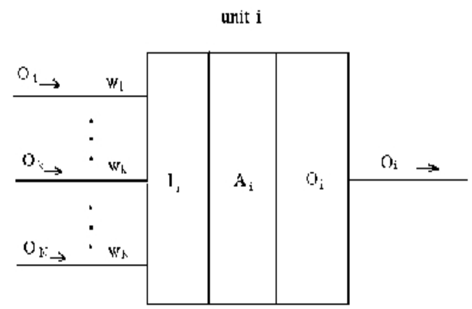


fig 1.NN

neuron performs calculations in three steps

$$I_i = \sum_k w_{ik} O_k, \qquad A_i(I) = \frac{1}{1 + e^{-(I_i + b_i)}}, \qquad O_i = \Theta(A_i - A_{0i}), \qquad (1)$$

Neural Network

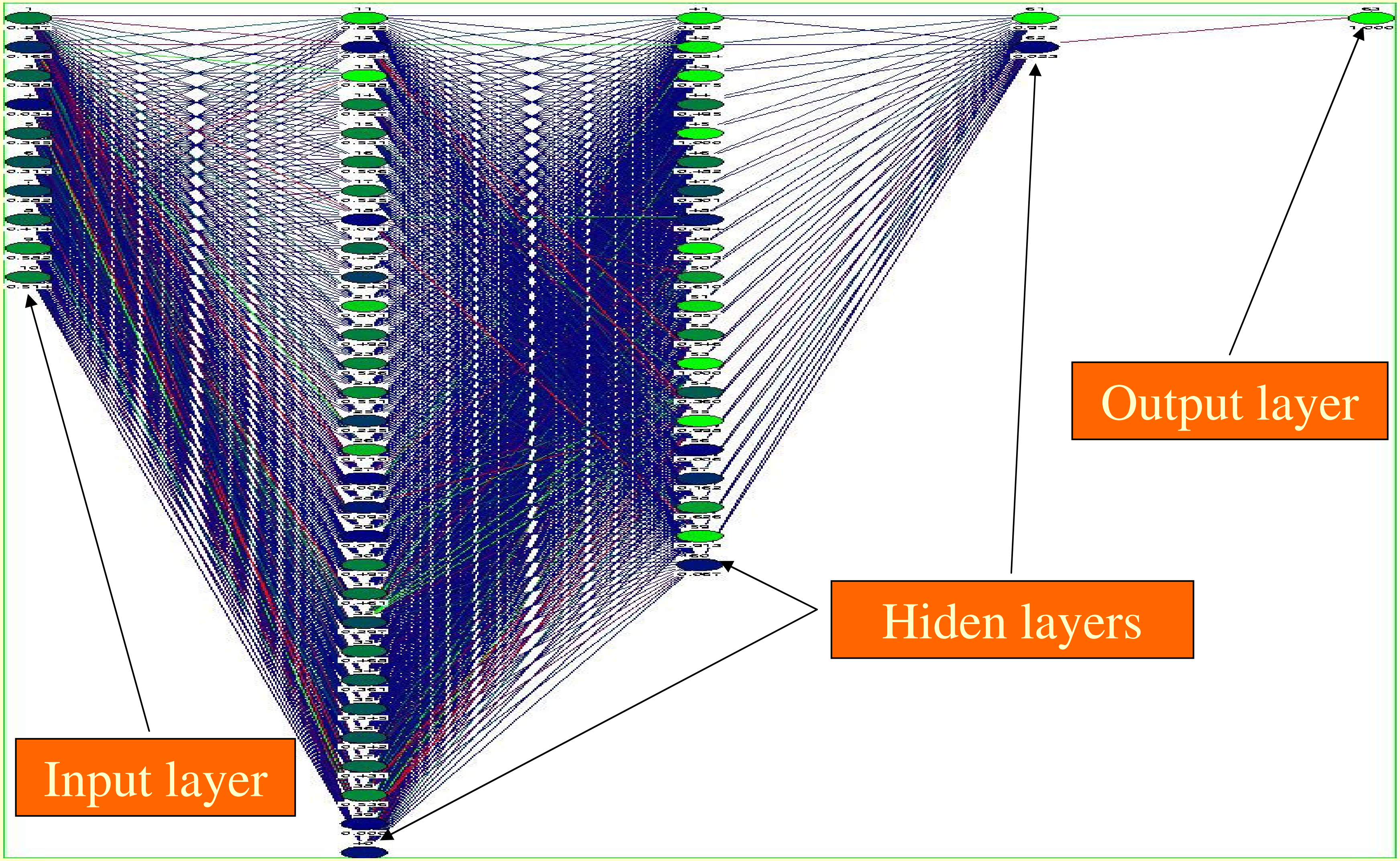
Neural Network

- Multi-Layer-Feed Forward network consists of:
  - Set of input neurons
  - One or more layers of hidden neurons
  - Set of output neurons
  - The neurons of each layer are connected to the ones to the subsequent layer

- Training
  - Presentation of pattern
  - Comparison of the desired output with the actual NN output
  - Backwards calculation of the error and adjustment of the weights
- Minimization of the error function

$$E = \frac{1}{2}\sum_{j} (t_j - o_j)^2$$

NN 10-30-20-2-1



Neural Network

- Backpropagation learning algorithm

$$\Delta w = -\eta \frac{\partial E}{\partial w}$$

- η - learning rate - varies significantly
- Rprop - uses individual learning rate and Manhattan updating rule

$$\Delta w = -\eta sign[\frac{\partial E}{\partial w}]$$

At every step, η is adjusted as:

$$\eta_{w,t+1} = \gamma^{+} \eta_{w,t} \qquad \text{if} \qquad \partial E_{t+1} . \partial E_t > 0,$$

$$\eta_{w,t+1} = \gamma^{-} \eta_{w,t} \qquad \text{if} \qquad \partial E_{t+1} . \partial E_t < 0$$

$$0 < \gamma^{-} < 1 < \gamma^{+}$$

Experimental data

- E/pi separation – to teach and test the performance of NN

  We have used experimental data from two different runs

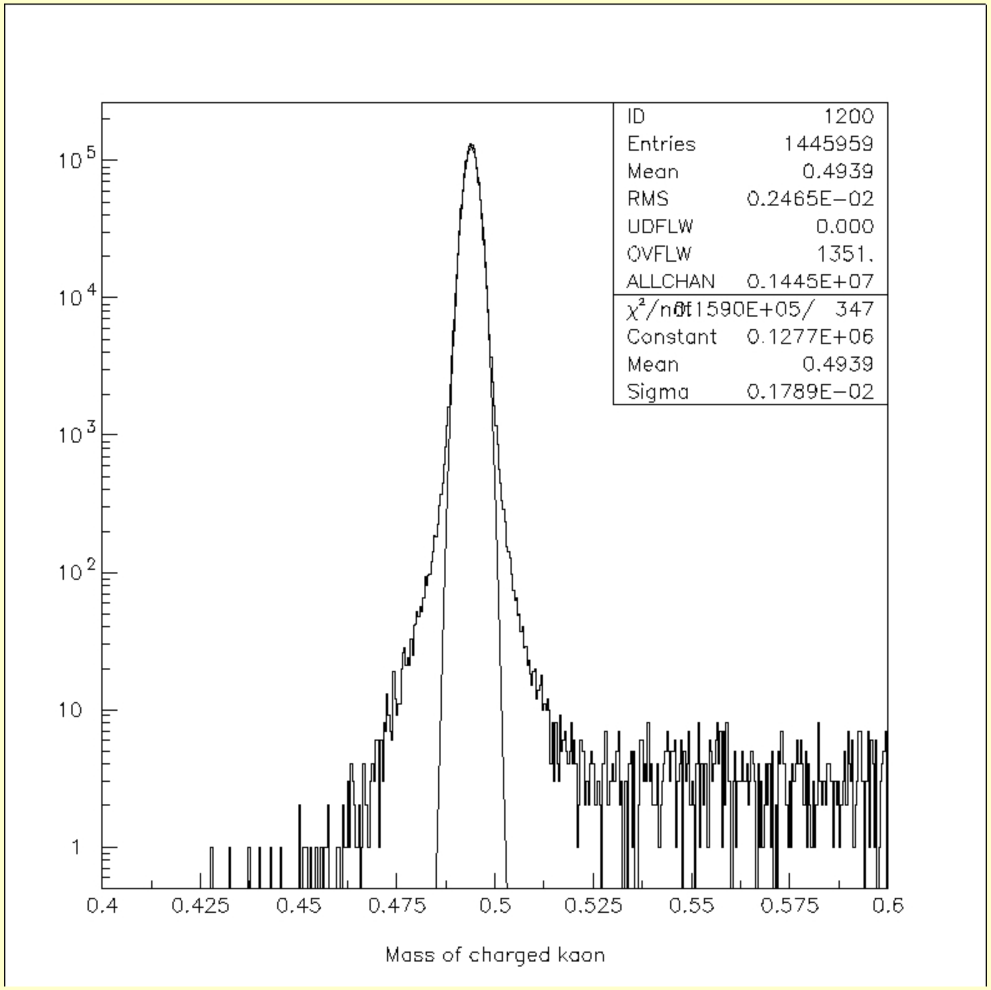
- Charged kaon test run # 1 2001
  - electrons from $K^{\pm} \rightarrow \pi^{\pm}\pi^{0} \rightarrow \pi^{\pm}e^{+}e^{-}\gamma$
  - pions from $K^{\pm} \rightarrow \pi^{\pm}\pi^{\pm}\pi^{\mp}$
- $K^{0}e4$ run 2001
  - electrons from $K^{0} \rightarrow \pi^{\pm}e^{\mp}\nu$
  - pions from $K^{0} \rightarrow \pi^{+}\pi^{-}\pi^{0}$

Charged run

$K^{\pm} \rightarrow \pi^{\pm}\pi^{\pm}\pi^{\mp}$

Pions

- Track momentum > 3 GeV
- Very tight $K^{\pm} \rightarrow \pi^{\pm}\pi^{\pm}\pi^{\mp}$ selection
- Track is chosen randomly
- Requirement – E/p < 0.8 for the other two tracks



