BROWN

Data Analysis: Algorithms and Tools

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Introduction

XII International Workshop on Advanced Computing and Analysis Techniques in Physics Research

Are we ready for LHC era experiments?

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  - Small signals with large backgrounds

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- Challenge for all 3 tracks !
  - Track 1: Computing Technology for Physics Research
  - Track 2: Data Analysis - Algorithms and Tools
  - Track 3: Methodology of Computations in Theoretical Physics

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- Challenge for all 3 tracks !
  - Track 1: Computing Technology for Physics Research
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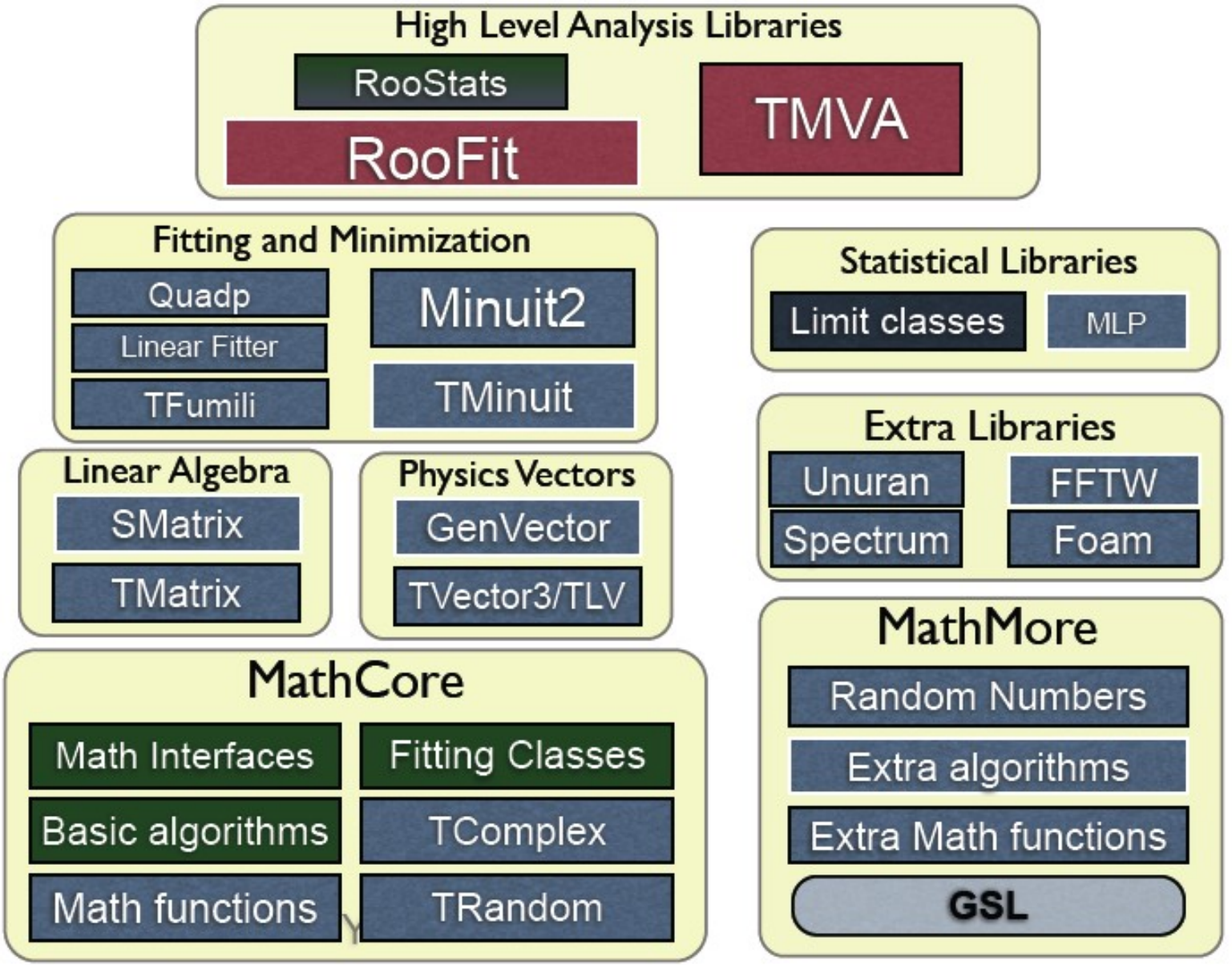
  - Track 3: Methodology of Computations in Theoretical Physics
- Challenge spawns many activities, research and innovation in a vast field

Structure of ROOT Math & Statistical Libraries:

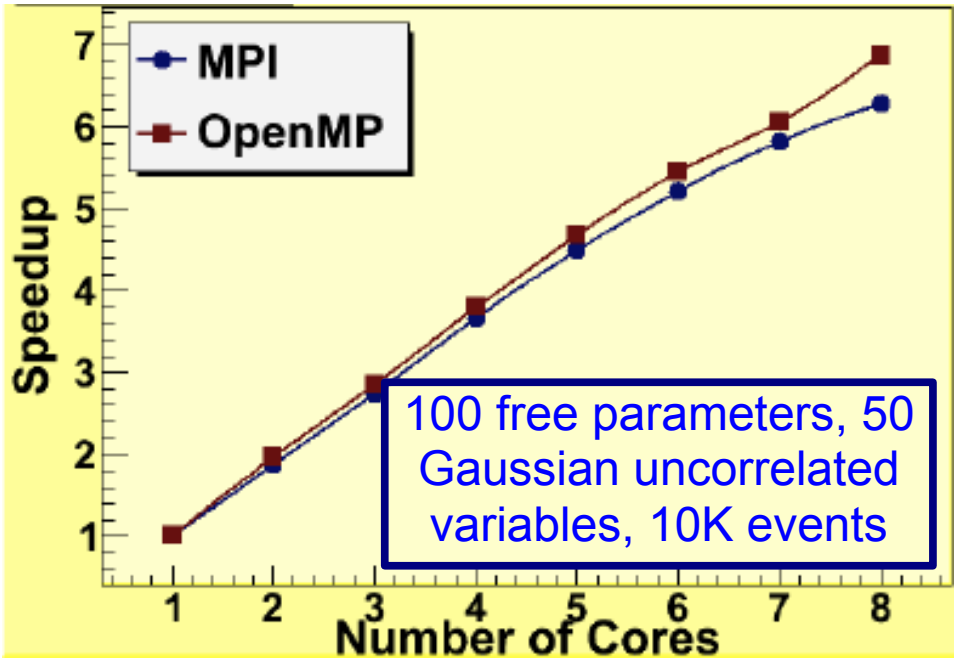


L. Moneta: Improvements of the ROOT Fitting and Minimization Classes

- Large collection of math and statistical tools available in ROOT
  - Large number of improvements, too many to list alll here!
    - Improvement of basic functionality of MathCore (e.g. numerical algorithms)
    - Improved fitting and minimization classes
    - RooStats: New statistical framework for discovery, confidence levels and result combination
  - Improved overall quality and better usability (e.g. GUI FitPanel)
  - Improved modularity and removal of duplications
- Considerable efforts from external contributors in developing tools for physics analysis
  - RooFit: Complex fitting
  - TMVA: Multivariate analysis
  - RooStats
- Large effort on improving validation and test suites
- Good documentation for reference and maintainability

