



Summary of Session 2

Christian Kiesling
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- A total of 27 talks were presented
- Thanks to the speakers for delivering high quality presentations
- Apologies for not being able to mention all due to time constraints

Session 2: Data Analysis – Algorithms & Tools

Analysis Frames (common Session 1 & 2)	3 talks:	René Brun, Valeri Tioukov, Jens Zimmermann
Mathematical Methods	6 talks:	Florent de Dinechin, Vladislav Matouchek, Miroslav Morhac, Wolfgang Rolke, Jens Zimmermann, Victor Zlokazov
Analysis Methods	3 talks:	Mostafa Mjahed, Are Strandlie, Andre van Hameren
Simulation	3 talks:	Frank Gaede, Daniel Pomarede, Andreas Schaelicke
Tracking	4 talks:	Sergey Gorbunov, Takanori Kohno, Thomas Speer; Are Strandlie
Reconstruction	4 talks:	Paulo Vitor Magacho da Silva, Jose Seixas, Sergey Gorbunov
Neural Networks	4 talks:	Aatos Heikkinen, Ulrich Kerzel, Mostafa Mjahed, Andrea Piccione

René Brun:

Bitmap Indices for Fast End-User Physics Analysis in ROOT

- ◆ Bitmap indices are efficient data structures for accelerating **multi-dimensional** queries
- ◆ Supported by most **commercial** database management **systems** and data warehouses

	$\pi_A(R)$	E^9	E^8	E^7	E^6	E^5	E^4	E^3	E^2	E^1	E^0	R^8	R^7	R^6	R^5	R^4	R^3	R^2	R^1	R^0
1	3	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	0	0	0
2	2	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	0	0
3	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
4	2	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	0	0
5	8	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
6	2	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	0	0
7	9	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
9	7	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
10	5	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0
11	6	0	0	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
12	4	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	0	0

