

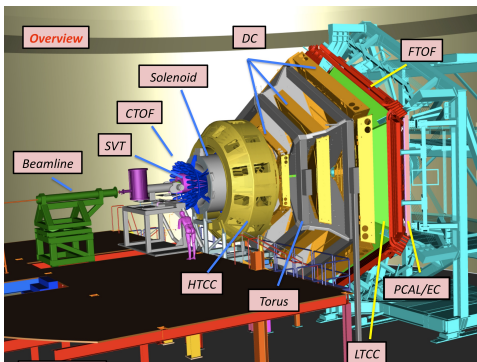
CLAS12 PID and Machine Learning

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Introduction

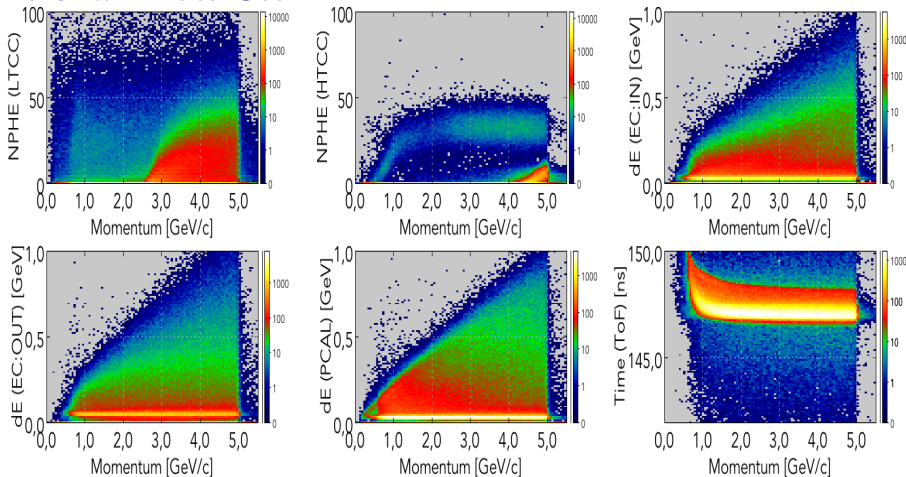


- **Wanted:** Particle masses
 $m_{e^\pm}$, $m_{\pi^\pm}$, m_p , $m_{K^\pm}$, ...
- **Given:** Information from CLAS12 sub detector systems
- **Approach:** Combine detector information and feed them into a machine learning algorithm
⇒ Get particle type
- All results shown here are based on:
 - ▶ Simulated single particle tracks
 - ▶ GEMC 4a.2.1
 - ▶ COATJAVA 4a.8.1
 - ▶ Apache-Spark 2.20 framework

⇒ **Today's focus:** Separation of e^- / π^-

- i) Which variables (or combination of variables) to choose for PID?
- ii) Which machine learning algorithm / classifier is "the best"?
- iii) Quality of results ⇔ systematic checks?

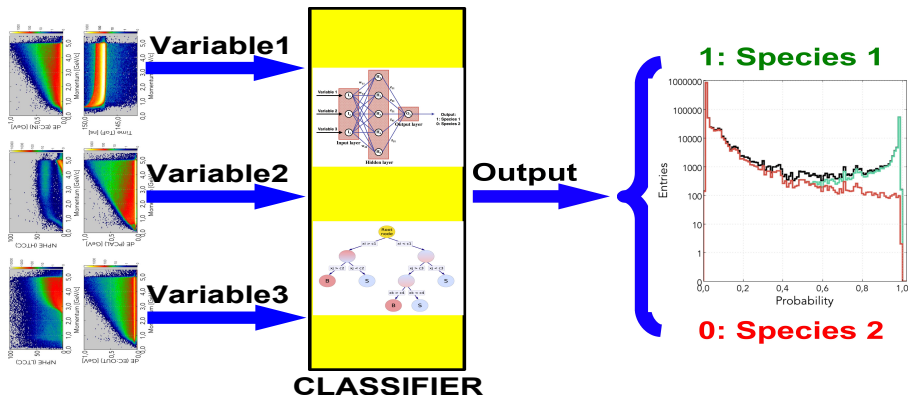
The $e^- \pi^-$ Data Set



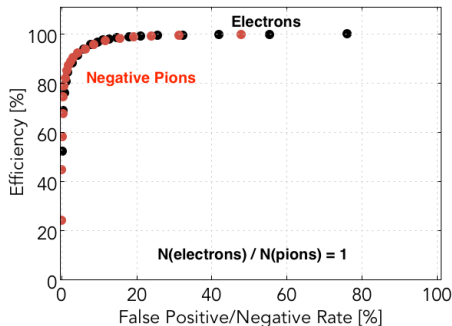
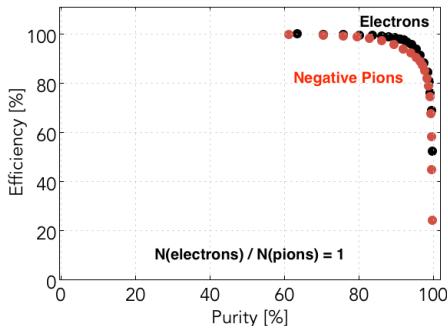
- Possible PID-variables:
 p , $nphe(LTCC)$, $nphe(HTCC)$, $\Delta E(pcal)$, $\Delta E(ec : in)$, $\Delta E(ec : out)$, $\Delta E(cal)$, t
- Ratio: $N(\pi^-)/N(e^-) = 10$
- Request particles to have: $p > 0$ and at least one other sub detector fired

Solving multivariate Classification Problems

- Several classifier algorithms available
(neural networks, boosted decision trees, support vector machines,...)
- Classifier internal parameters (weights, thresholds,...) are determined via training

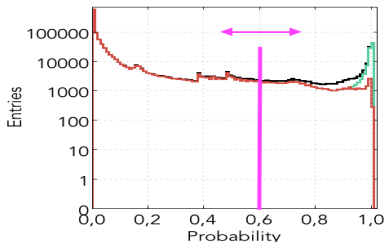


Evaluation of a trained Classifier: The ROC-Curve

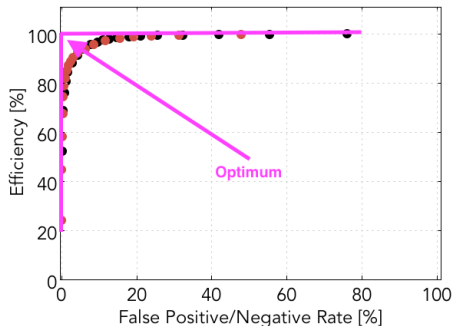
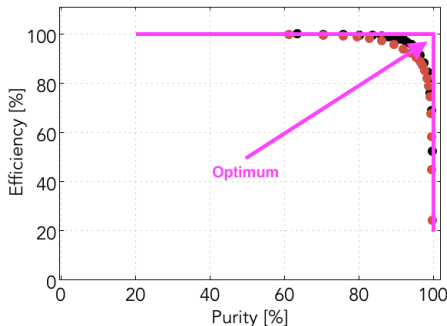