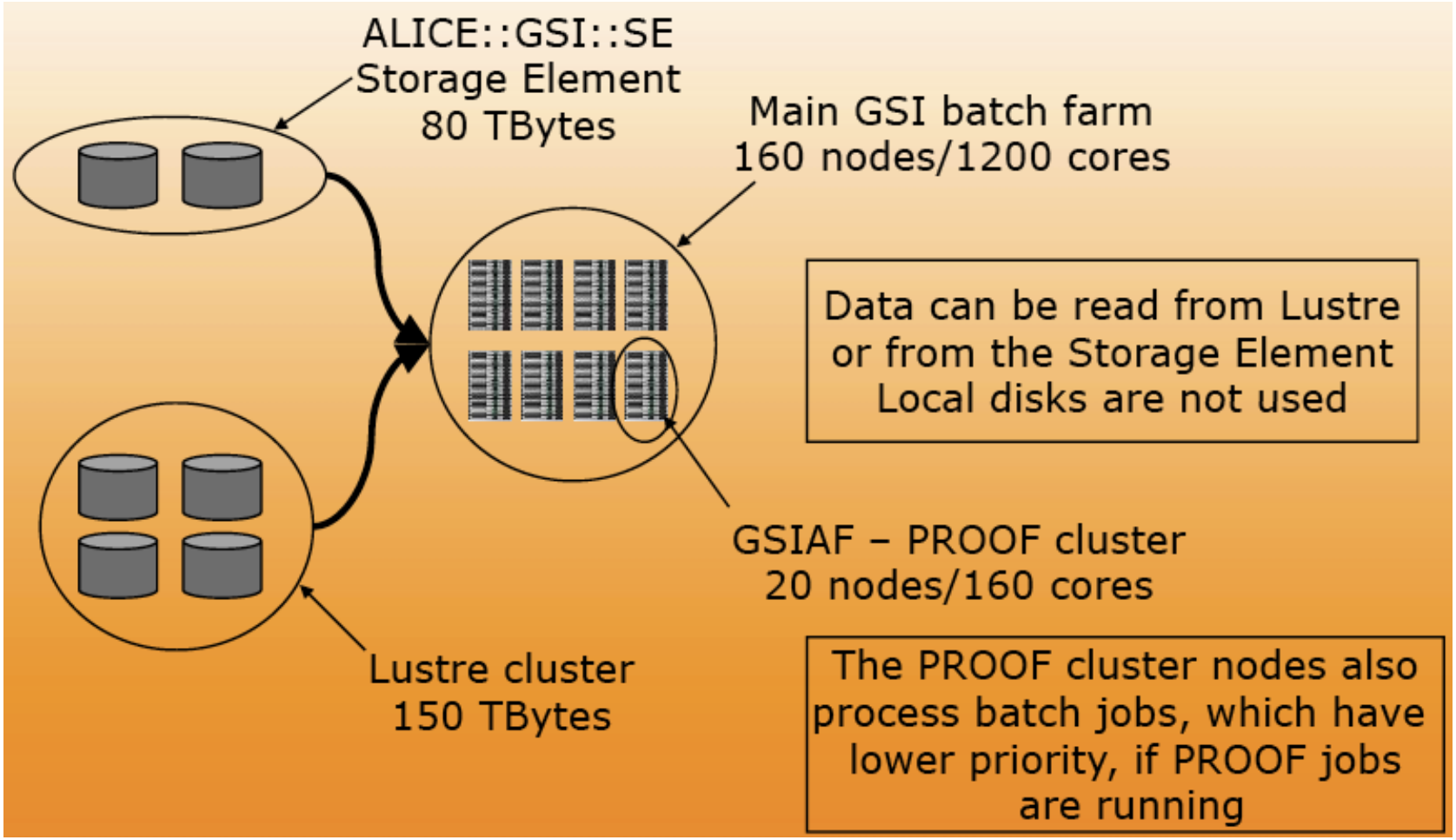
A. Lazzro: MINUIT Package Parallelization

- Large datasets are expected at the LHC
- Many data analysis techniques are very CPU-intensive
  - Optimization problems, some with many free parameters
- Parallelize algorithms to benefit from new multi/many core architectures or clusters
- Parallelization of Maximum Likelihood Fits in RooFit & Minuit2
  - RooFit implements the possibility to split the likelihood calculation over different threads
    - Likelihood calculation is done on sub-samples and the results are collected and summed
  - Split the derivative calculation over several OpenMP/MPI processes
  - Minuit2: parallelization of the minimization and log-likelihood calculation



A. Kreshuk: Interactive Data Analysis with PROOF at GSI

- Interactive data analysis for ALICE using PROOF at tier-2
- Possibility to switch dynamically resources between gird-jobs, jobs from the local batch system and the GSI Analysis Facility (GSIAF)
- Creating PROOF clusters on demand