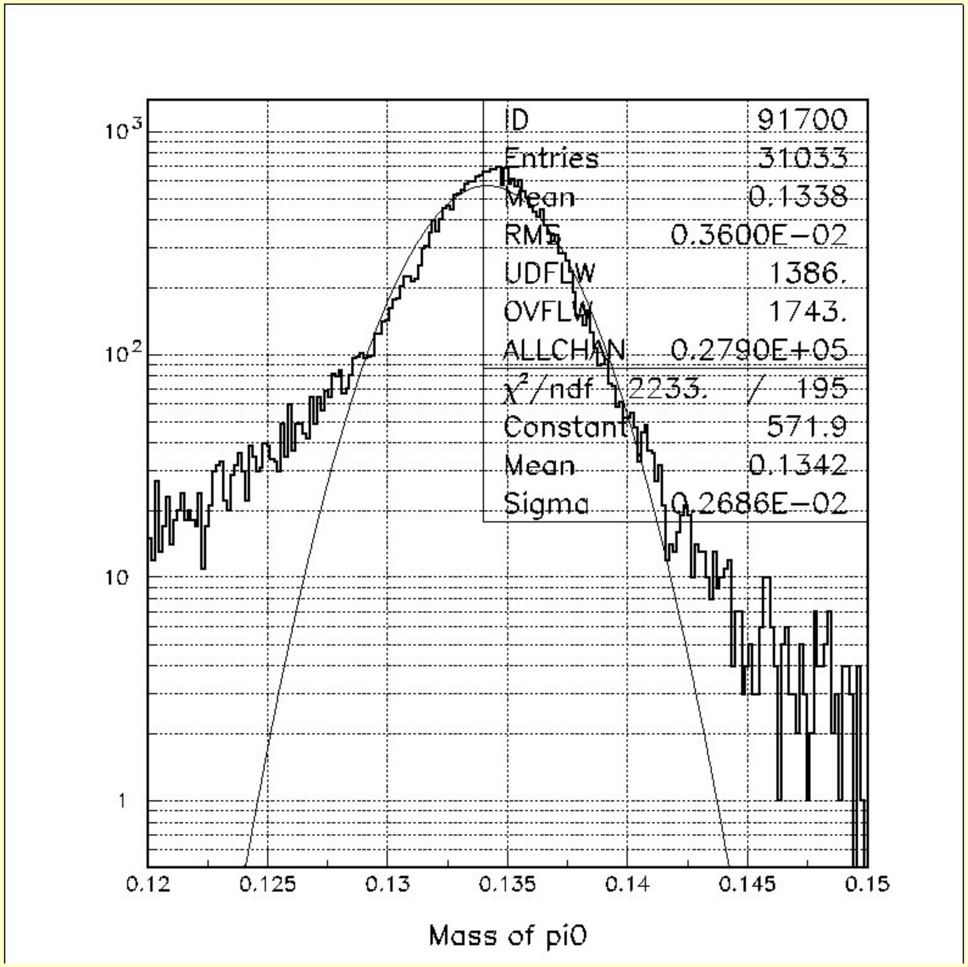
Electron selection

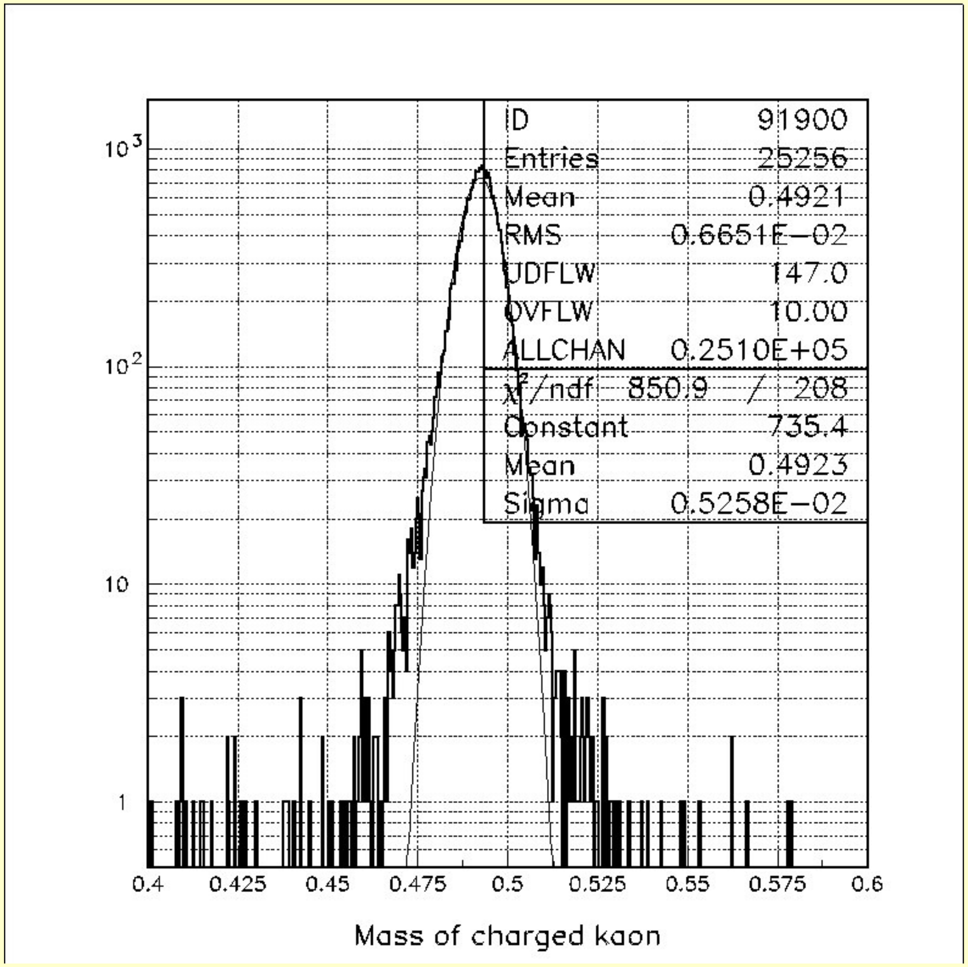
Selection :

- ❖3 tracks
- ❖Distance between each two tracks > 25 cm
- ❖All tracks are in HODO and MUV acceptance
- ❖Selecting one of the tracks randomly
- ❖Requirement – two are e (E/p > 0.9) and π (E/p < 0.8)
- ❖The sum of tracks charges is $\pm$1
- ❖Three-track vertex CDA < 3 cm
- ❖One additional γ in LKr, at least 25 cm away from the tracks
- ❖0.128 GeV < m_{π^0} < 0.140 Gev
- ❖0,482 GeV < m_k < 0.505 GeV