Receiver-Operating-Characteristics:

- **Efficiency:** $\epsilon_S = \frac{N_S^{acc}}{N_S^{all}}$, $\epsilon_B = \frac{N_B^{rej}}{N_B^{all}}$
- **Purity:** $P_S = \frac{N_S^{acc}}{N_S^{acc} + N_B^{acc}}$, $P_B = \frac{N_B^{acc}}{N_S^{acc} + N_B^{acc}}$
- **False Positive Rate:** $FPR = \frac{N_B^{acc}}{N_B^{all}}$
- **False Negative Rate:** $FNR = \frac{N_S^{rej}}{N_S^{all}}$

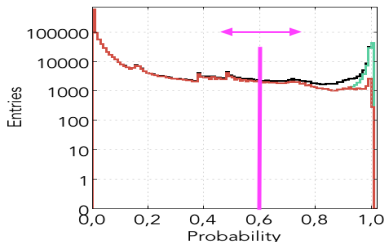


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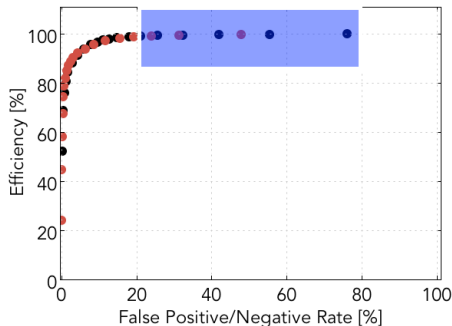
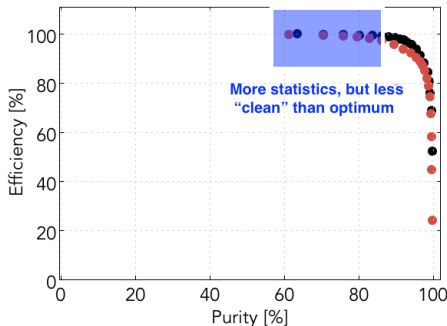


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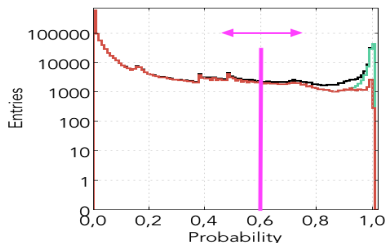


Evaluation of a trained Classifier: The ROC-Curve

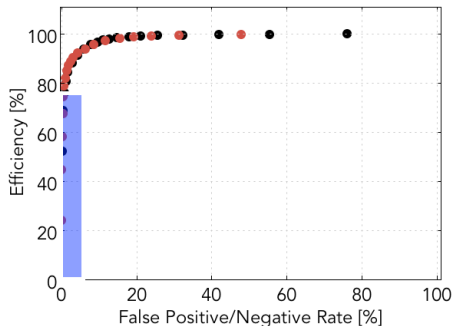
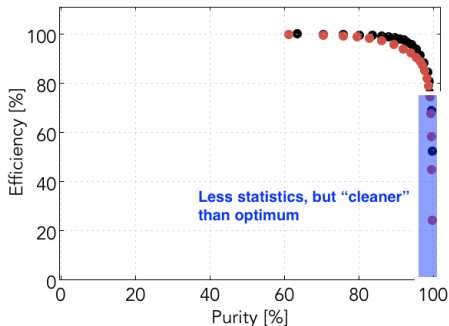


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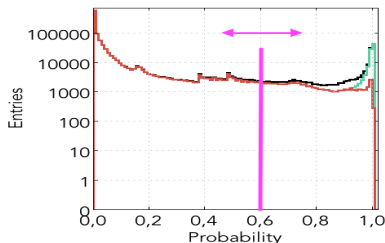


Evaluation of a trained Classifier: The ROC-Curve



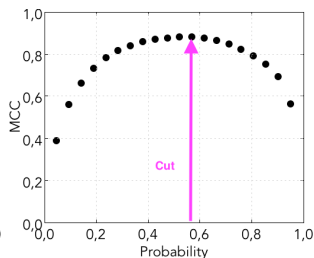
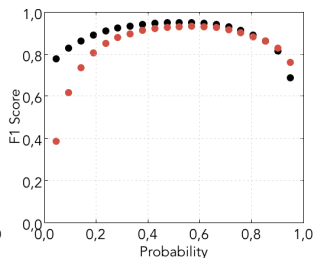
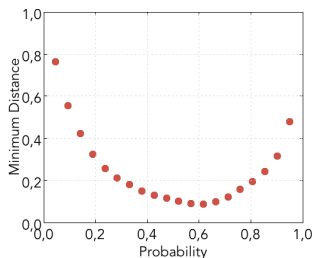
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Choosing the Classification Parameters: ROC-Metrics

- Use ROC-curve to:
 - i) Select probability cut
 - ii) Choose classifier
- Apply metric:
 - ▶ Distance: $d \equiv \sqrt{(1 - \epsilon_S)^2 + (0 - FPR)^2} \in [0, \infty)$ (left plot)
 - ▶ F1 score: $f_1 \equiv 2 \frac{\epsilon_S \times P_S}{\epsilon_S + P_S} \in [0, 1]$ (centre plot)
 - ▶ Mathews Correlation Coefficient: $MCC \equiv \frac{\epsilon_S \times \epsilon_B - FPR \times FNR}{\sqrt{\frac{\epsilon_S}{P_S} \times \frac{\epsilon_B}{P_B}}} \in [-1, 1]$ (right plot)