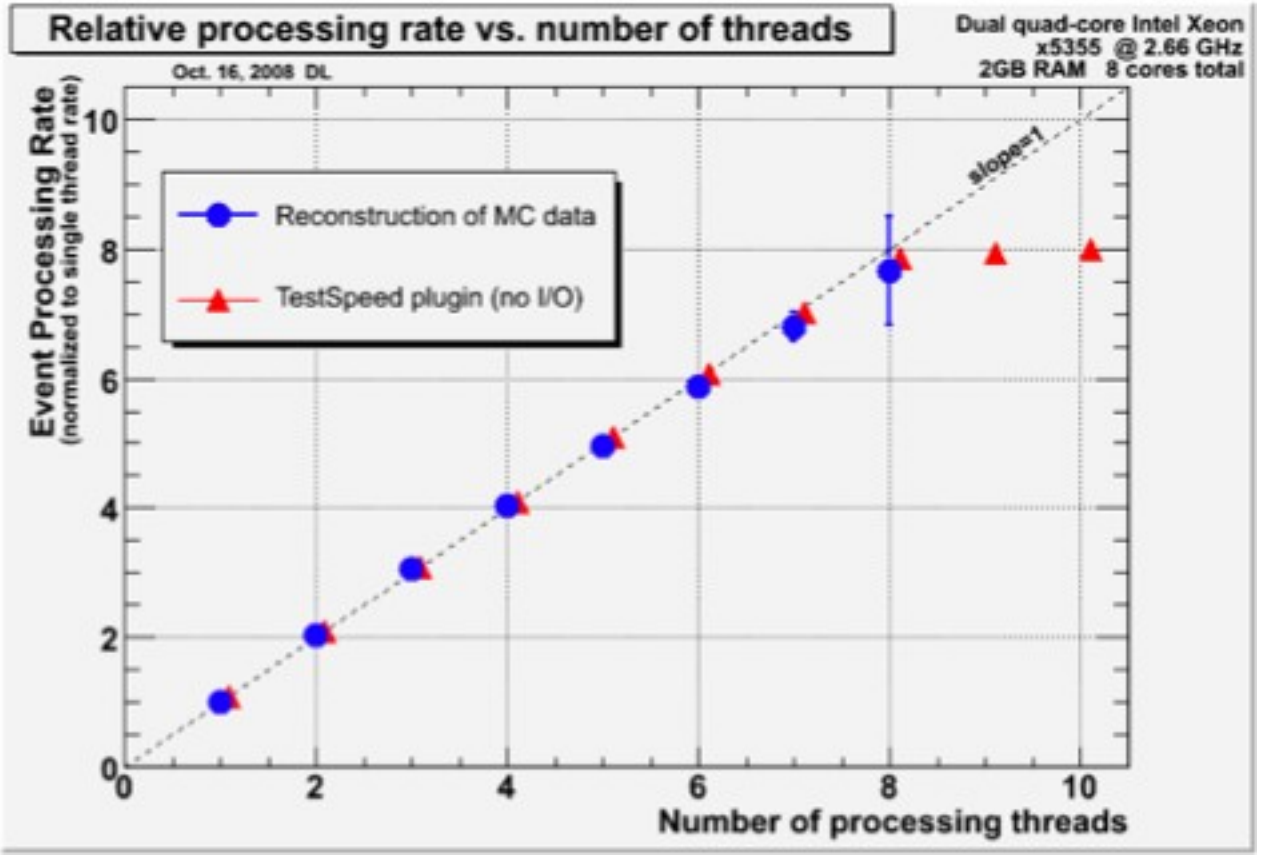


D.Lawrence: Multi-threaded Event Processing with JANA

GlueX experiment on the 6 GeV electron accelerator at jefferson Lab

The Event Processing Framework JANA includes the following features:

- C++ , object-oriented, STL
- Plug-ins
  - Reconstruction Algorithms
  - Event (Data) sources
  - Event Processors
- Multi-threaded
- Data on demand



Multi-variate analysis methods

- Excellent plenary presentation by Harrison Prosper (→ link)
- MVA methods gaining in acceptance in the last years
  - Several high-profile results published
  - Get much attention at the LHC experiments since 2 / 3 years
  - Experiments want to get the most out of their data ! (and be the first...)

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- Several packages implementing MVAs available:
  - Standardized implementations
  - Common platform & interface for all MVA classifiers
  - Consistent training, testing and evaluation of the MVAs
  - TMVA, SPR, WEKA, R

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- This year, less emphasis in presentations on new classifiers:
  - RIPPER
  - PDE-FOAM
- Presentations on examples of usage and comparison with. other methods

J.Stelzer: TMVA

- Implementation of many MVA methods:
  - Integrated in ROOT:
  - Open-source: http://tmva.sf.net
  - Common platform / interface for all MVA classifiers
  - Common data pre-processing capabilities
  - Provide common data input and analysis framework (ROOT scripts)
  - Train and test all classifiers on same data sample and evaluate consistently
  - Classifier application w/ and w/o ROOT, through macros, C++ executables or python
- TMVA 4 to come with new features
  - Current stable TMVA version 3.9.5 for ROOT 5.22 (middle of December)

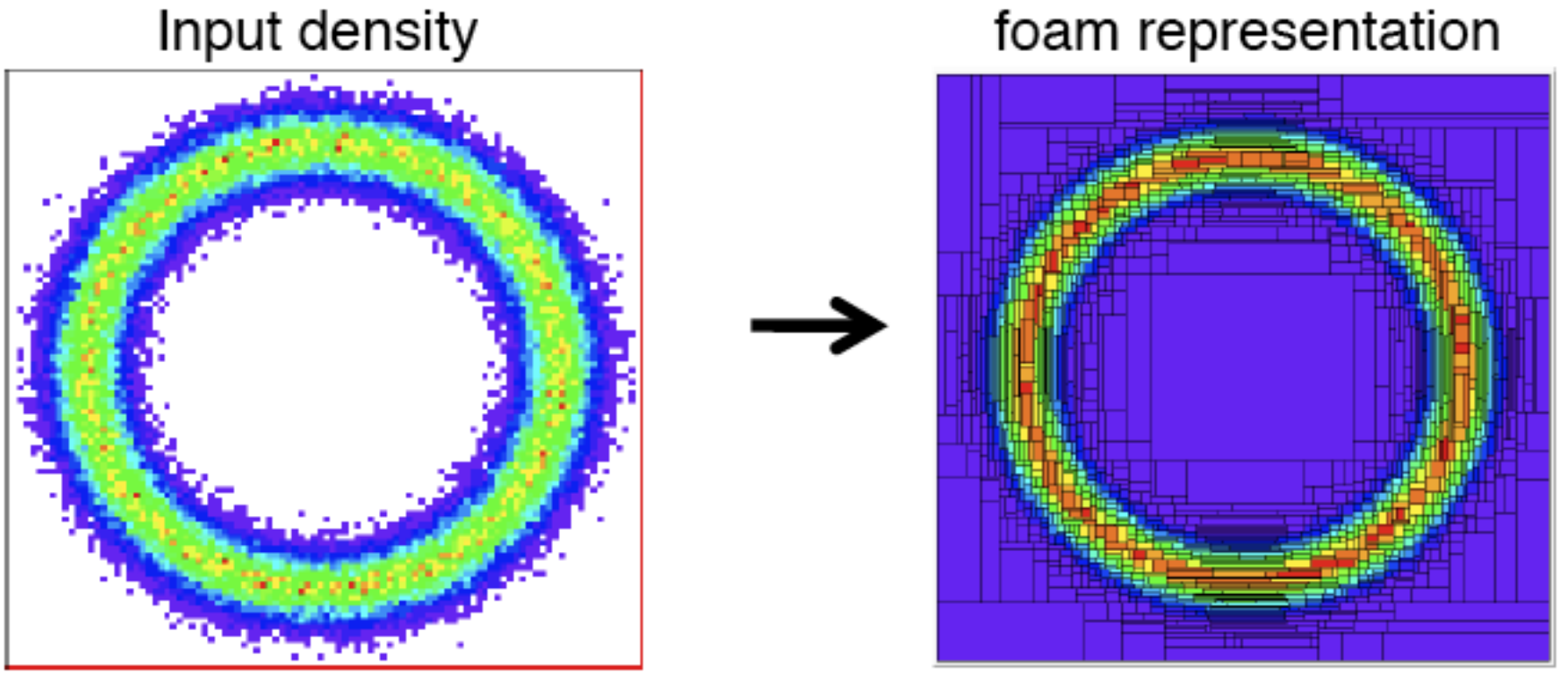
J.Stelzer: TMVA

New developments foreseen:

- Data Regression
- Categorization: multi-class classification
- Automated classifier tuning: using cross-validation method
- Generic boost or bag of any classifiers
- Composite classifiers (parallel training in different phase space regions)
- Input data handling
  - Arbitrary combination of dataset transformations possible
  - Changed TMVA framework in handling datasets and classifiers
  - Implemented regression training for most classifiers
  - User interface extended.
- New Method: PDE Foam
- TMVA to be made multi-threaded and run on multi-core architectures

D. Dannheim: PDE-FOAM

- PDE-FOAN: probability-density estimation method based on self-adapting binning method to divide d-dimensional phase space in finite number of hyper rectangles (cells)
- Iterative cell-split algorithm, starting from base cell containing all events
  - Density of distribution is sampled by counting events in a box of fixed size which is moved randomly across the cell
  - Split cell along plane with highest gain in variance reduction