list of attributes

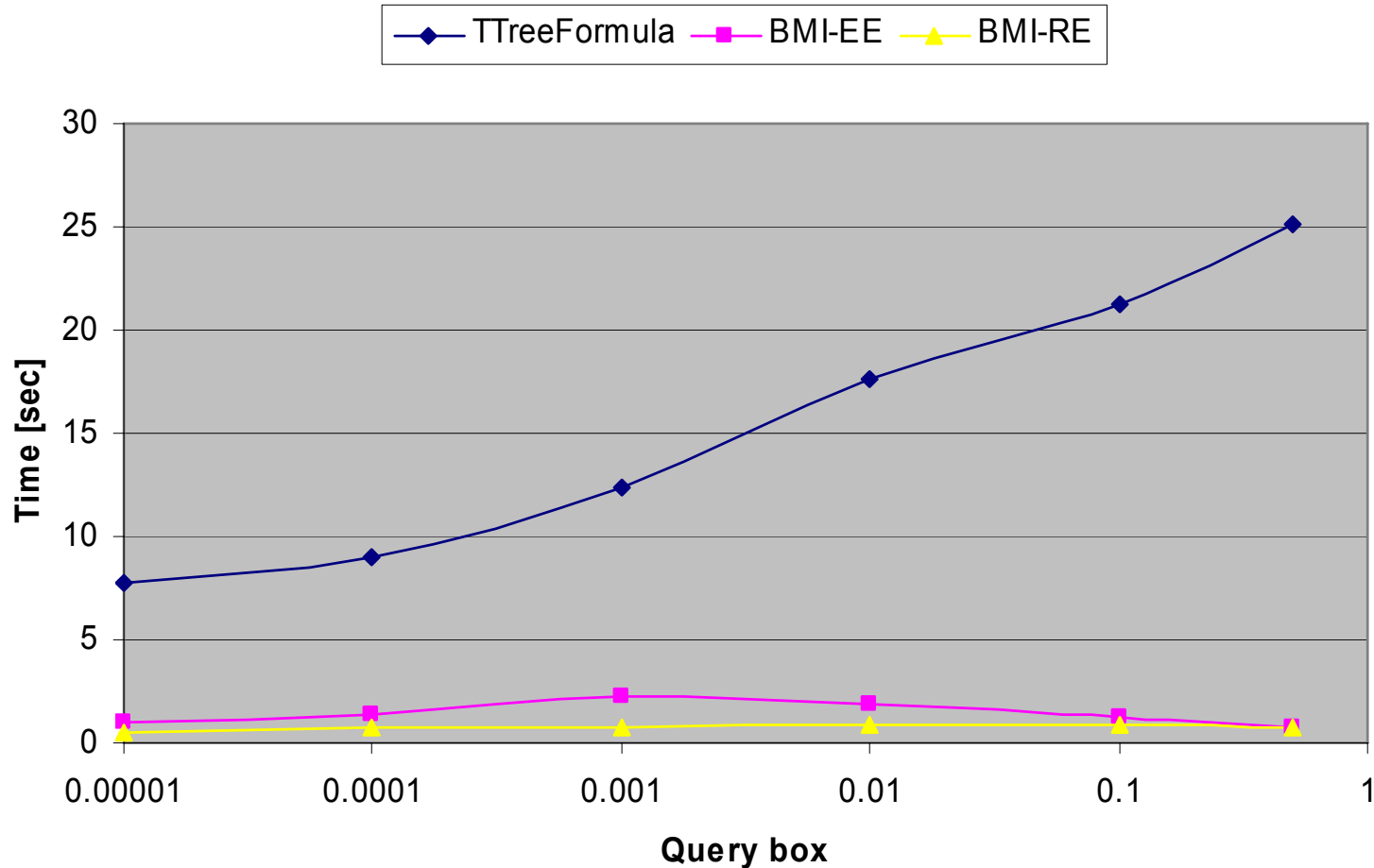
equality encoding

range encoding

(here: $a \leq 3$)

Query Performance - Approximate Answers (Error 0.1- 1%)

10-Dimensional Queries



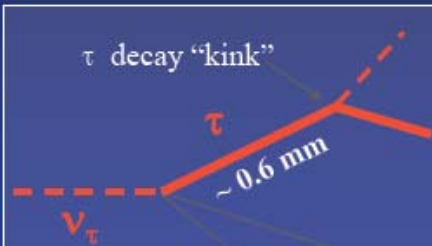
Performance improvement of bitmap indices over TTreeFormula up to a factor of 30.

Valeri Tioukov:

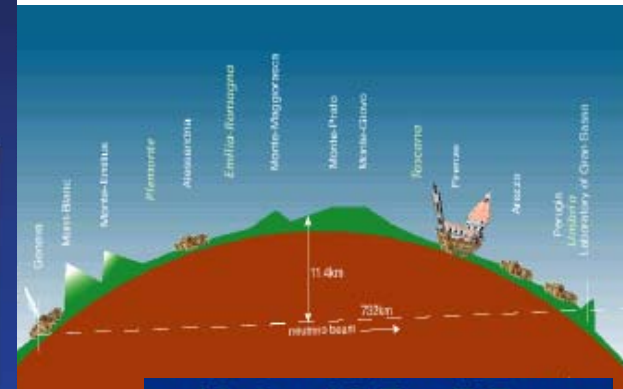
FEDRA – Framework for Emulsion Data Reconstruction and Analysis

Primary goal of OPERA:

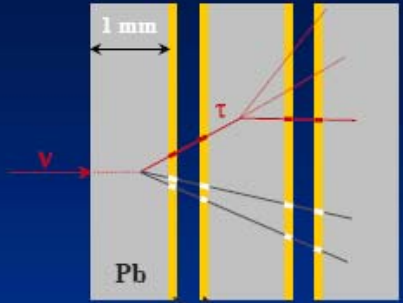
direct observation of τ leptons produced in ν_τ^{CC} interactions