$$K^{\pm} \rightarrow \pi^{\pm}\pi^{0} \rightarrow \pi^{\pm}e^{+}e^{-}\gamma$$

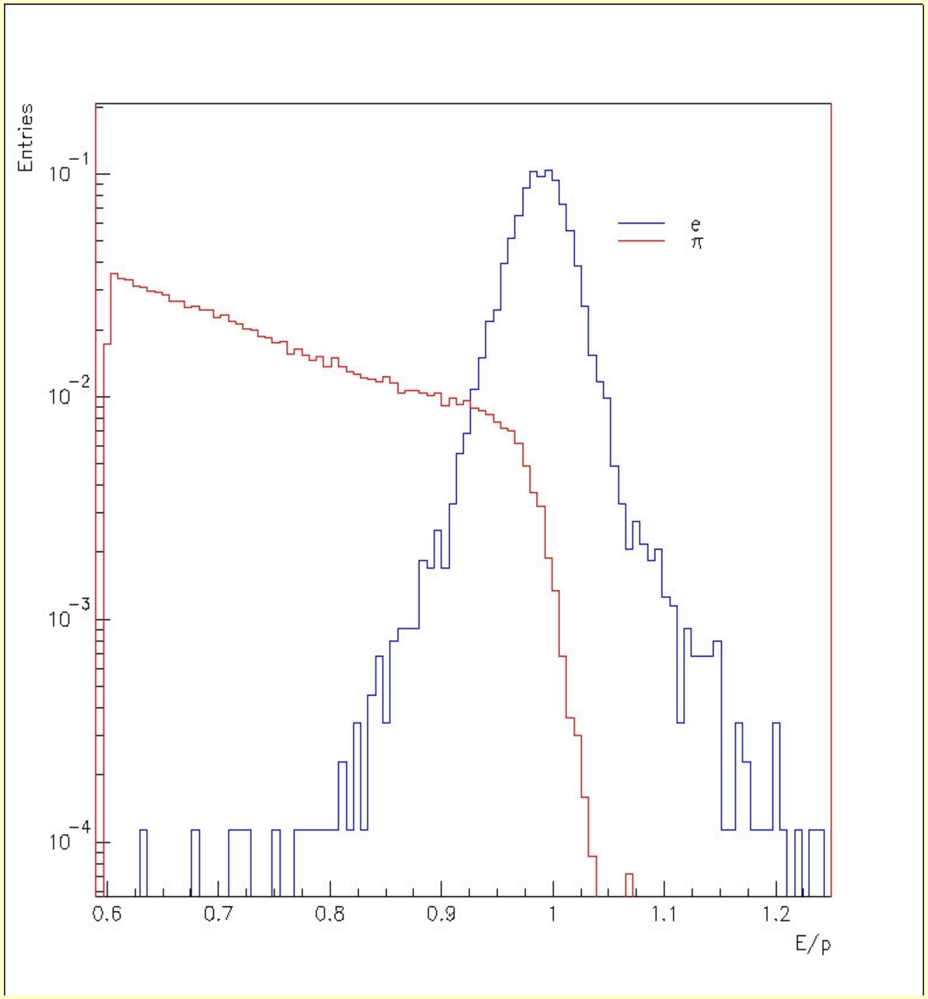
Electron selection

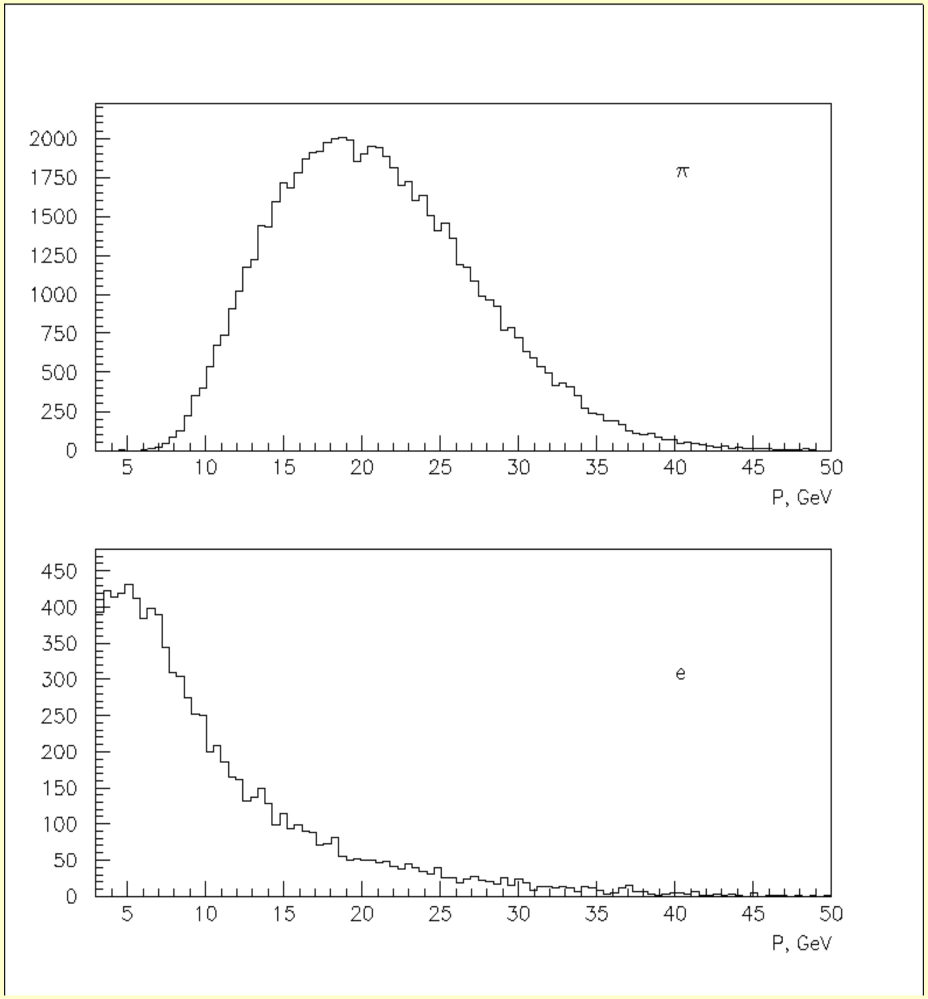




Charged run

E/p and momentum distributions

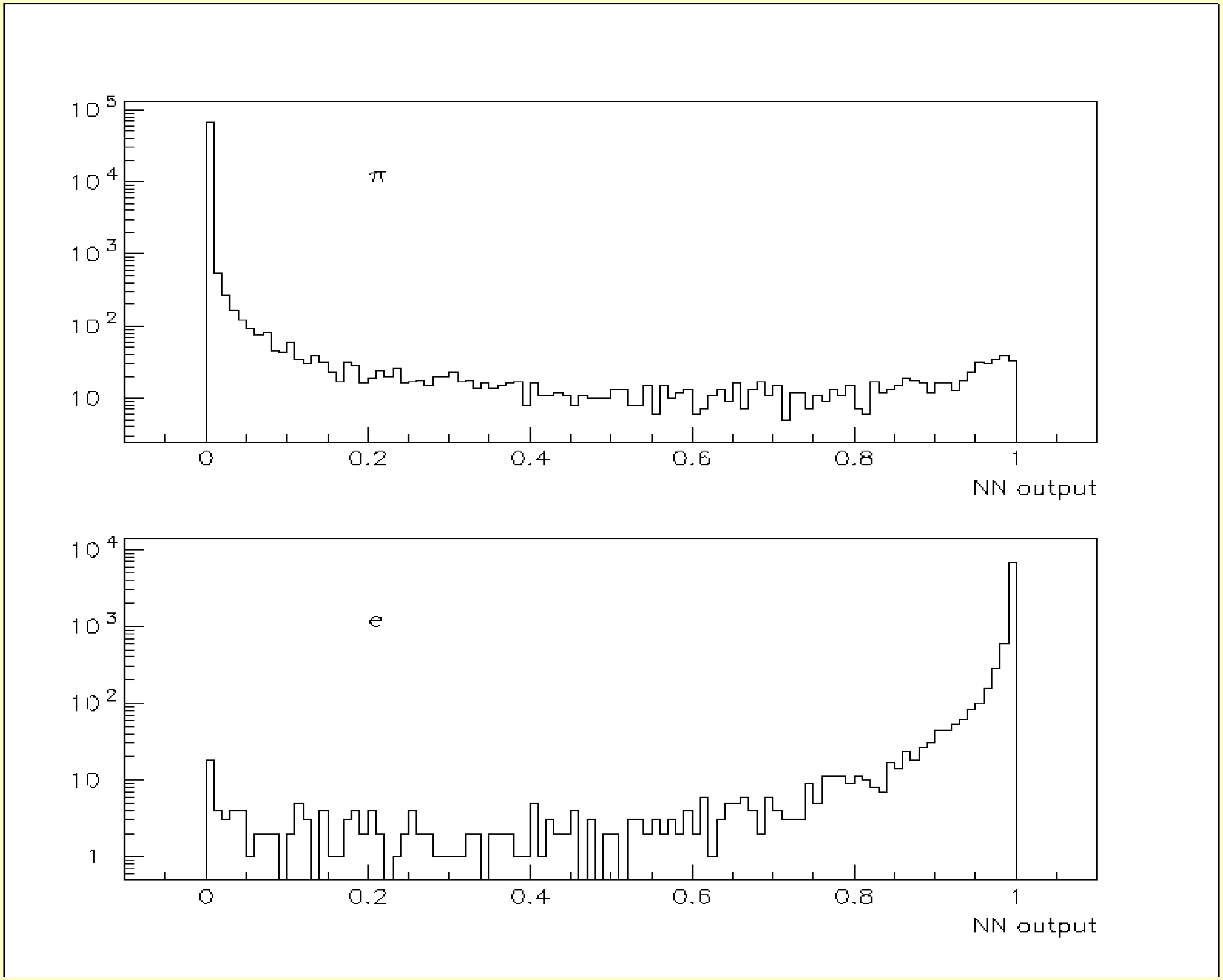




Charged run NN output

NN output

- Out → 0 for π
- If out > cut – e
- If out < cut - π



Charged run NN performance

- **Net**: 10-30-20-2-1
- **Input:** E/p, Dist, Rrms, p, RMSx, RMSy, dx/dz, dy/dz, DistX, DistY
- **Teaching**: 10000 π - $K^{\pm} \to \pi^{\pm}\pi^{\pm}\pi^{\mp}$, 5000 e - $K^{\pm} \to \pi^{\pm}\pi^{0} \to \pi^{\pm}e^{+}e^{-}\gamma$

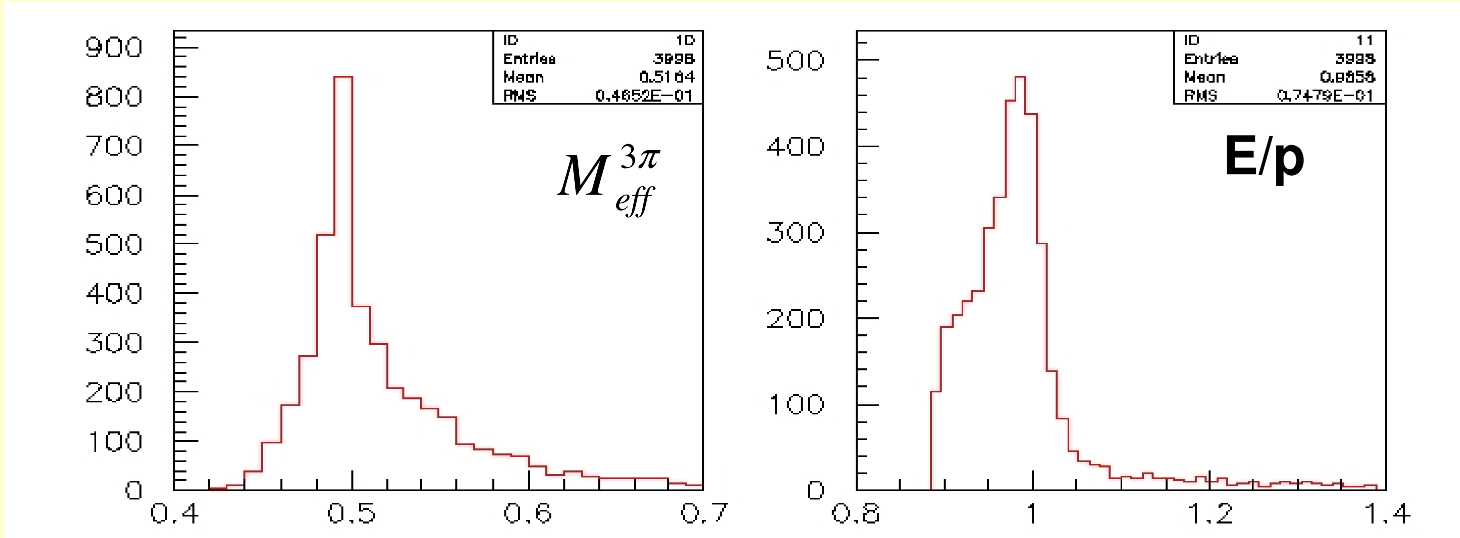
	$e^{\pm}$	$\pi^{\mp}$	ϵ^{e}_{eff},%
ALL	8889	912164	
$E/p > 0.6$	8776	69334	—
$E/p > 0.9$	8662	7533	97.4
out$>$ 0.9	8357	254	94.0
out$>$ 0.95	8070	168	90.8

	$\epsilon^{\pi \to e}$	ϵ^{e}_{eff},%
out$>$ 0.9/ALL	$2.8 \cdot 10^{-4}$	94.
out$>$ $0.9/E/p > 0.9$	$3.4 \cdot 10^{-2}$	96.5
out$>$ 0.95/ALL	$1.8 \cdot 10^{-4}$	90.8
out$>$ $0.95/E/p > 0.9$	$2.2 \cdot 10^{-2}$	93.2