Choosing the Classification Parameters: Result

Classifier	MCC
MLP-HL727K0	0.75/50/52/0.71
MLP-HL64V1357K0	0.75/54/89/0.75
MLP-HL85V1356K0	0.84/52/54/0.52
MLP-HL65V1356K0	0.83/85/35/0.48
MLP-HL65V1356K0	0.85/59/96/0.24
MLP-HL6V1357K0	0.77/55/86/0.78
MLP-HL68V1357K0	0.77/55/86/0.78
MLP-HL85V1356K0	0.86/96/32/0.52
MLP-HL85V1356K0	0.85/97/56/0.62
MLP-HL6V1356K0	0.82/95/36/0.78
MLP-HL85V1356K0	0.88/96/94/0.62
MLP-HL65V1356K0	0.84/77/47/0.52
MLP-HL85V1356K0	0.84/75/87/0.57
MLP-HL65V1357K0	0.78/77/97/0.38
MLP-HL6V1357K0	0.80/85/107/0.38
GB1-V1357K0	0.84/93/57/0.57
GB1-V1356K0	0.90/97/95/0.48
GB1-V1357K0	0.75/97/90/0.52
GB1-V1356K0	0.87/96/93/0.52
GB1-V1356K0	0.86/84/90/0.48
GB1-V1356K0	0.87/76/97/0.48

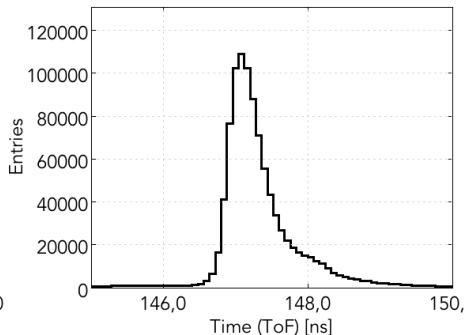
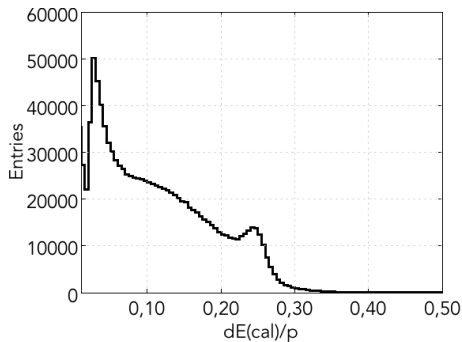
- Use MCC to choose a classifier, PID Variables and probability threshold:

- ▶ Boosted Decision Tree with 100 Trees and probability threshold: 0.48
- ▶ Neural Network with architecture {8 : 5} and probability threshold: 0.57
- ▶ Both classifier trained with:

- ★ p
- ★ $nphe(LTCC)$
- ★ $nphe(HTCC)$
- ★ $\Delta E(pcal)$
- ★ $\Delta E(ec : in)$
- ★ $\Delta E(ec : out)$
- ★ $N(\pi^-)/N(e^-) = 1$

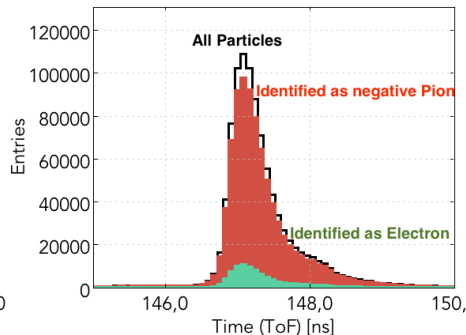
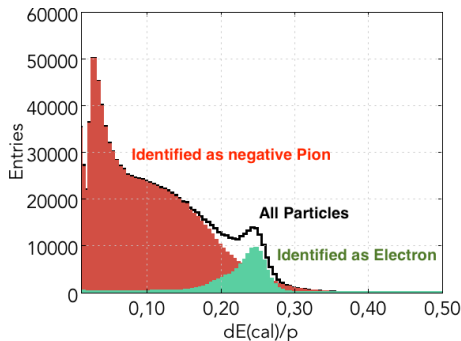
- Room for improvement: Automated Parameter Scan as a function of MCC (Or any other metric)

Application of the Classifier on the $e^-\pi^-$ Data Set



Classifier	Efficiency ϵ_S [%]	Purity P_S [%]	FPR [%]	$[N(\pi^-)/N(e^-)]_{rec}$
	—	—	—	—
	—	—	—	—

Application of the Classifier on the $e^- \pi^-$ Data Set

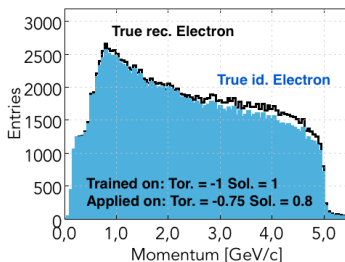
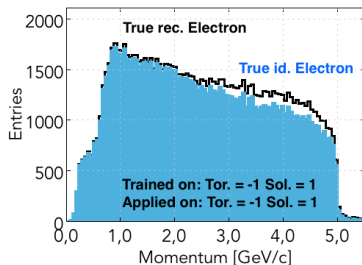


Classifier	Efficiency ϵ_S [%]	Purity P_S [%]	FPR [%]	$[N(\pi^-)/N(e^-)]_{rec}$
Decision Tree	96	58	7	6
Neural Network	94	61	6	6

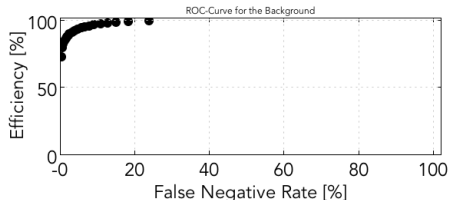
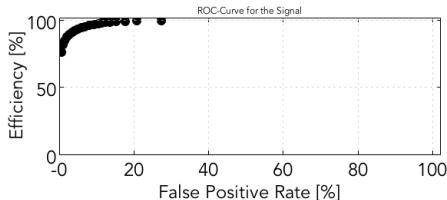
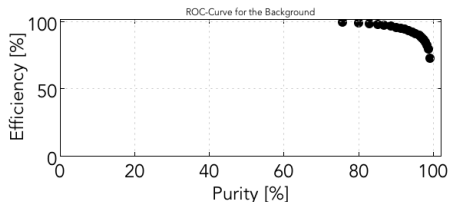
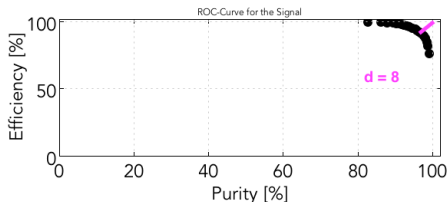
Changing the Magnetic Field

- Checked influence of different magnetic field settings on classifier performance
- Kept ratio: $N(\pi^-)/N(e^-) = 10$
- Three numbers in each cell of the table are:
 $\epsilon_S[\%] / P_S[\%] / FPR[\%]$