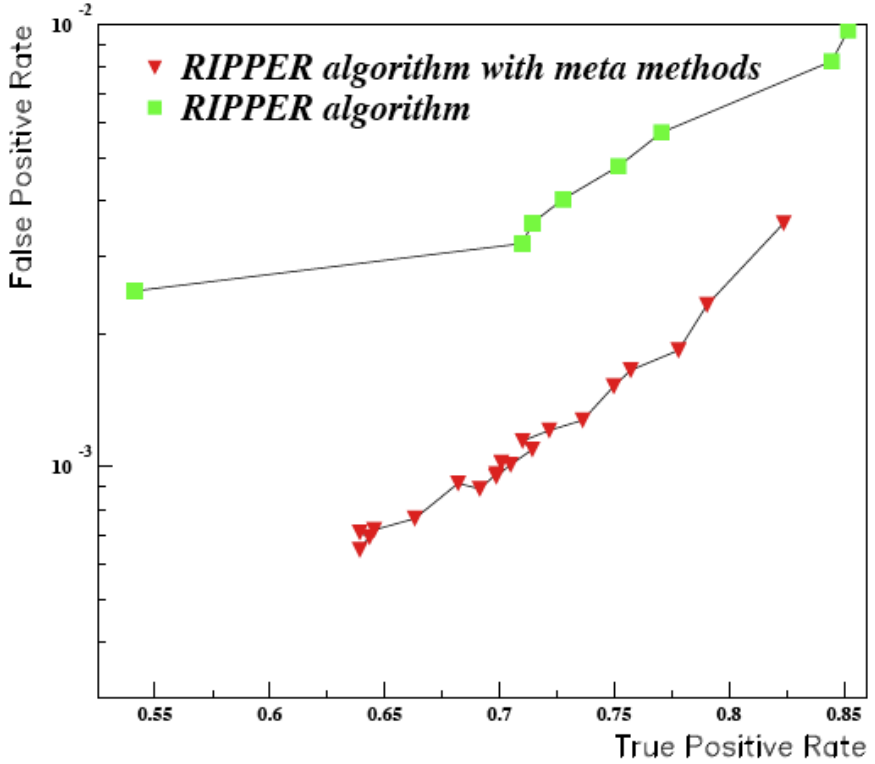


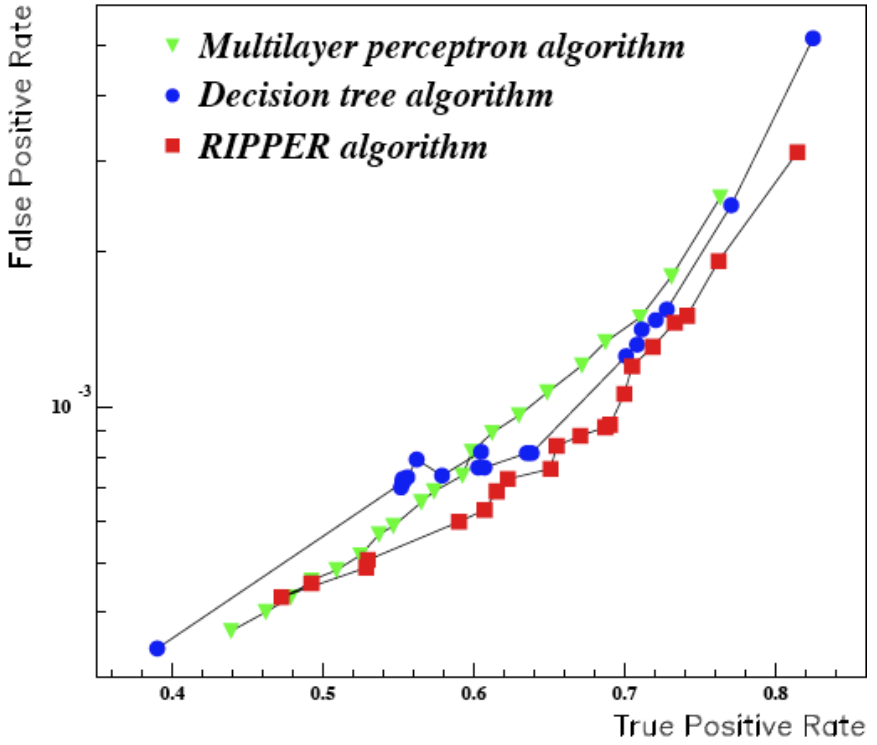
D. Dannheim: PDE-FOAM

- Foam of cells:
  - Few large cells in phase-space regions with constant likelihood density
  - Many small cells in regions with high gradients of likelihood density
- Preserve only binned averaged density information after training phase
  - Fast, memory efficient classification, independent of training sample size
  - Reduces sensitivity to statistical fluctuations for small training samples
- Implemented in TMVA
- Compared performance for various toy models and parameter settings
  - Performance exceeds PDE-RS for small training samples
  - Reduced classification time, independent of size of training sample
  - Reduced memory consumption, independent of size of training sample
- Adapted PDE-Foam for reconstruction of event variables

M. Britsch: RIPPER

- RIPPER:
  - Direct rule based classifier
  - Instance weighting: automated sampling/weighting of instances according to cost
  - Bagging
- Example: LHCb MC $\Lambda \rightarrow p^+ + \pi^-$





Examples of application at the LHC

A few examples of application were shown:

- Tau-tagging:
  - mostly 1-prong or 3-prong decays
  - Well-collimated calorimeter cluster
  - Small number of associated charged tracks
  - Displaced secondary vertex
- B-tagging:
  - Lifetime: τ ~1.5 ps ($c\tau$ ~450μm) $\rightarrow$ p = 20 GeV/c, decay length ~ 1.8 mm
    - secondary (tertiary) decay vertex; displaced tracks with large IP
  - High mass (~5.2 GeV) and decay multiplicity (~5 charged tracks)
  - Decay kinematics (e.g. rapidities)
  - Hard b-quark fragmentation function:
    - decay products with larger p_T relative to b hadron flight direction
  - Semi-leptonic decays (per lepton flavour: BR ~ 11%, ~20% incl. cascade)
- Large number of variable (8-10), non with sufficient separation power

M. Wolter: Tau identification using MVAm in ATLAS

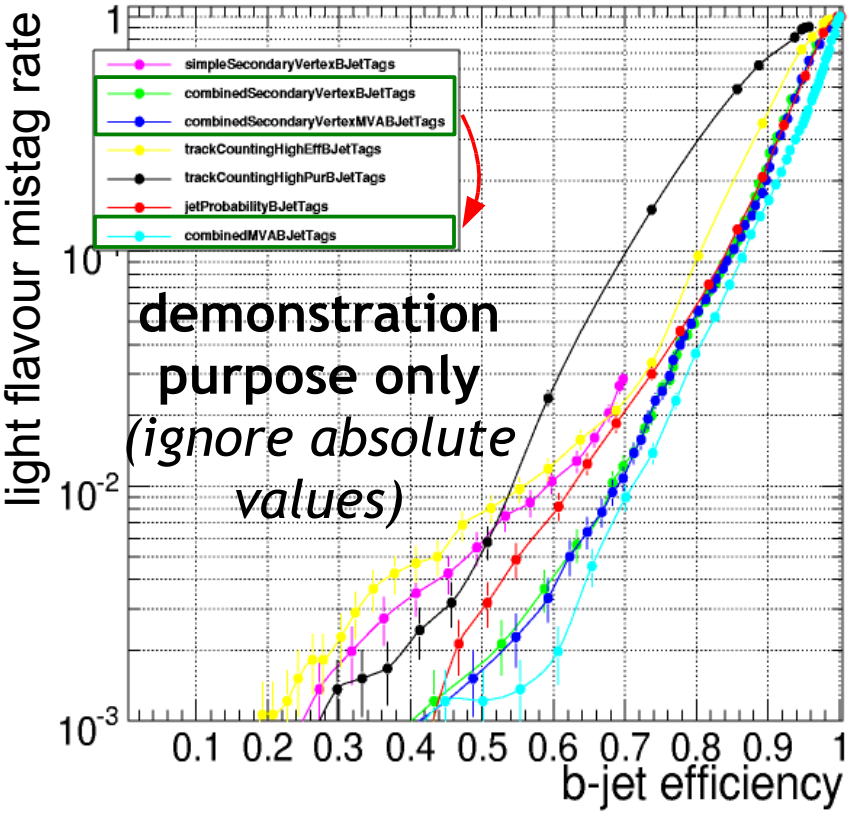
Several methods tried:

- Cut analysis:
  - baseline method, fast, robust, transparent
- Projected Likelihood:
  - popular and well performing tool
- PDE-RS – Probability Density Estimator with Range Searches:
  - robust and efficient, but large samples of reference candidates needed
- Neural Network – Stuttgart Neural Network Simulator (SNNS), feed-forward NN with two hidden layers:
  - Very fast, low memory consumption when trained network is converted to the C code
- Boosted Decision Tree:
  - fast and simple training, insensitive to outliers, good performance.
- For classification problems no single “best” method exists!
- What matters is also simplicity and speed of learning and fast and robust classification!

C.Saout: *b*-Tagging Algorithms in the CMS

Several different algorithms implemented, with different characteristics:

- Track Counting: sort tracks by descending Signed IP Significances (3D)
  - robust, simple and fast → suitable for HLT
- Jet probability: total probability that all tracks originate from PV
- Soft-lepton tagger, using electrons or muons
  - less reliance on IP and on tracker, fast, suitable for HLT
- Simple Secondary Vertex:
  - significance of flight distance
  - Robust wrt to misalignment
- Combined Secondary Vertex:
  - Using all variables in likelihood or NN
  - Highest performance, but more complex

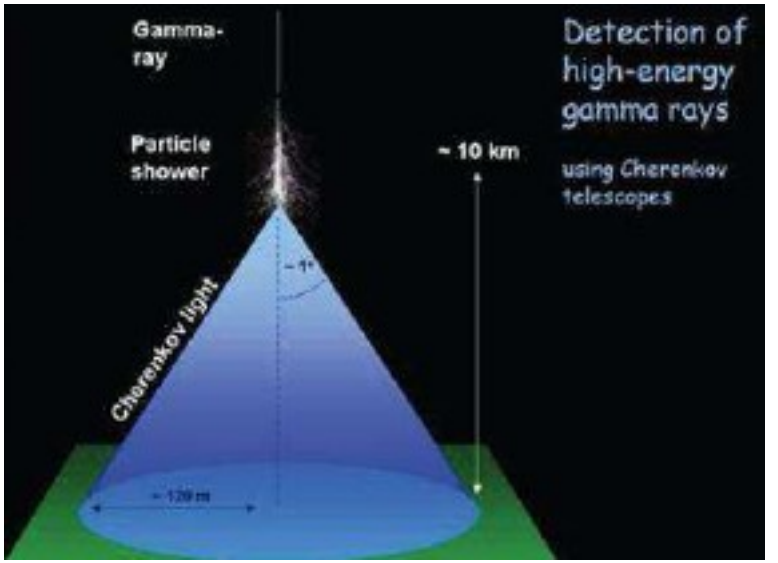


Examples of application at the LHC

- Many algorithms developed
  - Different characteristics, for different uses (e.g. HLT)
- Multivariate methods do show improvements
  - Further gain from MVA expected to be small
  - Complex algorithms
- But this is all Monte Carlo!
- Concentrate on preparation for real data:
  - Robust,simple algorithms needed first (mis-alignement, etc)
  - Validation of input data
  - Comparison of Monte Carlo with data
  - Measurement of efficiency and mistag rates from data (see poster by V.Bazterra “Strategies for btagging calibration using data at CMS”)
  - Calibration of MVA-based algorithms
  - Systematics...

S. Khatchadourian: ANN Level 2 Trigger for HESS

- HESS/HESS 2: Detection of High-energy gamma rays
- Detection of Cherenkov light:
  - As a high energy cosmic ray particle hits the atmosphere it creates an extensive air shower by interaction with the atmosphere.
  - 4 (HESS 2: 5) Cherenkov Telescopes located in Namibia



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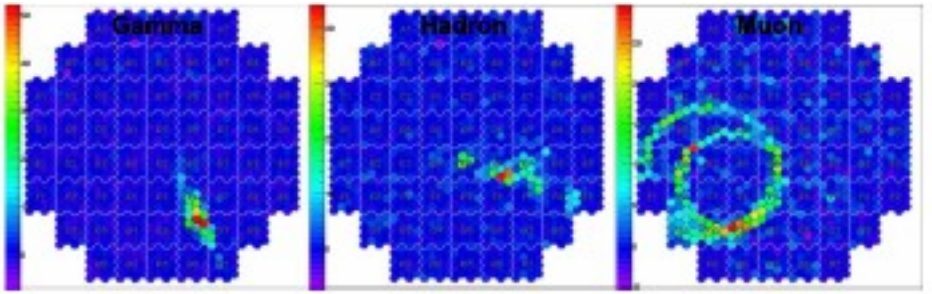
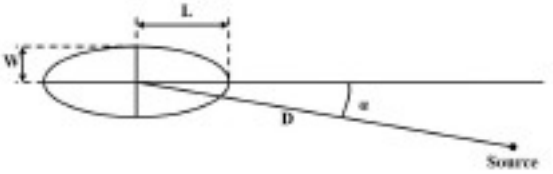


- Large amount of data
  - Trigger system to minimize the data flo
- Two level trigger system:
  - L1 : eliminate the NSB (thresholds, etc)
  - L2 : classify particles (γ, μ, Proton): pattern recognition
- Two approaches for L2 :



  - Classical method: Filter based on Hillas parameters
  - Neural System: Composed of 2 stages
    - Preprocessor: Describe image with small number of parameters (Zernike momentes)
    - Neural classifier: Multi-layer Perceptron
  - NN: Issue with timing: to be implemented in FPGA

	Gamma	Muon	Proton
Hillas filter	60%	56%	37%
NN with Hillas	71%	84%	82%
NN with Zernike	95%	58%	41%

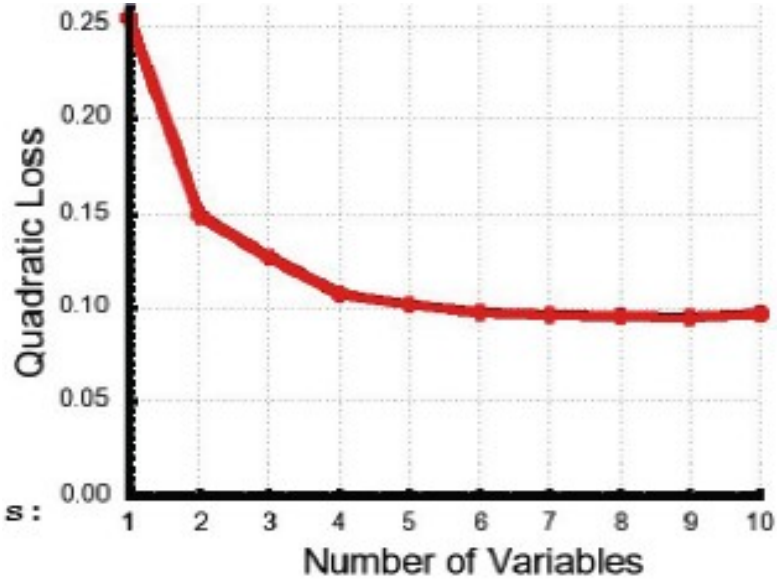
Gamma recognized	Hadron recognized
76%	80%
85%	70%