$K^{\pm} \rightarrow \pi^{\pm}\pi^{\mp}e^{\pm}\nu(\overline{\nu})$

E/p > 0.9

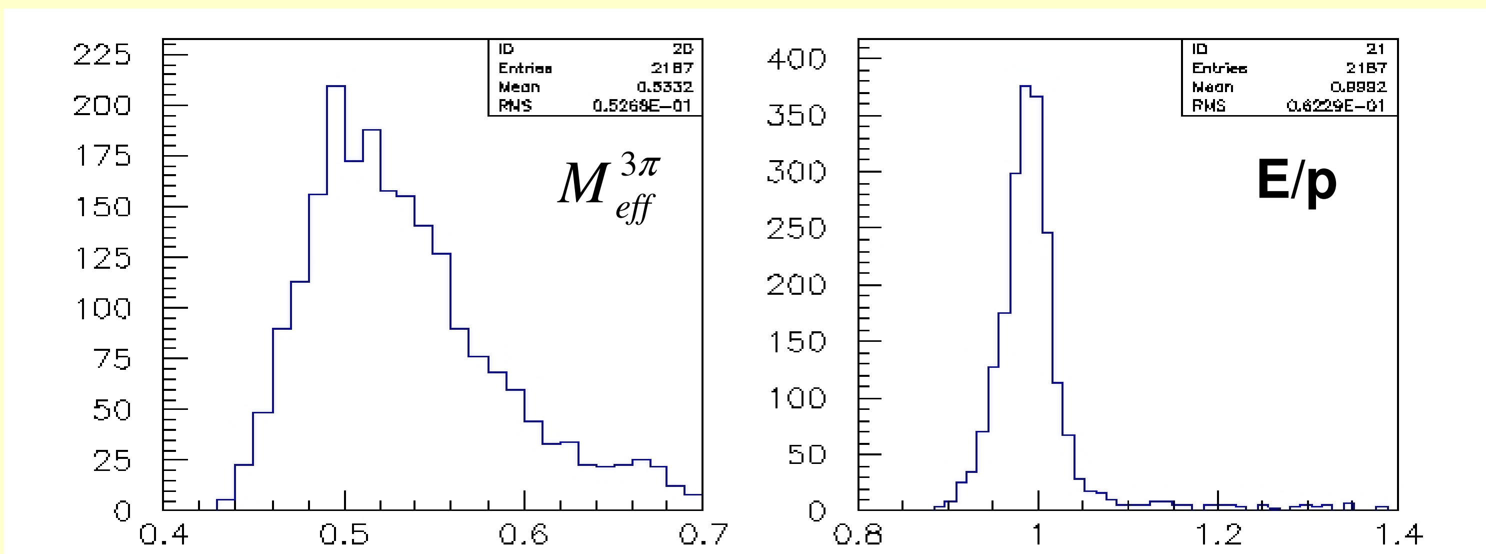
Non symmetric E/p distribution



E/p > 0.9

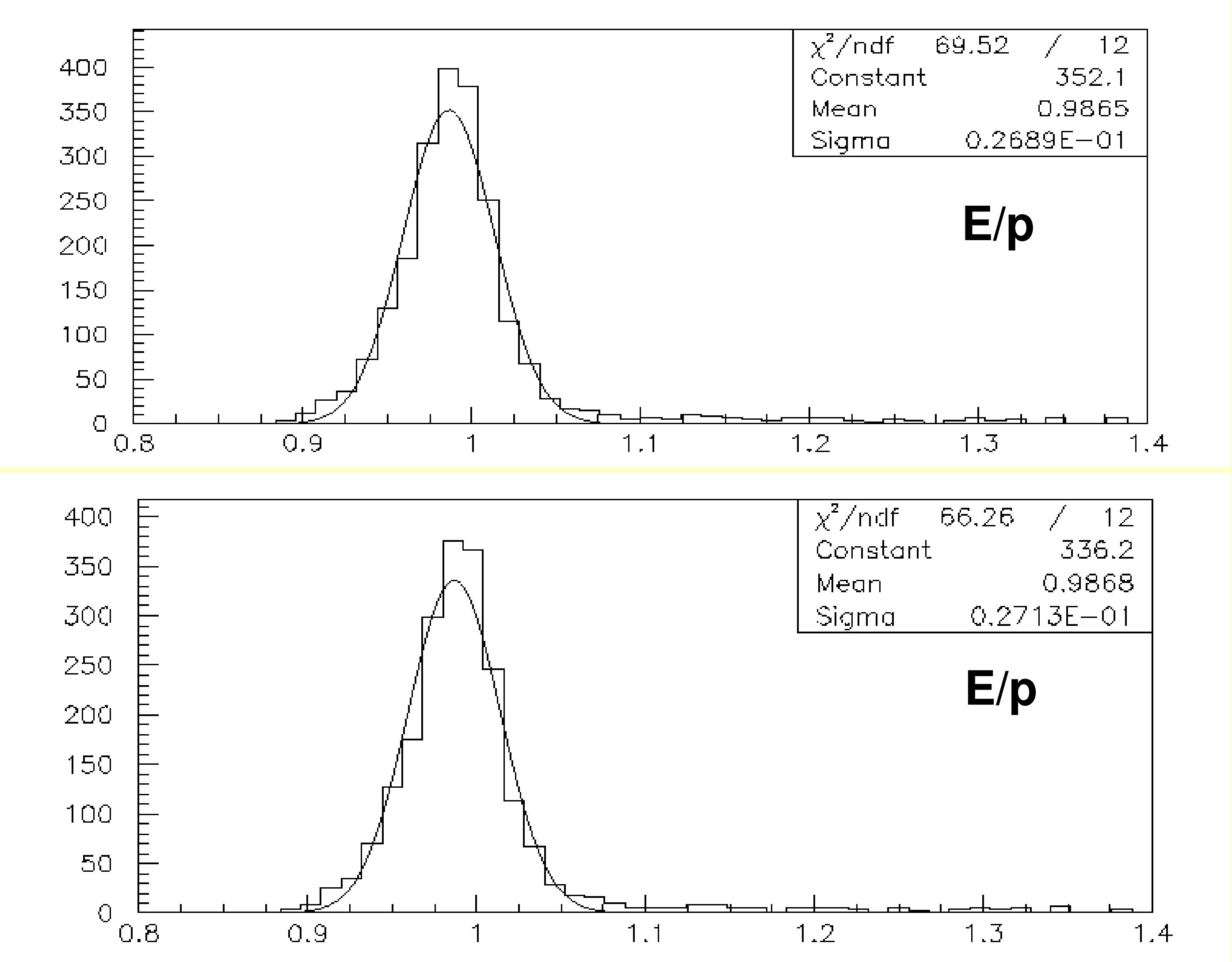
out > 0.9

Symmetric E/p distribution



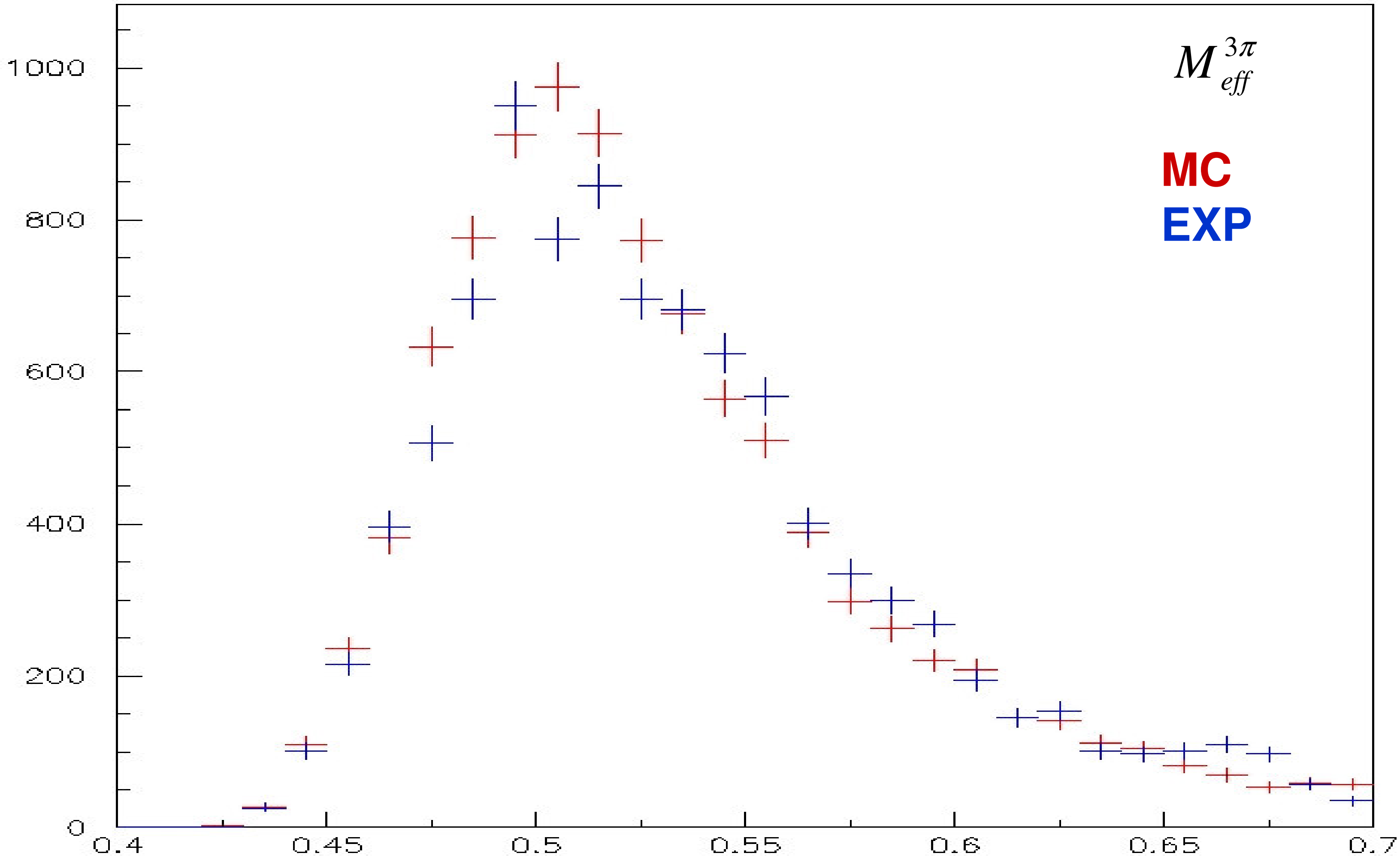
$K^{\pm} \rightarrow \pi^{\pm}\pi^{\mp}e^{\pm}\nu(\bar{\nu})$

out > 0.9
E/p distribution



- out > 0.8
- E/p distribution
- There is no significant change in the parameters

$K^{\pm} \rightarrow \pi^{\pm}\pi^{\mp}e^{\pm}\nu(\bar{\nu})$



There is a good agreement between MC and Experimental distributions

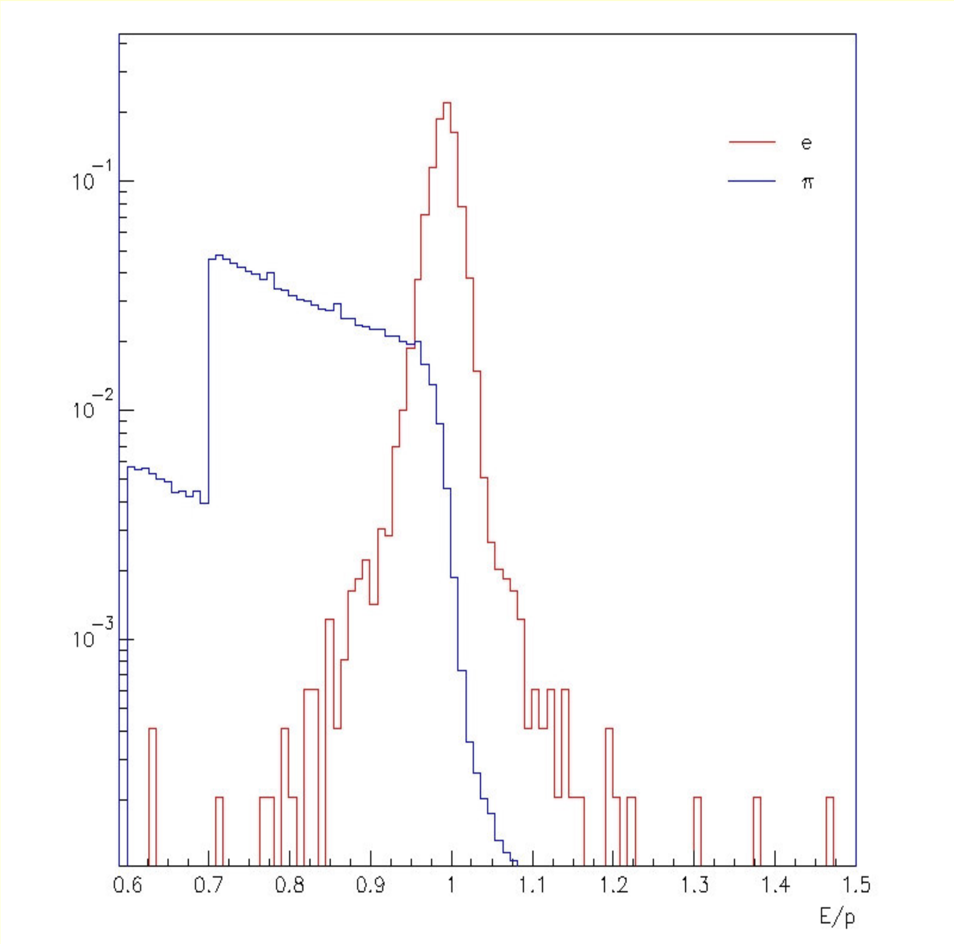
Decay $K^0 \to \pi^{\pm} e^{\mp} \pi^0 \nu$

- Significant background comes from $K^0 \to \pi^+ \pi^- \pi^0$
- when one π is misidentified as an e

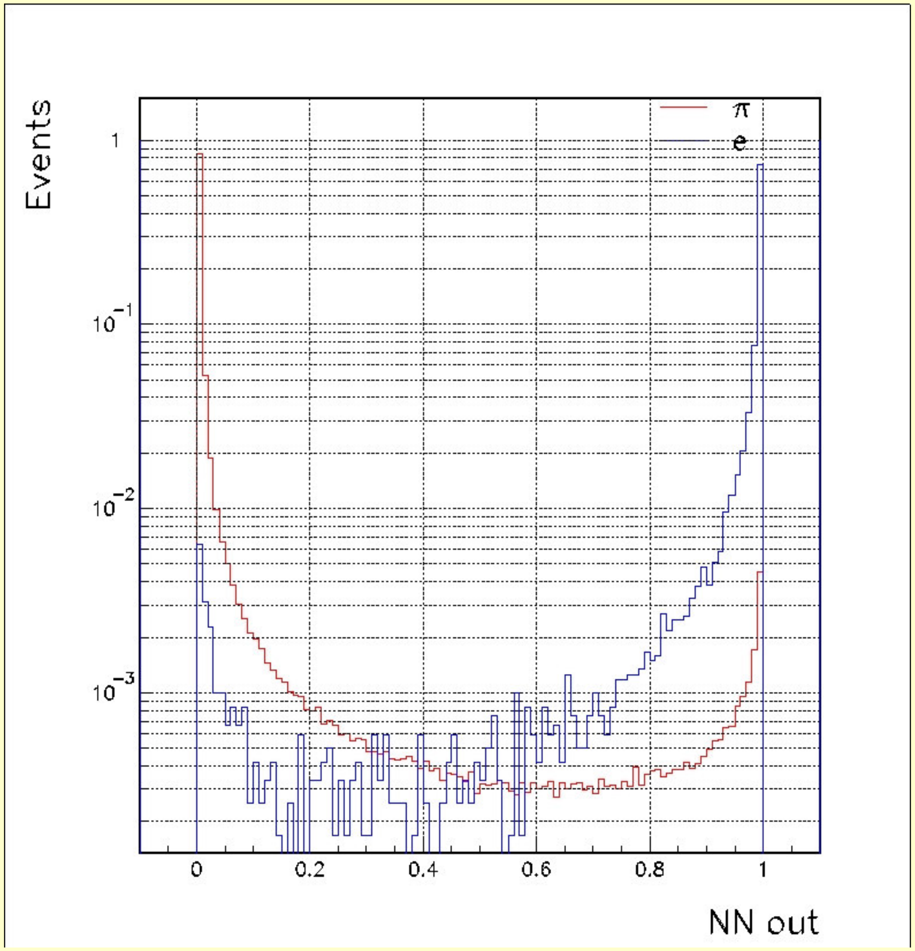
- Teaching sample:
  - Pions - from $K^0 \to \pi^+ \pi^- \pi^0$, 800 K events
  - Electrons - from $K^0 \to \pi^{\pm} e^{\mp} \nu$, 22 K events