Applied Field $\Rightarrow$ Trained Field $\Downarrow$	$Tor. = -1$ $Sol. = 1$	$Tor. = -0.75$ $Sol. = 0.6$	$Tor. = -0.75$ $Sol. = 0.8$
$Tor. = -1$ $Sol. = 1$	94 / 61 / 6	95 / 62 / 6	95 / 61 / 6
$Tor. = -0.75$ $Sol. = 0.6$	94 / 53 / 8	95 / 57 / 8	95 / 55 / 8
$Tor. = -0.75$ $Sol. = 0.8$	95 / 56 / 6	95 / 59 / 6	95 / 57 / 7

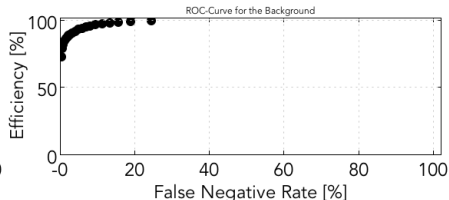
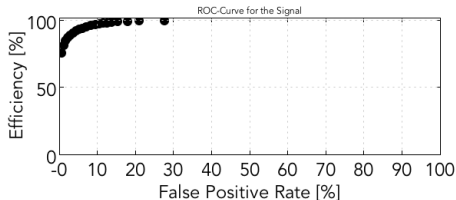
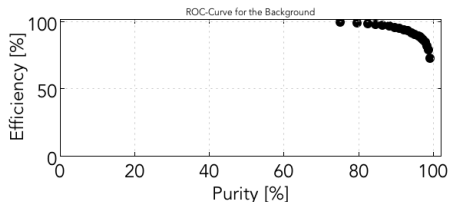
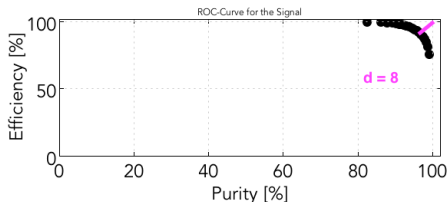


Resolution Effects for $N(\pi^-)/N(e^-) = 1$



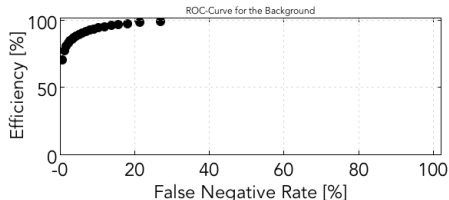
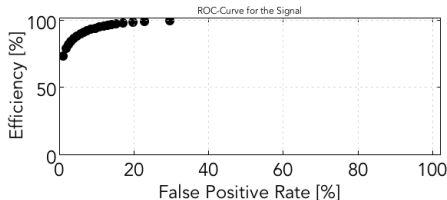
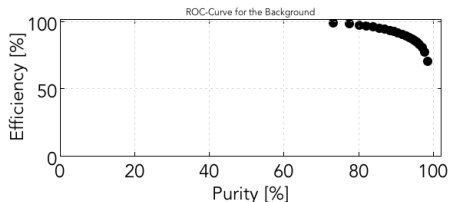
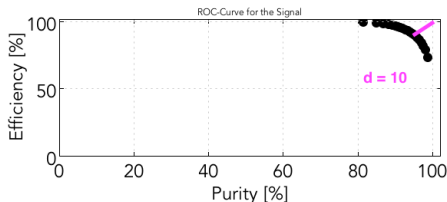
- **Basic question:** What happens if resolution in measured data is different from the resolution the classifier has been trained on?
- **Simple Test:** Apply trained classifier on a data set with different resolution than the training set
- Smeared all PID variables by a Gaussian distribution: $x \mapsto x + \text{Gauss}(0, \delta \cdot x)$
- Shown above: ROC-curves for $\delta = 0.0$

Resolution Effects for $N(\pi^-)/N(e^-) = 1$



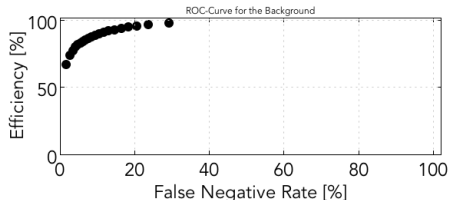
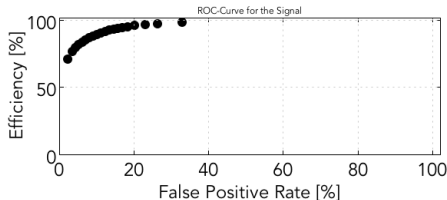
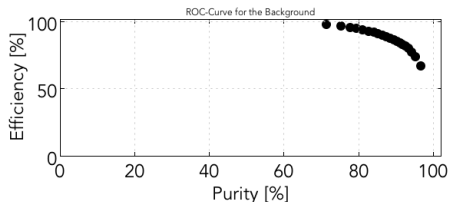
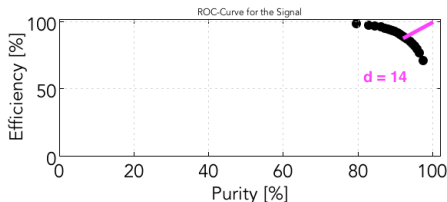
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- Shown above: ROC-curves for $\delta = 5\%$

Resolution Effects for $N(\pi^-)/N(e^-) = 1$



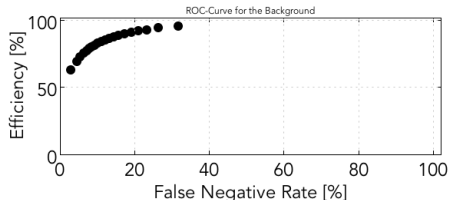
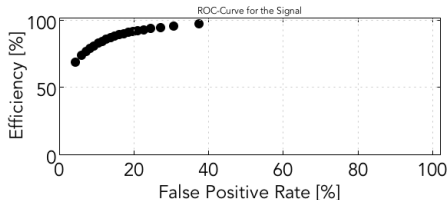
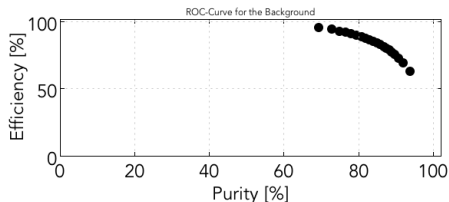
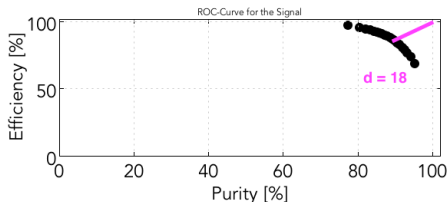
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- Shown above: ROC-curves for $\delta = 15\%$