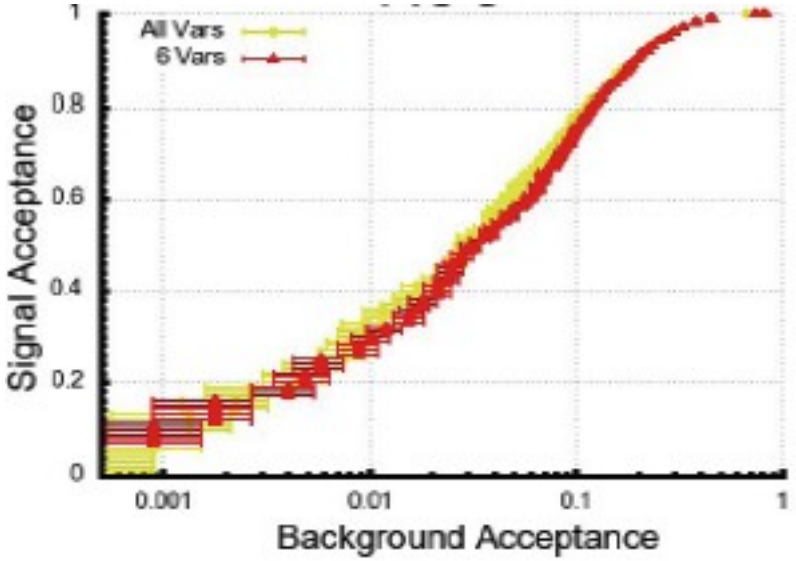
G. Palombo: Feature Selection Algorithms for Supervised Learning

- In same applications, large number of variables, huge number of events
  - Usually, not all the variables are useful for a classification problem
  - Selection of the most powerful discriminating features needed
- Feature Selection: reduce the feature-set to the smallest subset that gives the same or better quality of separation between signal and background as the full set does
  - Independent of classifier
  - Reduces data analysis time.
  - Easier analysis and interpretation of the results
  - For some algorithms: Can improve performance
- Several FS algorithms presented
  - *Add n Remove r*: Start with a null set. Add *s* variables at a time. For each added variable, train the classifier and compute FOM. Choose the variables that improve FOM most. Then remove *r* variables that improve FOM least. Continue as long as it is possible to improve FOM.
- Comparison on several datasets shown

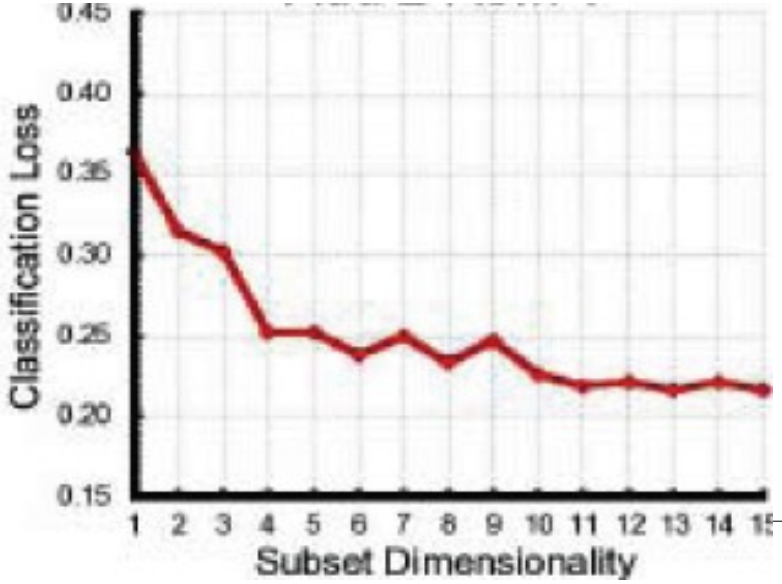
G. Palombo: Feature Selection Algorithms

- Magic Gamma-ray Telescope data: 10 variables – 4 irrelevant





- Arrhythmia dataset: Multi-class classification problem–12 classes
  - 261 variables, 250 irrelevant!

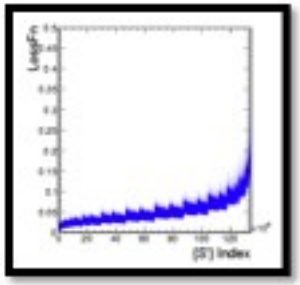


Features set	accuracy (%)	p-value
Best 11 Add2Rem1	80.95	
Best 11 Add1Rem0	76.19	0.49 (-)
Best 3 Add2Rem1	71.90	0.04 (-)
Best 4 Add2Rem1	75.24	0.22 (-)
All 261 SPR	75.95	0.10 (-)

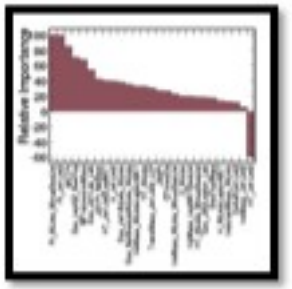
S. Gleyzer: PARADIGM

- PARADIGM: Decision Making Framework for HEP
  - Tool that helps make decisions based on critical information
  - Classifier independent, provides a way to compare and select an optimal choice for a particular analysis
- Variable Selection and Reduction
- Classifier Relevance, Performance & Improvement
- Analysis Optimization