$K^0 \to \pi^\pm e^\mp \pi^0 \nu$ reconstruction with NN

E/p distribution



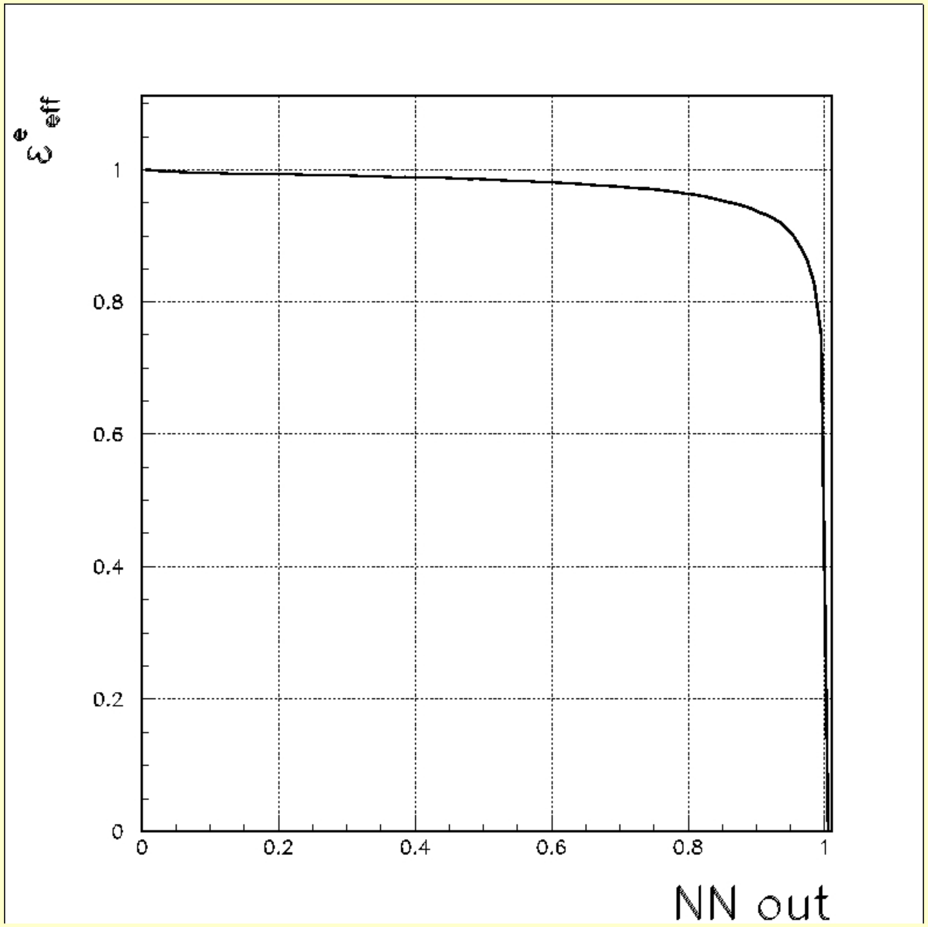
NN output

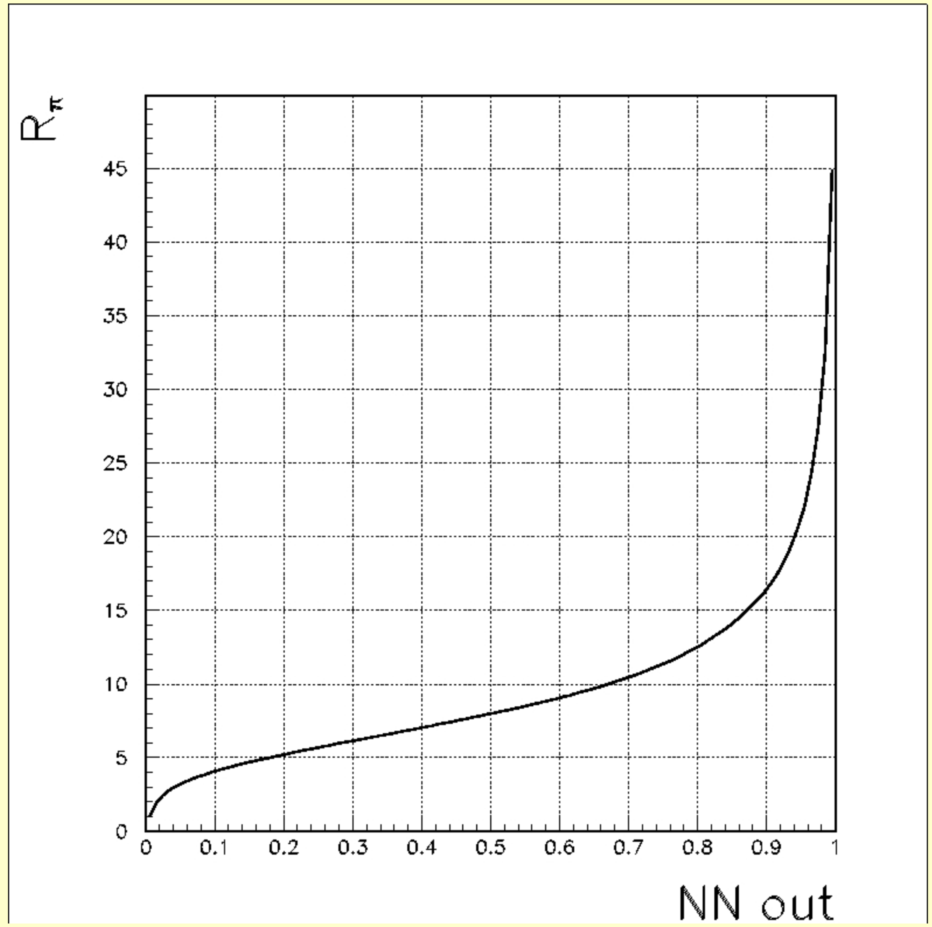


$K^0 \to \pi^{\pm} e^{\mp} \pi^0 \nu$ reconstruction with NN

e identification efficiency

π rejection factor





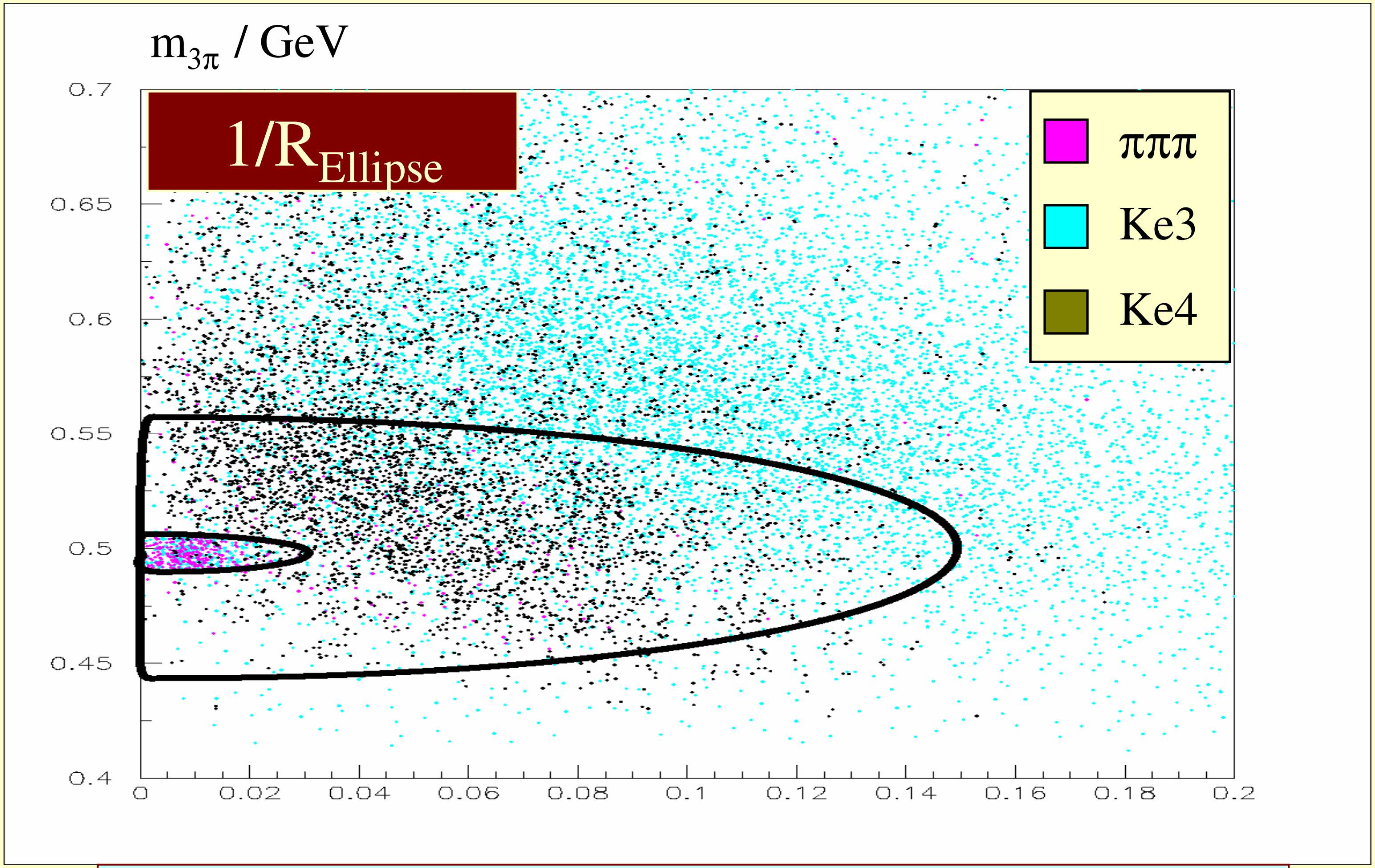
Ke4 run NN performance

- **Net**: 10-30-20-2-1
- **Input:** E/p, Dist, Rrms, p, RMSx, RMSy, dx/dz, dy/dz, DistX, DistY
- **Teaching**: 10000 π - $K^0 \to \pi^+\pi^-\pi^0$, 5000 e - $K^0 \to \pi^\pm e^\mp \nu$

	$e^\pm$	$\pi^\mp$	ϵ^e_{eff},%
ALL	4940	616705	
$E/p > 0.6$	4915	461856	—
$E/p > 0.9$	4857	89605	98.3
out> 0.85	4667	4630	94.5
out> 0.9	4386	3729	88.8

	$\epsilon^{\pi\to e}$	ϵ^e_{eff},%
out> 0.85/ALL	$7.5 \cdot 10^{-3}$	94.5
out> 0.85/$E/p > 0.9$	$5.1 \cdot 10^{-2}$	95.0
out> 0.9/ALL	$6.0 \cdot 10^{-3}$	92.7
out> 0.95/$E/p > 0.9$	$3.2 \cdot 10^{-2}$	89.2