Resolution Effects for $N(\pi^-)/N(e^-) = 1$



- **Basic question:** What happens if resolution in measured data is different from the resolution the classifier has been trained on?
- **Simple Test:** Apply trained classifier on a data set with different resolution than the training set
- Smeared all PID variables by a Gaussian distribution: $x \mapsto x + \text{Gauss}(0, \delta \cdot x)$
- Shown above: ROC-curves for $\delta = 25\%$

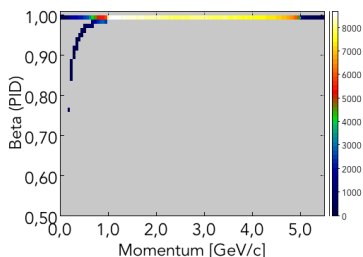
Resolution Effects for $N(\pi^-)/N(e^-) = 1$



- **Basic question:** What happens if resolution in measured data is different from the resolution the classifier has been trained on?
- **Simple Test:** Apply trained classifier on a data set with different resolution than the training set
- Smeared all PID variables by a Gaussian distribution: $x \mapsto x + \text{Gauss}(0, \delta \cdot x)$
- Shown above: ROC-curves for $\delta = 35\%$

Summary and Outlook

- ☑ Set up and use Machine Learning for PID
- ☑ Performed identification of e^- in a π^- -dominated data set
 - ▶ Key variables: p , $\text{nphe}(\text{LTCC})$, $\text{nphe}(\text{HTCC})$, $\Delta E(pcal)$, $\Delta E(ec : in)$, $\Delta E(ec : out)$
 - ▶ Use two classifier $\Rightarrow$ chosen by ROC-metric $\Rightarrow$ Both performed equally: $\epsilon_{e^-} \sim 95\%$
 - ▶ Checked influence of magnetic field settings $\Rightarrow$ No significant impact indicated
 - ▶ Studied resolution effects $\Rightarrow$ In this analysis: manageable performance for $\delta < 15\%$
- ☐ Test methods on KPP-Data
- ☐ Perform PID studies for e^+ , π^+ , $K^\pm$ and p (ongoing)
- ☐ Estimation of Variable Importance (ongoing)
- ☐ Include further classifier algorithms (e.g. SVM, Likelihood,...) (ongoing)
- ☐ Possible X-check of PID-results (e.g. compare $\beta(\text{PID})$ with $\beta(\text{ToF})$)



Content

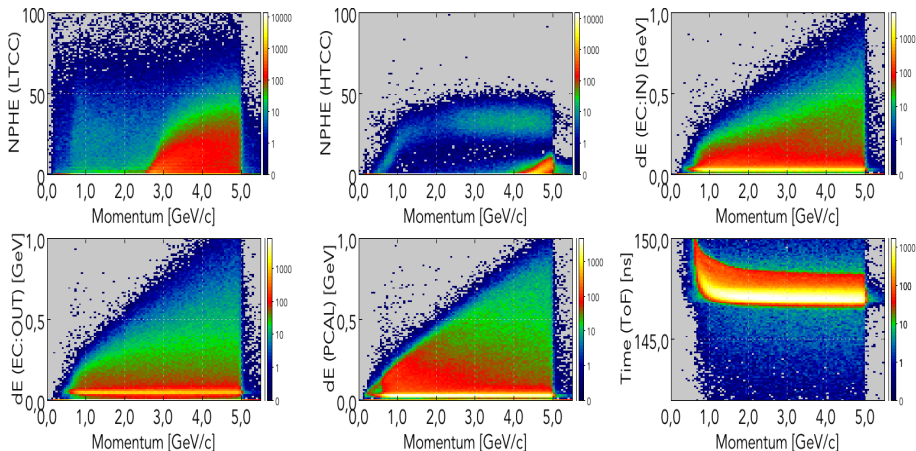
1. Introduction (2)
2. The $e^- \pi^-$ Data Set (3)
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Backup Stuff

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4. Compare True and ID Distributions for true Electrons (17)
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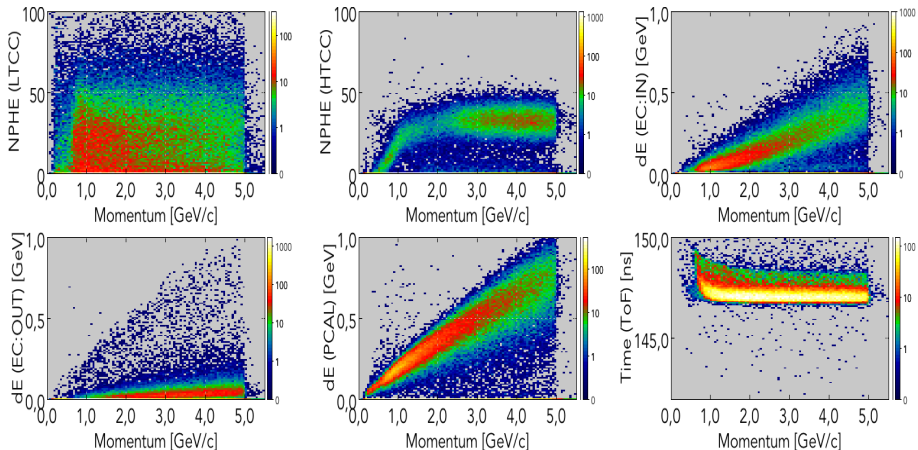
Backup: The $e^- \pi^-$ Data Set