Global Loss Function



Relative Variable Importance

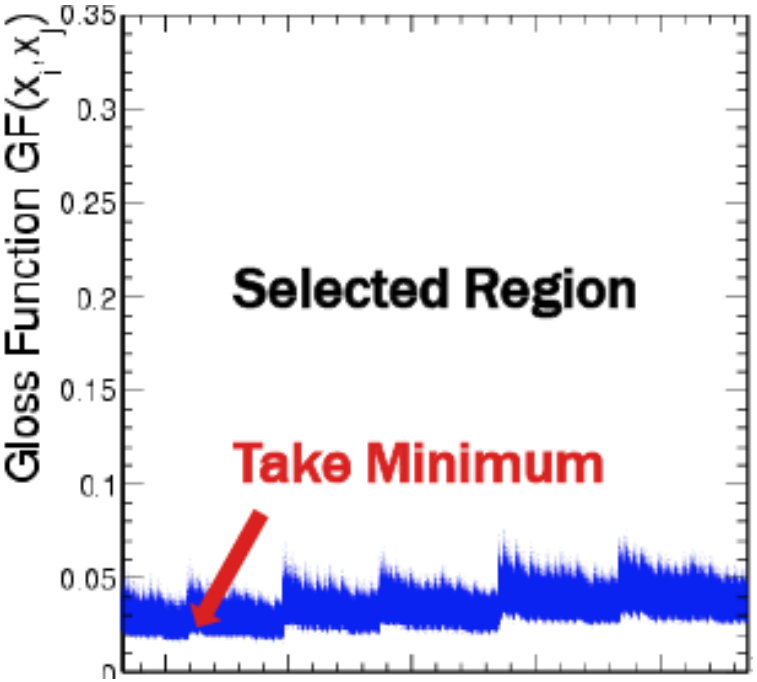


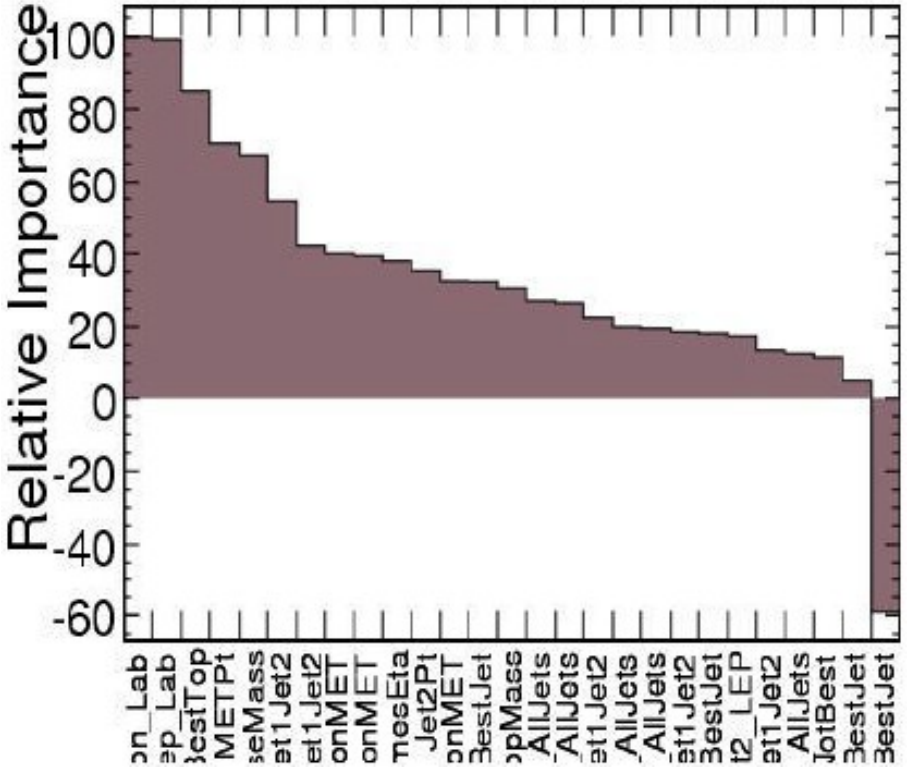
Reduce Variables
Choose Classifier

Improve Classifier

S. Gleyzer: PARADIGM

- Global Loss Function
  - Variable Reduction, Classifier Selection
  - Global measure of loss: global optimization of predictive performance
  - Select variable subsets for global removal
  - Select optimal classifier for given problem: minimum area under the curve





- Relative Variable Importance
  - Variable Selection, Classifier Improvement
  - Measures whether variables are desirable or valuable relative to other variables for a particular problem

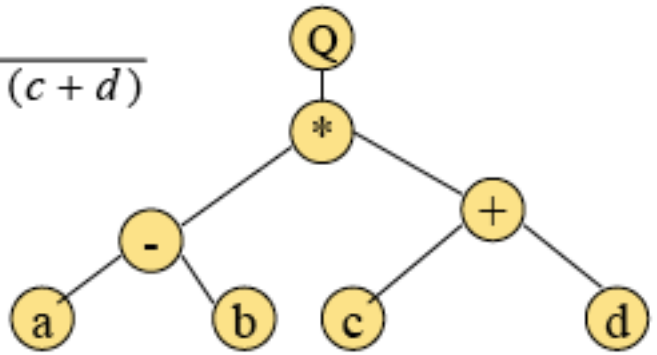
L. Teodorescu: Enhanced Gene Expression Programming

- Evolutionary computation simulates the natural evolution on a computer
  - Generate a population of individuals with increasing fitness to environment
- GEP: Works with two entities, chromosomes and expression trees

Candidate solution represented by an expression tree (ET)

ET encoded in a chromosome: read ET left - right and top - down

$\sqrt{(a-b)\cdot(c+d)}$



Q*-+abcd

Q means sqrt

Chromosome – has one or more genes of equal length

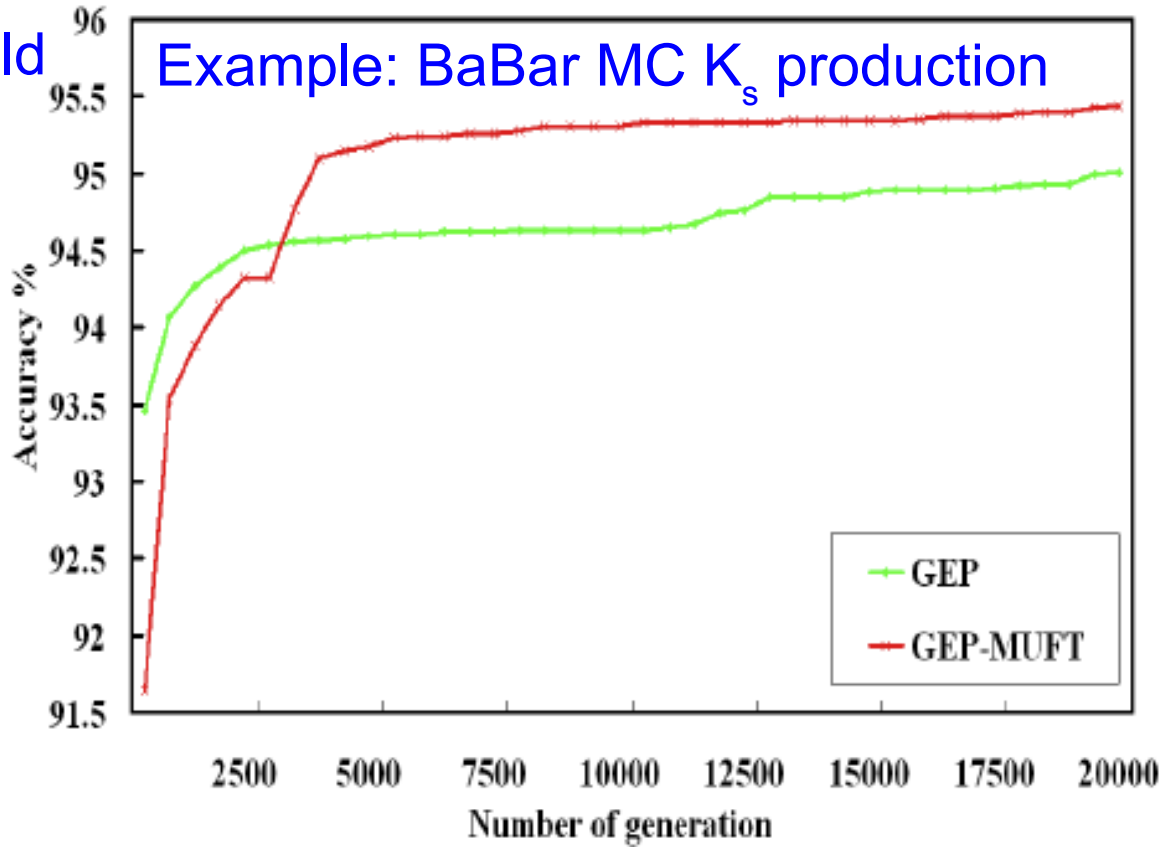
Gene – head: contains both functions and terminals (length h)
- tail: contains only terminals (length t)