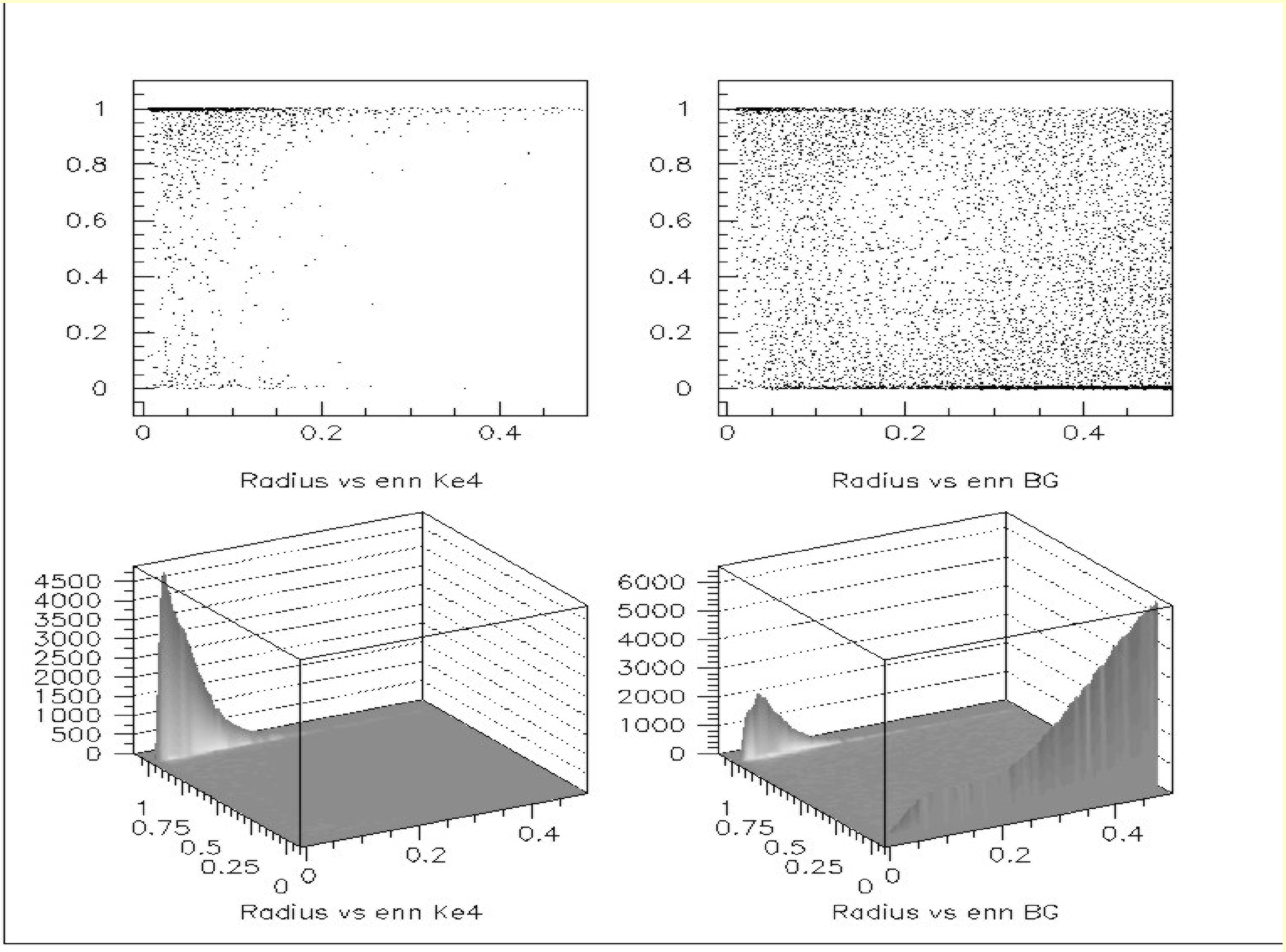
$K^0 \to \pi^\pm e^\mp \pi^0 \nu$ reconstruction with NN



$$R^2 = \left(\frac{p_t - 6MeV}{7MeV}\right)^2 + \left(\frac{M_{K_{3\pi}} - 498MeV}{2.5MeV}\right)^2$$

$K^0 \rightarrow \pi^{\pm} e^{\mp} \pi^0 \nu$ recognition with NN

NN output versus 1/R



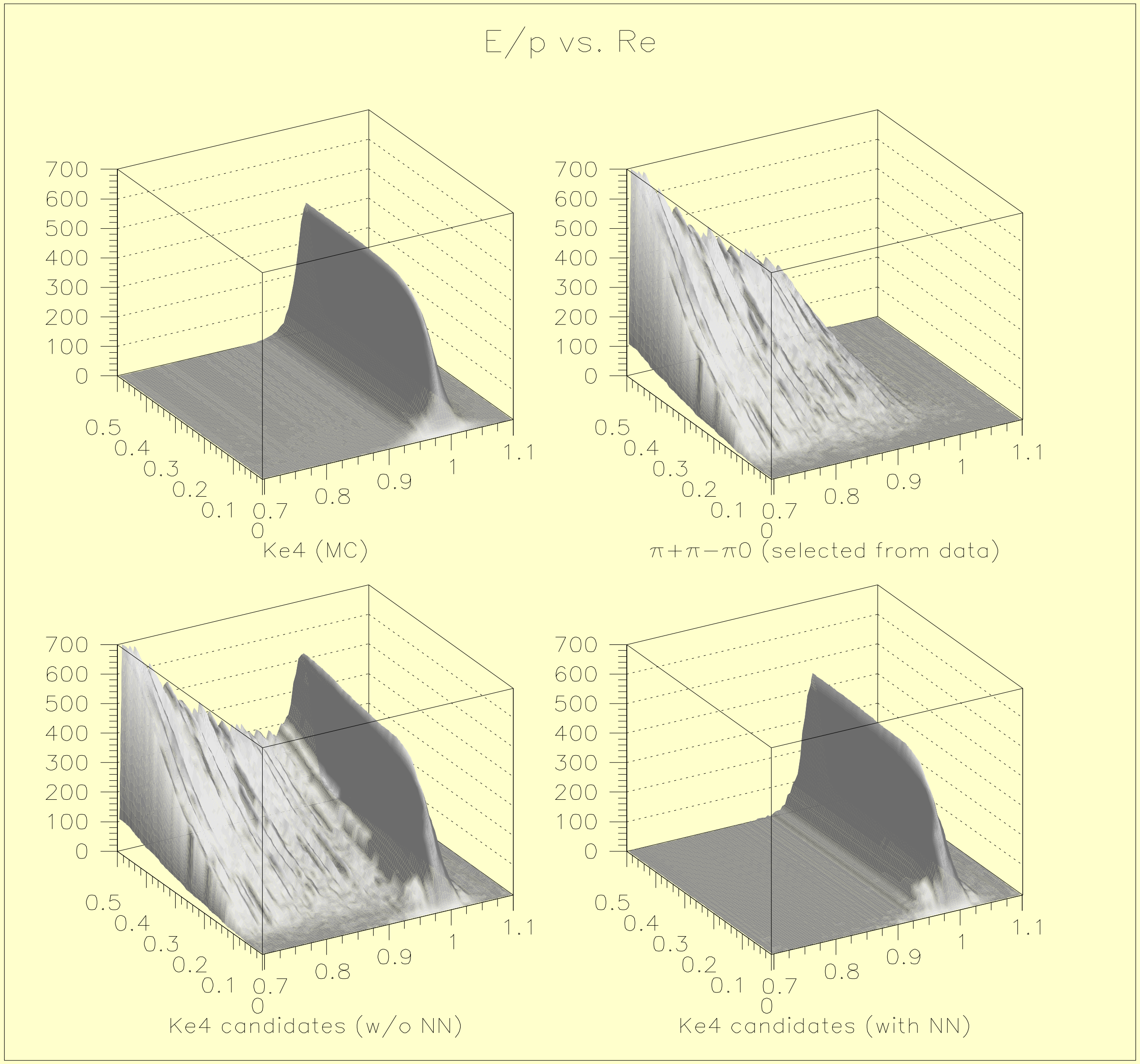
- the background from K3π is clearly separated

$K^0 \rightarrow \pi^{\pm} e^{\mp} \pi^0 \nu$

e/π Neural Network

Performance

- no bkg subtraction!
- using nnout > 0.9 cut
- works visibly very well
- but what about bkg?