All Particles



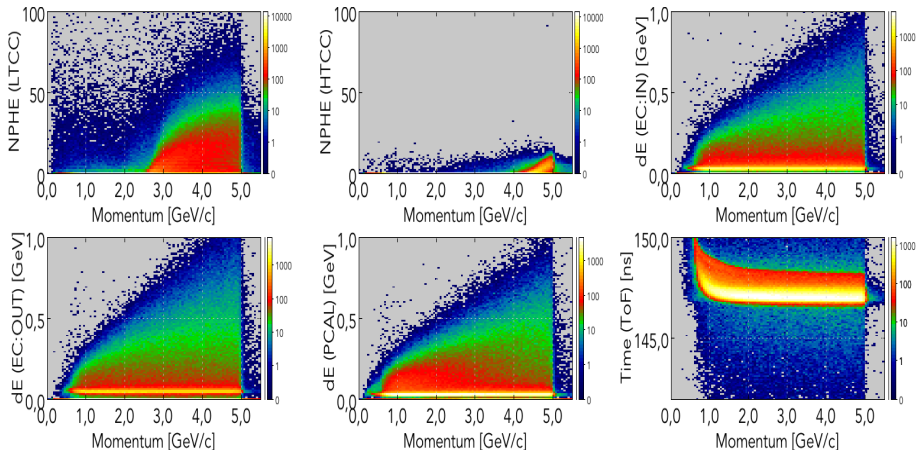
Backup: The $e^-\pi^-$ Data Set

Electrons

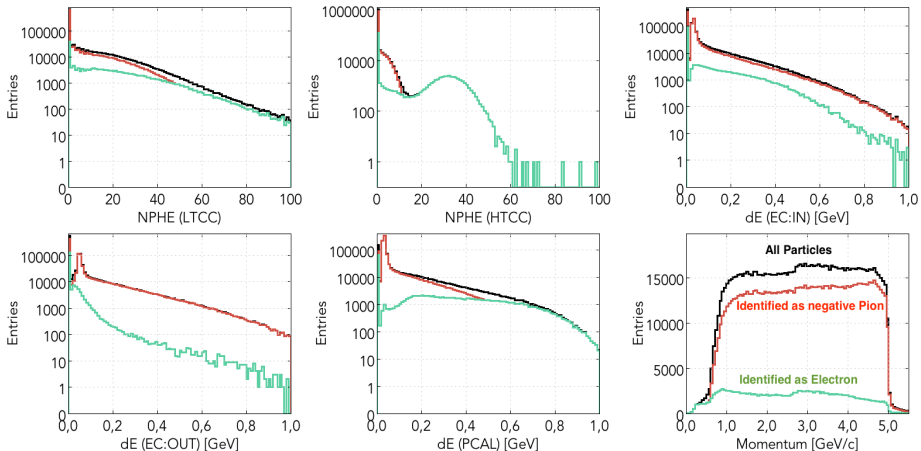


Backup: The $e^- \pi^-$ Data Set

Negative Pions



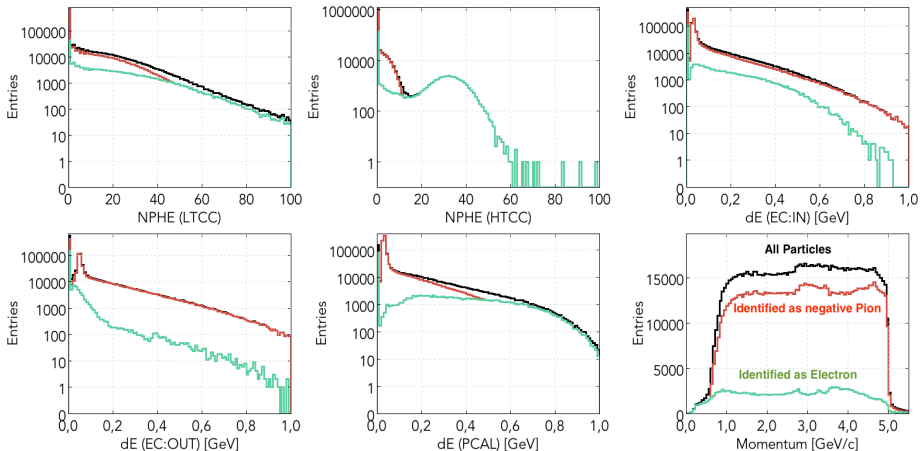
Backup: 1D Distributions before and after PID



Apply neural network algorithm on $e^- \pi^-$ data set:

- $\epsilon_S = 94\%$
- $P_S = 62\%$

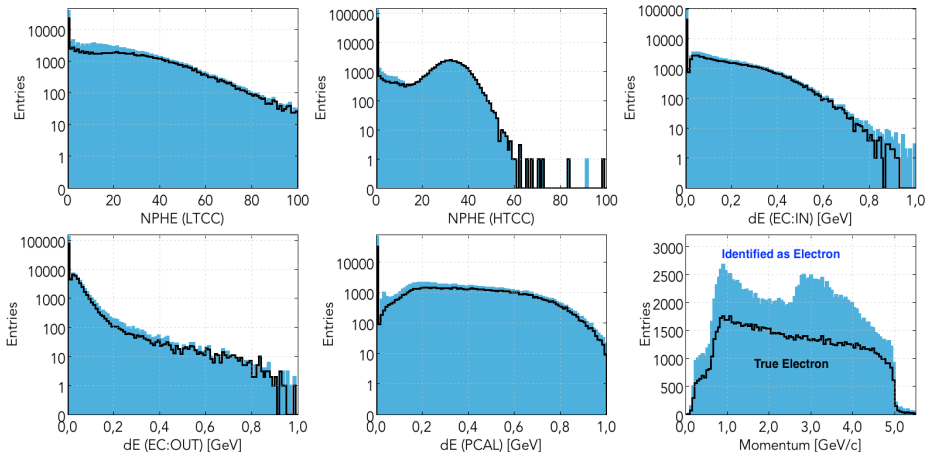
Backup: 1D Distributions before and after PID



Apply boosted decision tree algorithm on $e^- \pi^-$ data set:

- $\epsilon_S = 96\%$
- $P_S = 58\%$

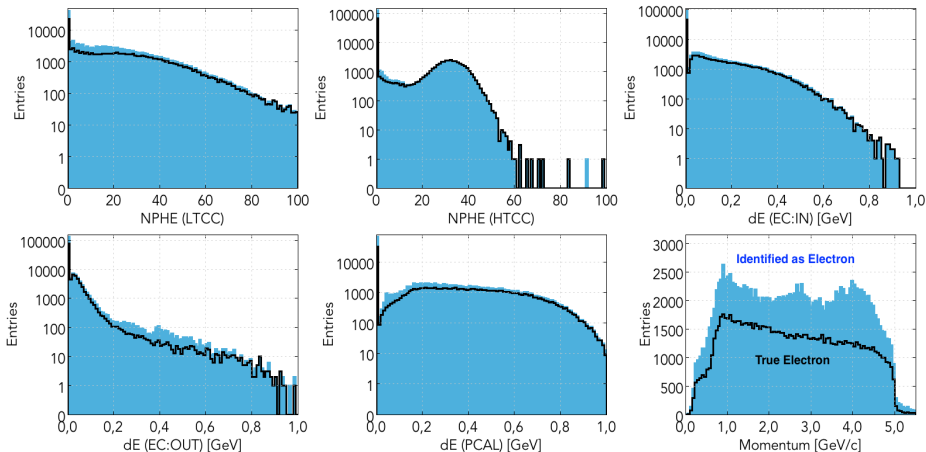
Backup: Compare True and ID Distributions