- Reproduction: Genetic operators applied on chromosomes
  - Recombination: exchange parts of two chromosomes
  - Mutation: change the value of a node
  - Transposition: move part of chromosome to another location

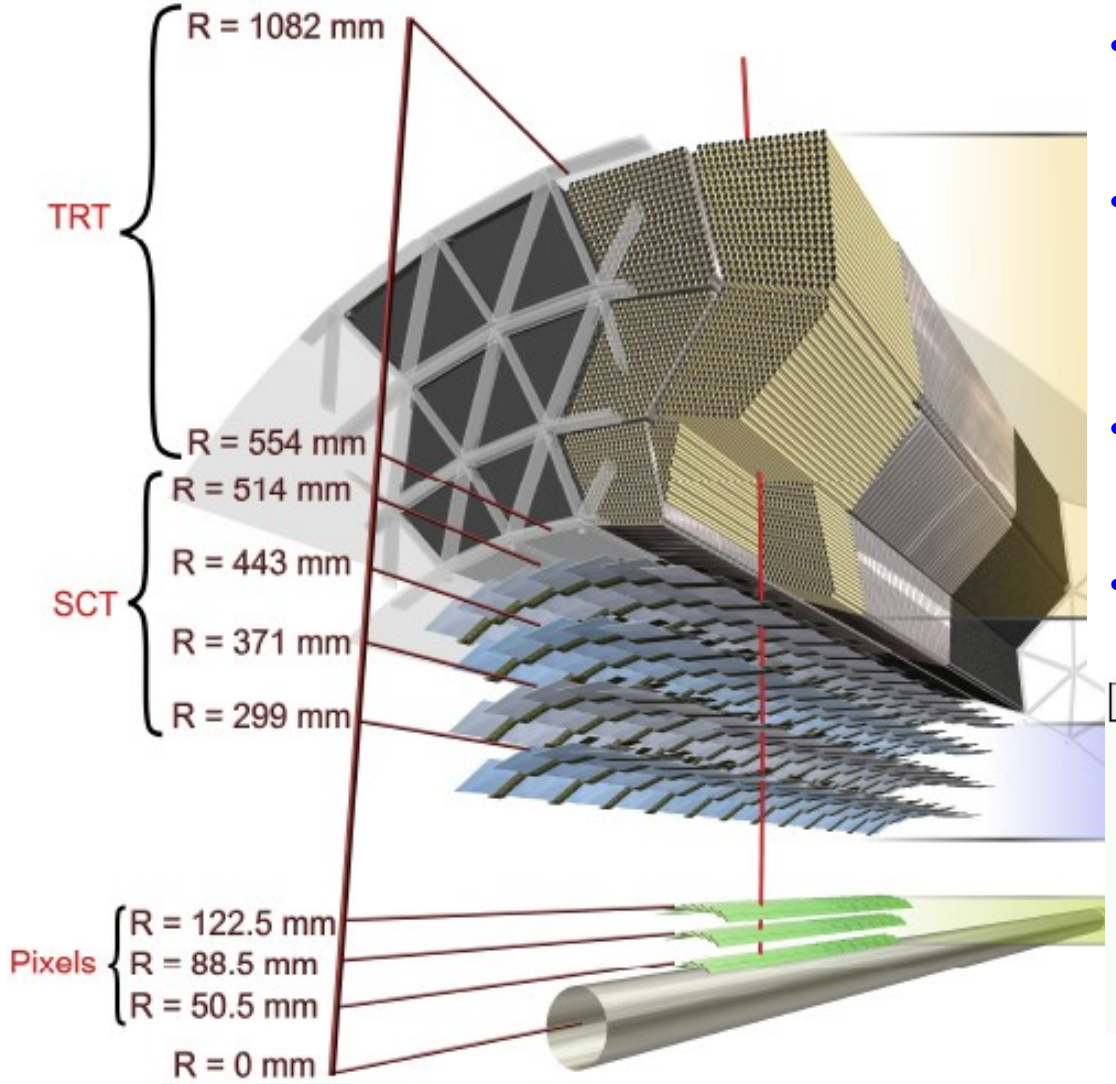
L. Teodorescu: Enhanced Gene Expression Programming

Several new developments since ACAT07:

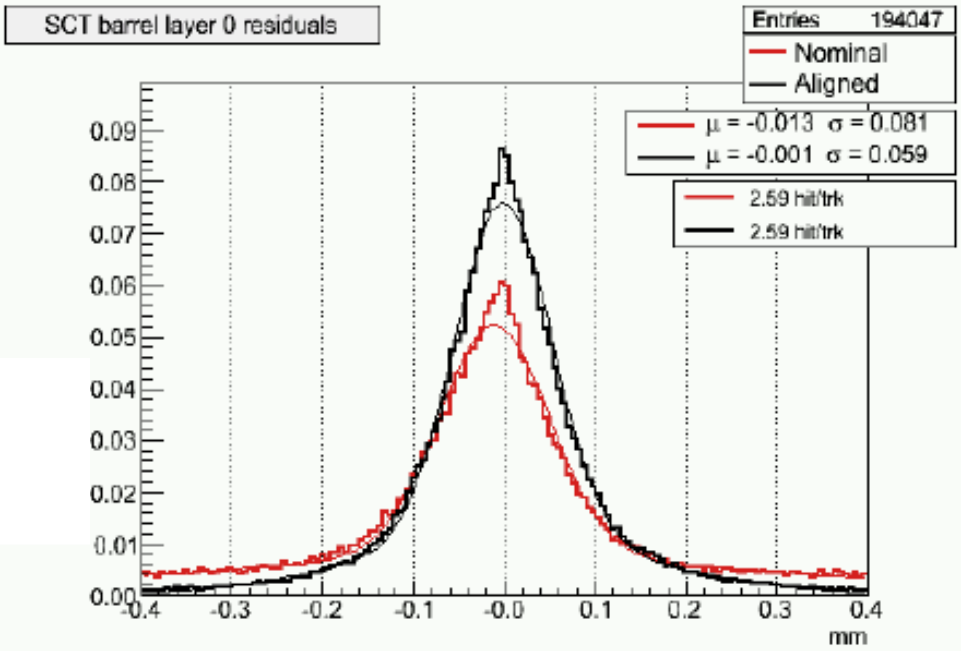
- Different ordering of symbols in chromosome:
  - Keeps the proximity of the genetic material during the translation process → expected lower destructive effect of the genetic operators
- Controlled evolution through fitness threshold
  - Eliminate the weak individuals from the evolution process
- Dynamic classification threshold
  - Threshold value adapted to each individual
- Improvements:
  - earlier convergence
  - slightly higher accuracy



J.Alison: Alignment of the ATLAS Inner Detector



- Trackers of LHC experiments are very complex detectors
- Very sensitive to mis-alignment
  - Directly affects physics measurements
- Comprehensive description of alignment algorithm
- First results with cosmic rays



Conclusion

- Large number of presentations: 26 Presentations
  - And another few which have been presented in track 1 !
  - Very high quality
  - Many posters as well !
- Large number of topics, on many diverse subjects
  - Not all were related to the LHC
  - Sorry for my LHC-bias !
- I was not be able to mention each presentation
  - Subjective choice
  - Apologies for not mentioning yours!