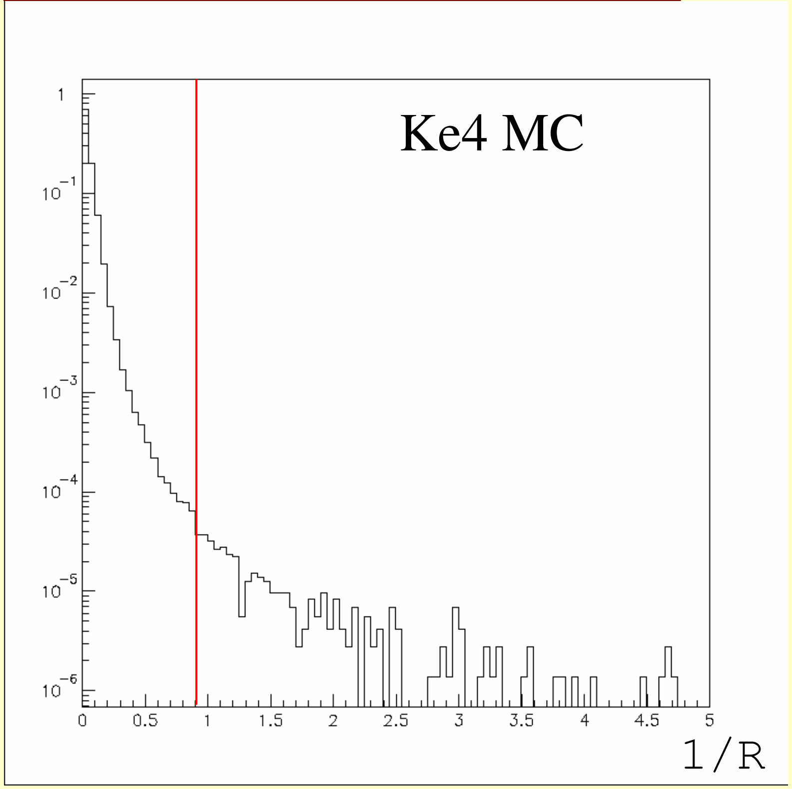


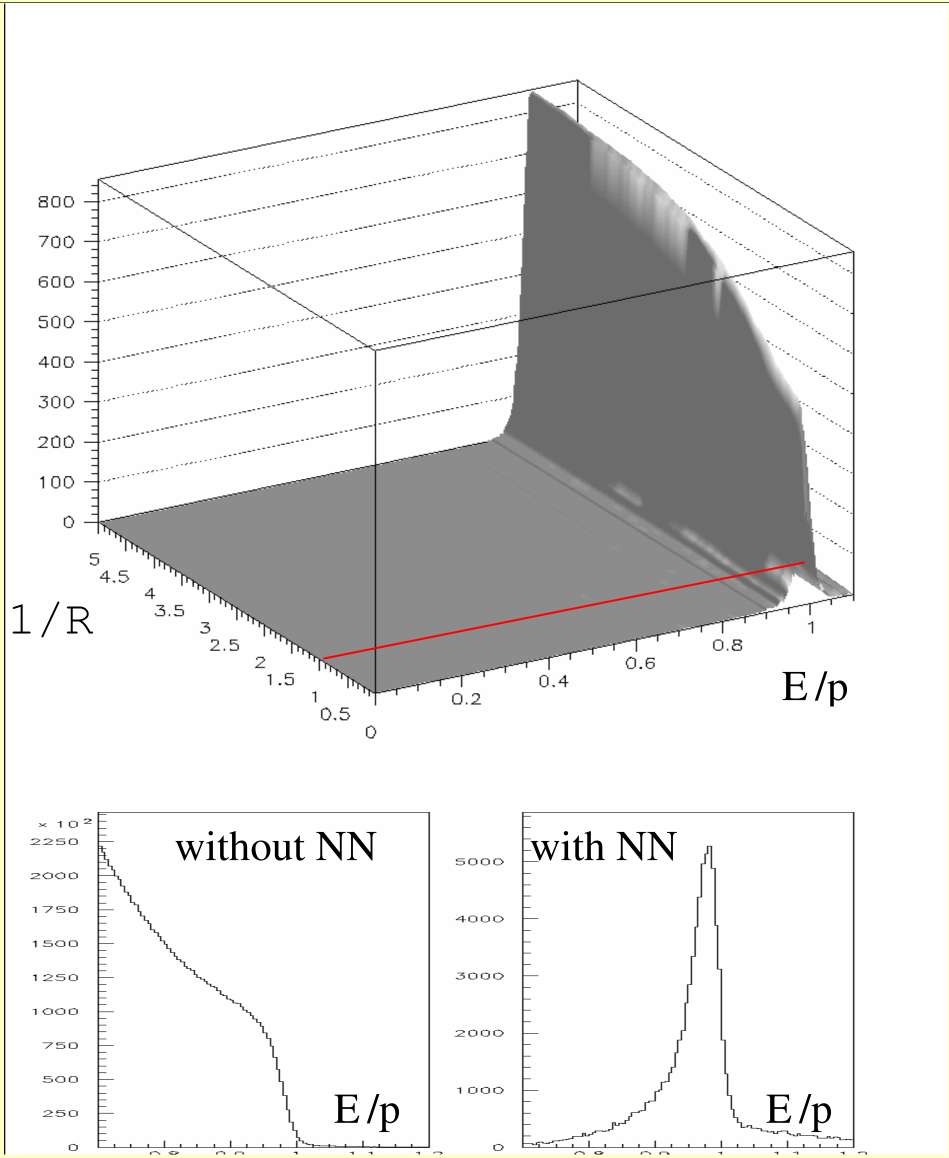
$K^0 \rightarrow \pi^{\pm} e^{\mp} \pi^0 \nu$ reconstruction with NN

e/π Neural Network

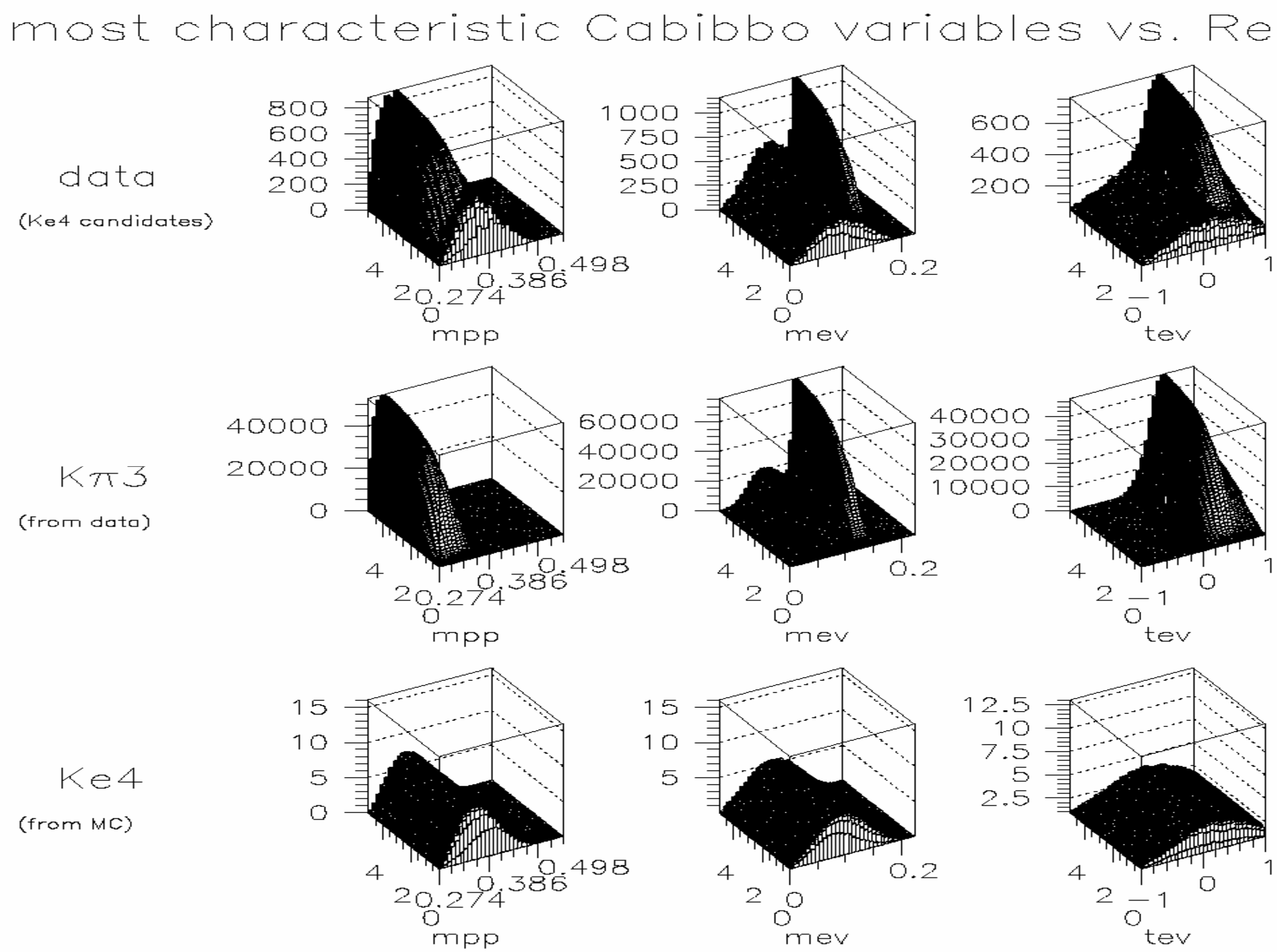
Background

- extending range of 1/R to 5
- obviously there is bkg!





$K^0 \rightarrow \pi^{\pm} e^{\mp} \pi^0 \nu$ reconstruction with NN

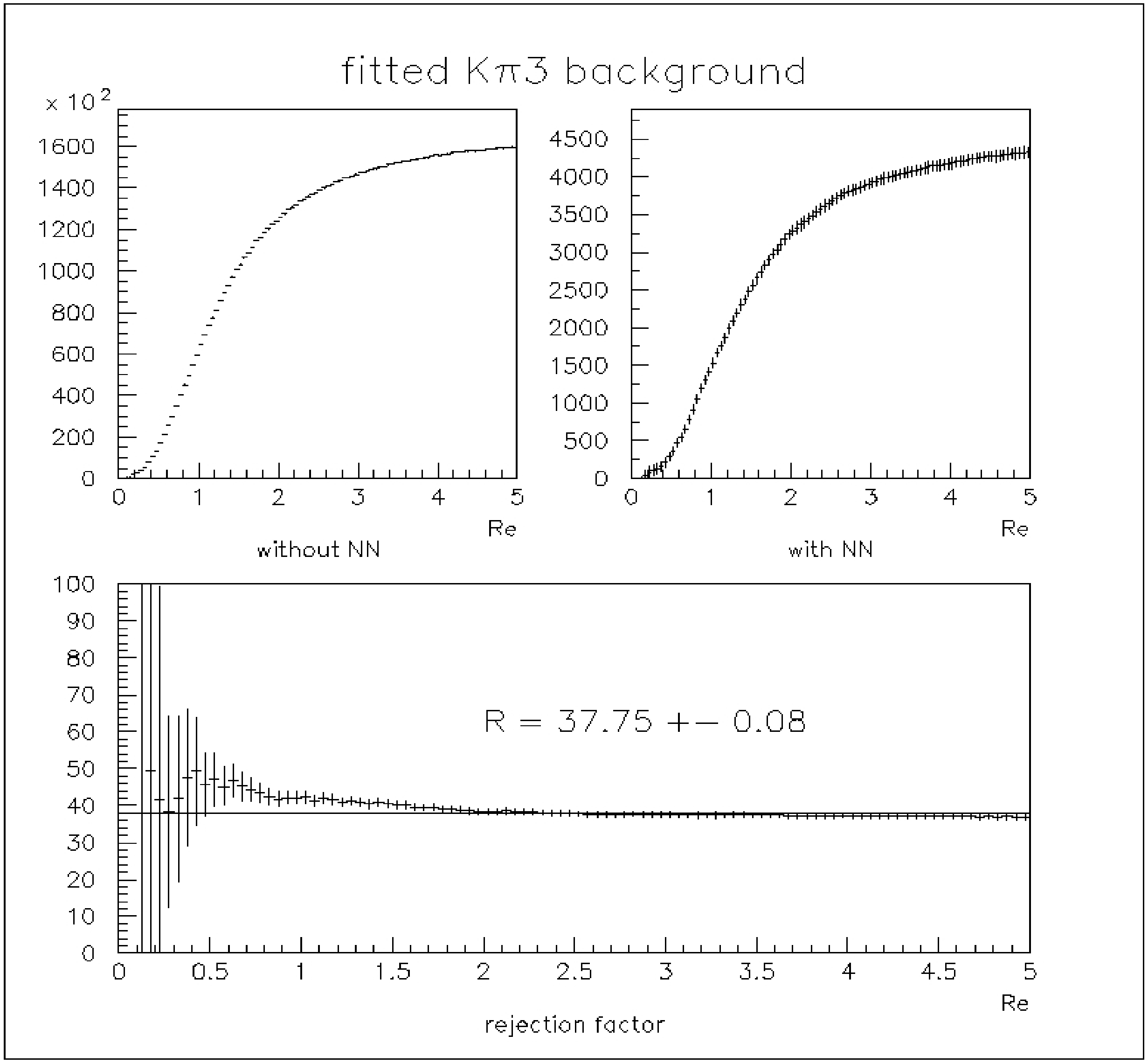


$K^0 \to \pi^\pm e^\mp \pi^0 \nu$ reconstruction with NN

e/π Neural Network

Performance

- background is fitted both with and without NN
- ratio R (rejection factor) is measure of performance