Apply neural network algorithm on $e^- \pi^-$ data set:

- $\epsilon_S = 94\%$
- $P_S = 62\%$

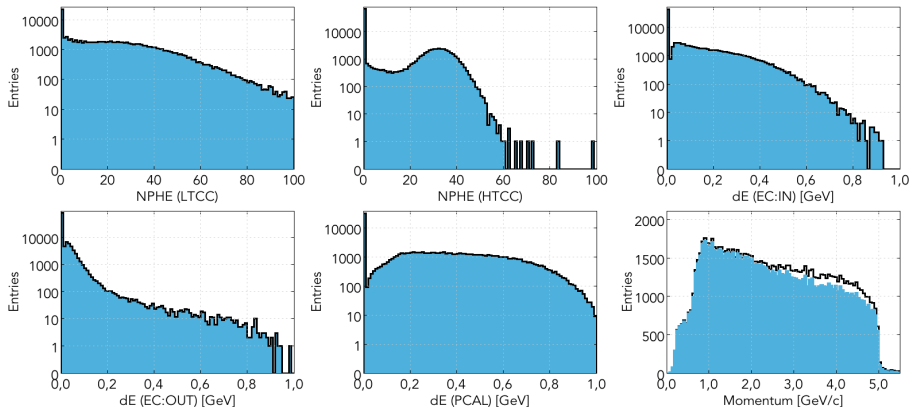
Backup: Compare True and ID Distributions



Apply boosted decision tree algorithm on $e^- \pi^-$ data set:

- $\epsilon_S = 96\%$
- $P_S = 58\%$

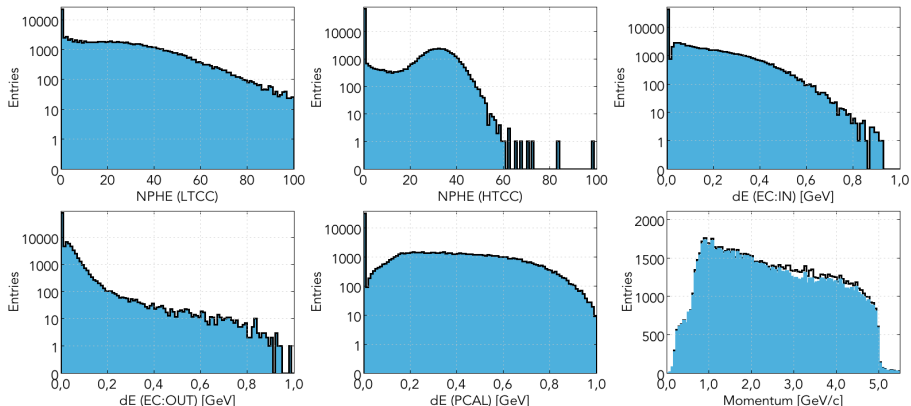
Backup: Compare True and ID Distributions for true Electrons



Apply neural network algorithm on $e^-\pi^-$ data set:

- $\epsilon_S = 94\%$
- $P_S = 62\%$

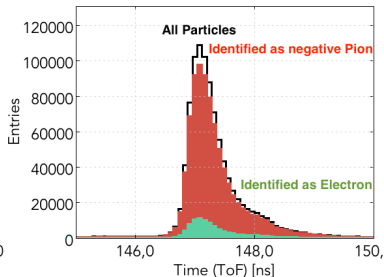
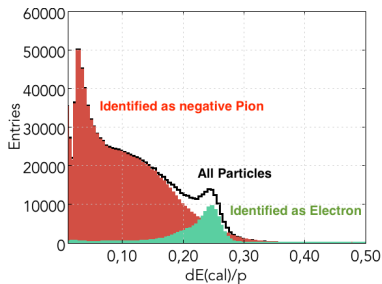
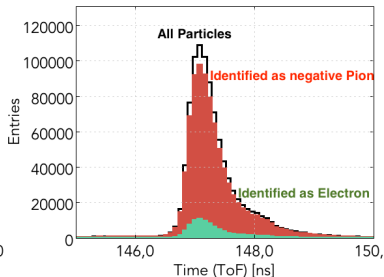
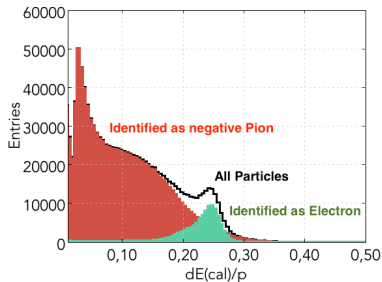
Backup: Compare True and ID Distributions for true Electrons



Apply boosted decision tree algorithm on $e^- \pi^-$ data set:

- $\epsilon_S = 96\%$
- $P_S = 58\%$

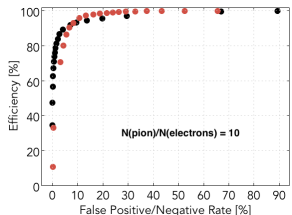
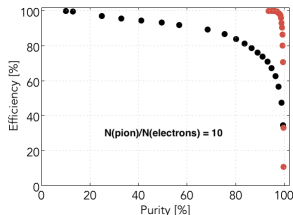
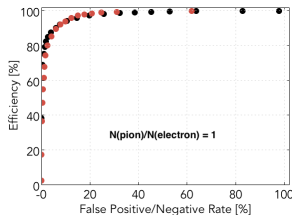
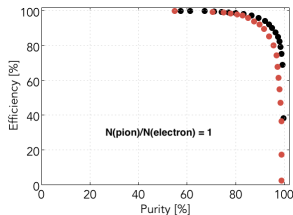
Backup: Comparison of PID-Plots



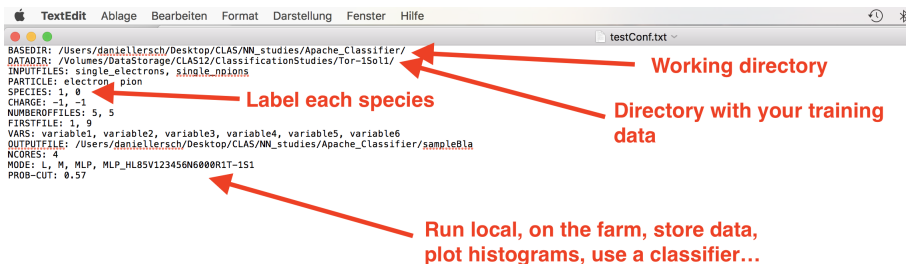
Top: MLP / Bottom: GBT

Backup: Useful Relations

- ϵ_S and FPR are features of the classifier and (ideally) independent of the ratio between the species
- $\left(\frac{N_B^{all}}{N_S^{all}}\right)_{rec} = \left[\frac{P_S}{\epsilon_S} \times \frac{\epsilon_B}{P_B}\right] \times \left(\frac{N_B^{all}}{N_S^{all}}\right)_{true}$
- $P_S = \epsilon_S \times \left[\epsilon_S + FPR \times \left(\frac{N_B^{all}}{N_S^{all}}\right)_{true}\right]^{-1}$

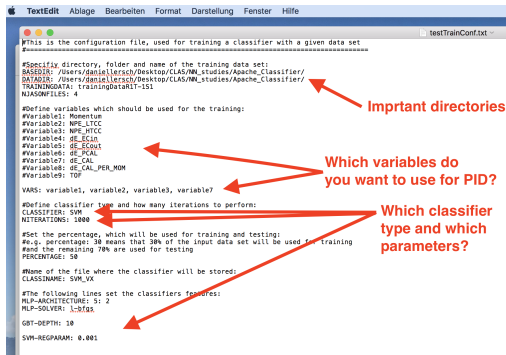


Backup: Generating single Track Training Data



- Java-based Module:
 - ▶ Generate training data from reconstructed CLAS12 data
 - ▶ Test a classifier on reconstructed CLAS12 data
 - ▶ Can be run by/with multiple users/configurations
- Module parameters are specified in a txt-file (see top figure)
- Txt-file generation and submission to farm are run by a single script

Backup: Training and Choice of the Classifier



```
TextEdit  Ablage  Bearbeiten  Format  Darstellung  Fenster  Hilfe
testTrainConf.txt

#This is the configuration file, used for training a classifier with a given data set
#-----
#Specify directory, folder and name of the training data set:
BASEDIR: /Users/daniel.lersch/Desktop/CLAS/NN_studies/Apache_Classifier/
DATADIR: /Users/daniel.lersch/Desktop/CLAS/NN_studies/Apache_Classifier/
TRAININGDATA: trainingDataIT-151
NJJSONFILES: 4

#Define variables which should be used for the training:
#Variable1: Momentum
#Variable2: NPE_LTCC
#Variable3: NPE_PTCC
#Variable4: de_ECIn
#Variable5: de_ECout
#Variable6: de_PCAL
#Variable7: de_CAL
#Variable8: de_CAL_PER_MOM
#Variable9: TOP

VARS: variable1, variable2, variable3, variable7

#Define classifier type and how many iterations to perform:
CLASSIFIER: SVM
ITERATIONS: 1000

#Set the percentage, which will be used for training and testing:
#e.g. percentage: 30 means that 30% of the input data set will be used for training
#and the remaining 70% are used for testing
PERCENTAGE: 50

#Name of the file where the classifier will be stored:
CLASSNAME: SVM_YX

#The following lines set the classifiers features:
MLP-ARCHITECTURE: 9: 2
MLP-SOLVER: l-bfgs
GBT-DEPTH: 10
SVM-REGPARAM: 0.001
```

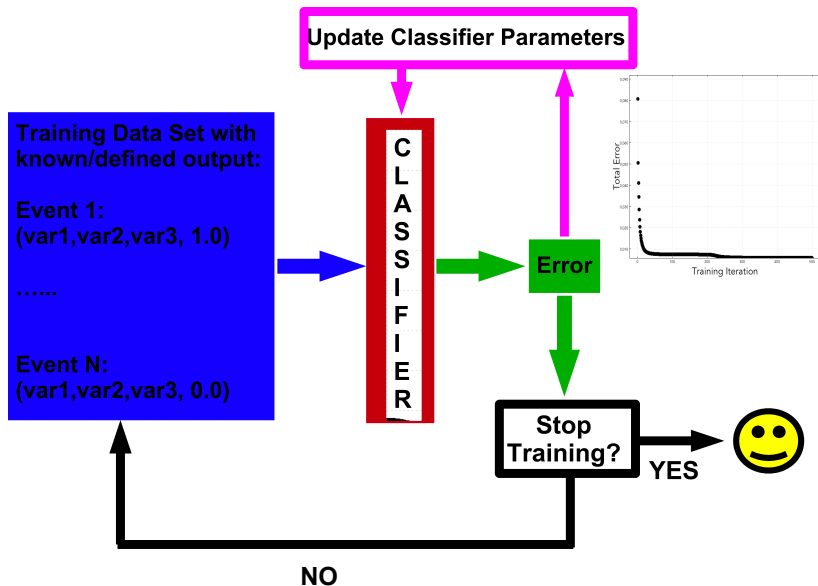
Important directories

Which variables do you want to use for PID?

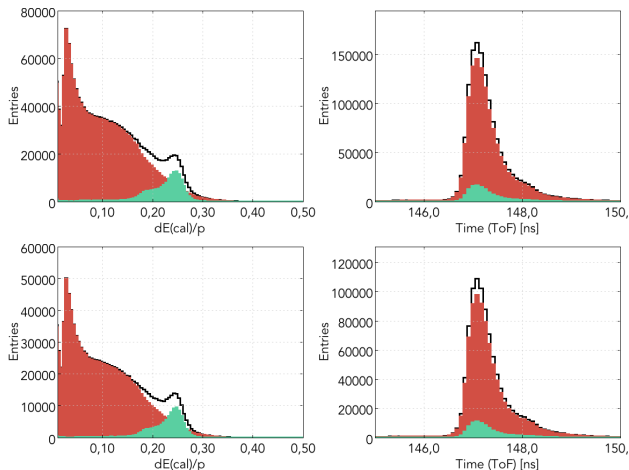
Which classifier type and which parameters?

- Java-based Module:
 - ▶ Specify the variables used for training
 - ▶ Select the classifier that shall be trained
 - ▶ Define how the classifier shall be trained
 - ▶ Can be run by/with multiple users/configurations
- Module parameters are specified in a txt-file (see top figure)
- Txt-file generation and submission to farm are run by a single script

Backup: Training a Classifier



Backup: Changing the Magnetic Field



- Top: Classifier trained on: Tor. = -0.75 and Sol. = 0.8 and applied on: Tor. = -0.75 and Sol. = 0.8
- Bottom: Classifier trained on: Tor. = -0.75 and Sol. = 0.8 and applied on: Tor. = -1 and Sol. = 1