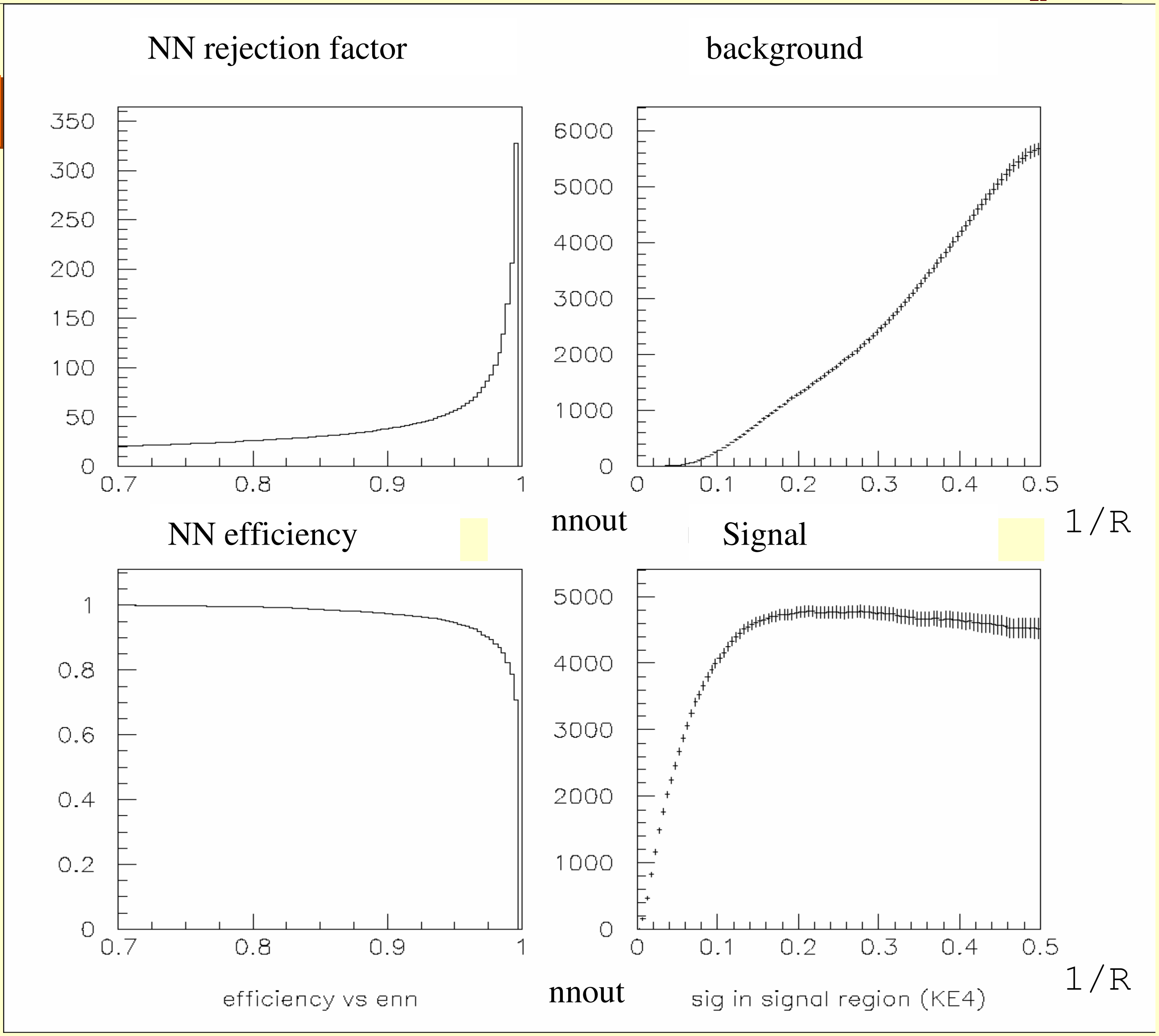


$K^0 \to \pi^{\pm} e^{\mp} \pi^0 \nu$ reconstruction with NN

e/π Neural Network

Optimization

- goal: optimize the cut values for nnout and **1/R**

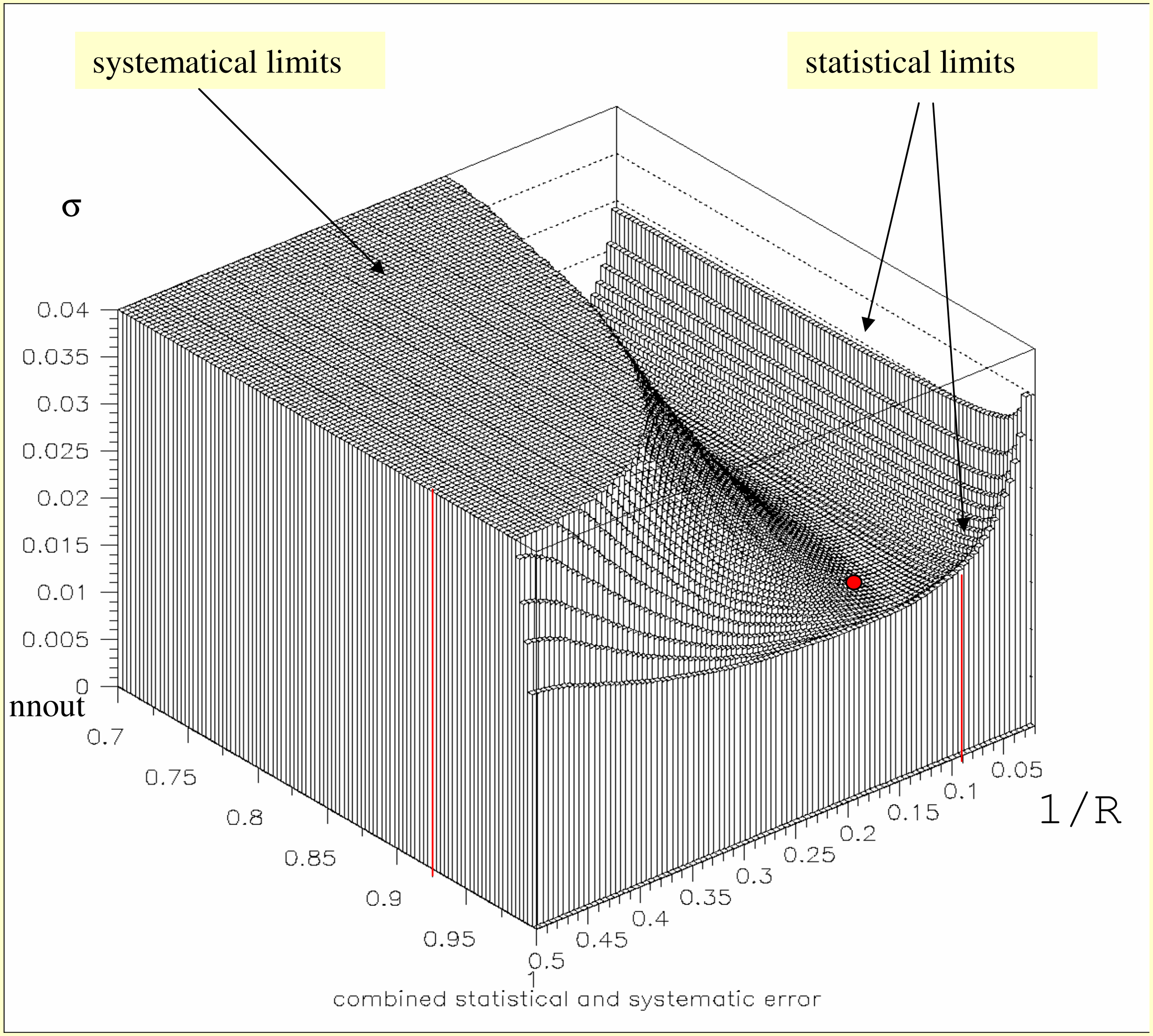


e/π Neural Network

Optimization

- value to minimize: combined statistical and systematical error
- statistical error goes with $N^{-1/2}$
- systematical error grows with background

$$\sigma = \frac{1}{\sqrt{N}} \oplus c \cdot \frac{bkg}{sig}$$

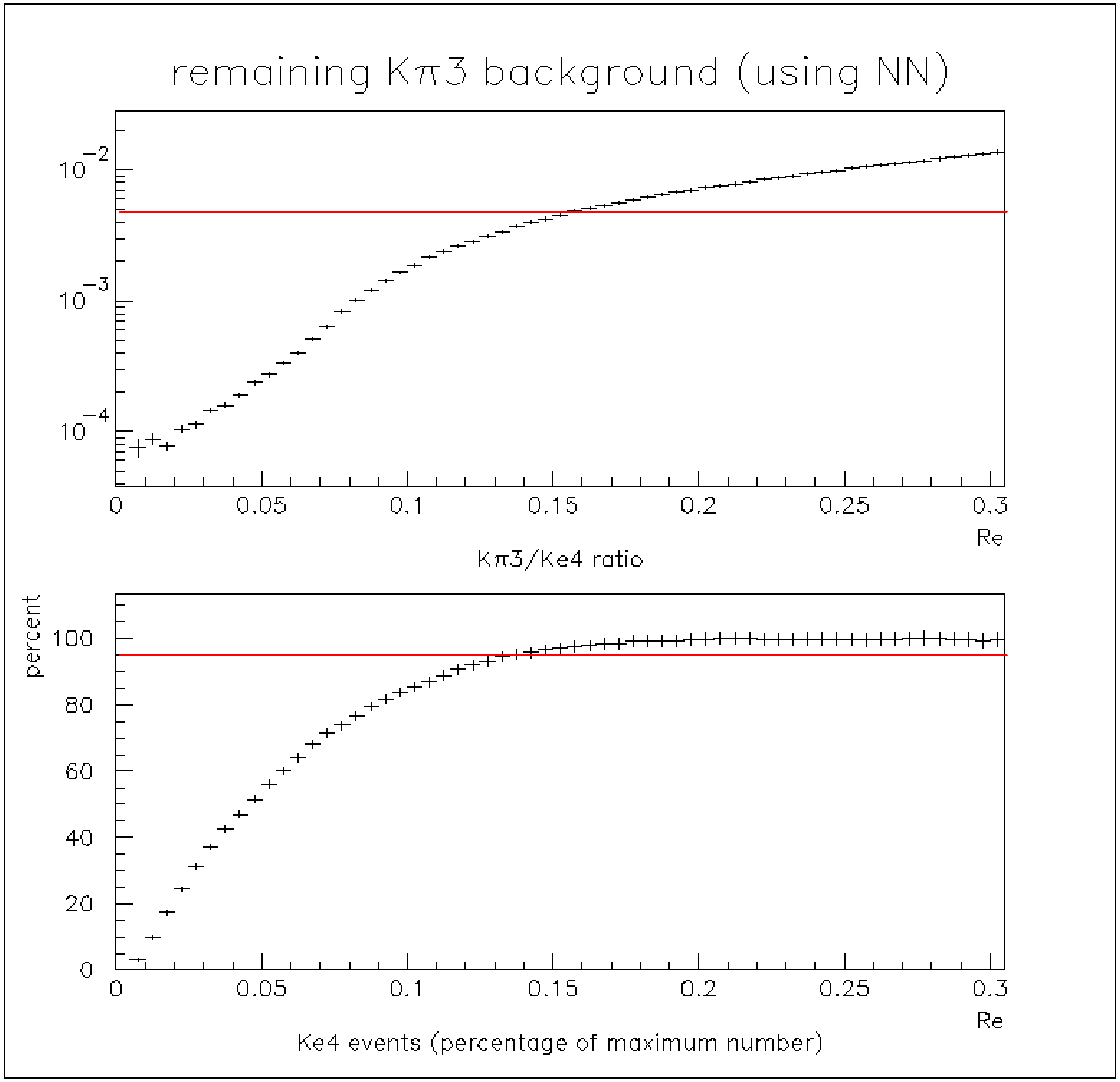


$K^0 \to \pi^{\pm} e^{\mp} \pi^0 \nu$ reconstruction with NN

e/π Neural Network

Performance

- background can be reduced at level 0.3 %
- Ke4 reconstruction efficiency at level 95%



Conclusions – e/pi separation

- e/π separation with NN has been tested on experimental data
- For charged K run we have obtained:
  - Relatively to E/p < 0.9 cut $\varepsilon_{eff}^{\pi\to e} \sim 3.4\times10^{-2}$
  - At ε_{eff} ~96%
  - A correct Ke4 analysis can be done without additional detector (TRD)
  - Background can be reduced at the level of ~ 1%
  - ~ 5 % of the Ke4 events are lost due to NN efficiency

- For Ke4 run we have obtained:
  - Rejection factor ~ 38 on experimental data
  - Background ~ 0.3% at ε_{eff} ~ 95%

Conclusions – NN analysis

- Additionally Neural Network for Ke4 recognition has been developed
- The combined output of the two NN is used for selection of Ke4 decays
- NN approach leads to significant enrichment of the Ke4 statistics ~2 times

❖ This work was done in collaboration with
C. Cheshkov, G. Marel, S. Stoynev and L. Widhalm