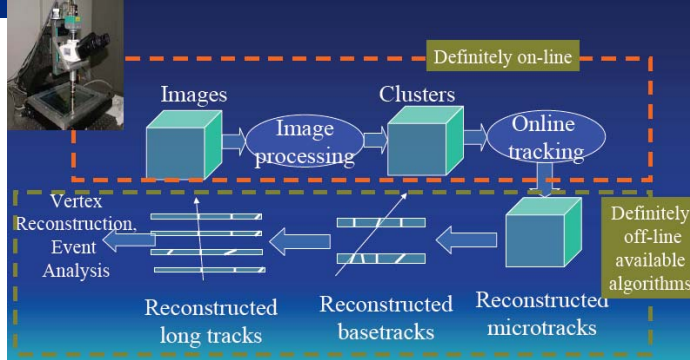
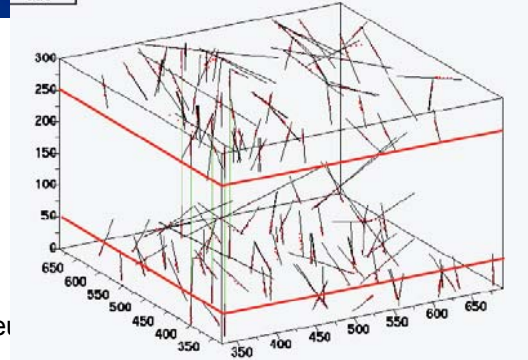
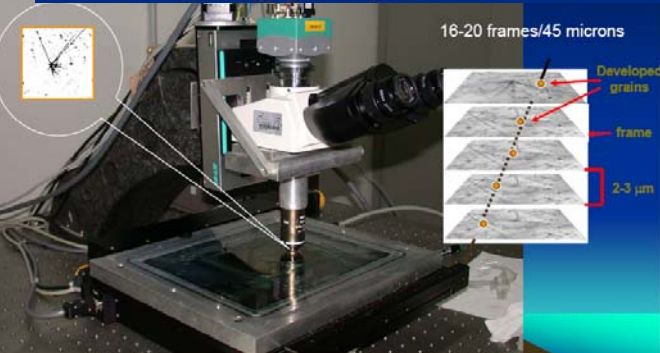
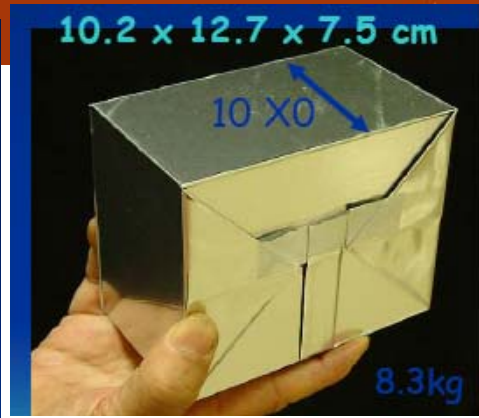
Detector resolution must be $O(1 \text{ mm})$



OPERA emulsion target



- Based on the concept of the Emulsion Cloud Chamber (**ECC**)
- **56 Pb sheets 1mm + 57 emulsion plates**
- Solves the problem of compatibility of large mass for neutrino interactions + high space resolution in a completely **modular** scheme



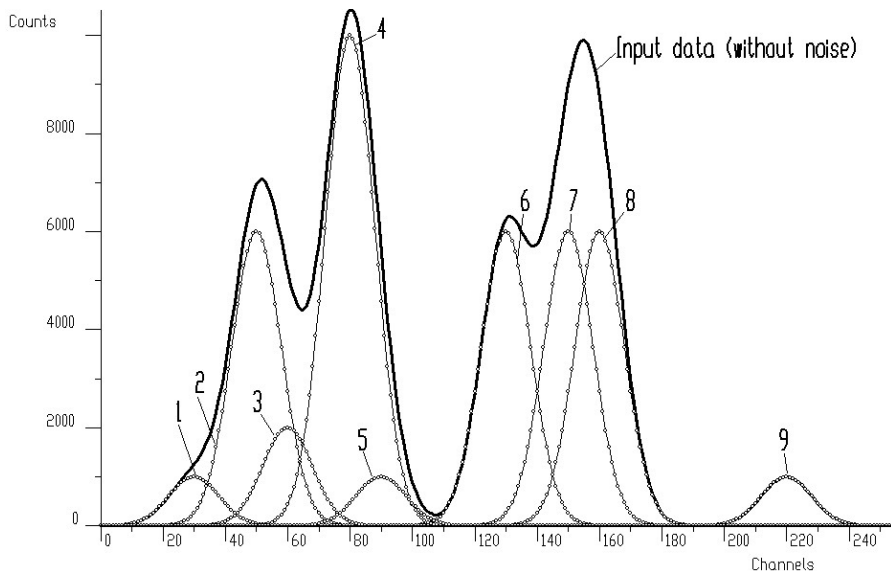
Basic FEDRA modules

libraries of C++ classes based on ROOT structures

Neutrino vertexes with background
fast simulation with EMC to test vertex finding and fitting

High level emulsion data order GeV/event
Analysis & visualization in C++ (ROOT framework)
System used for test-beams & simulation

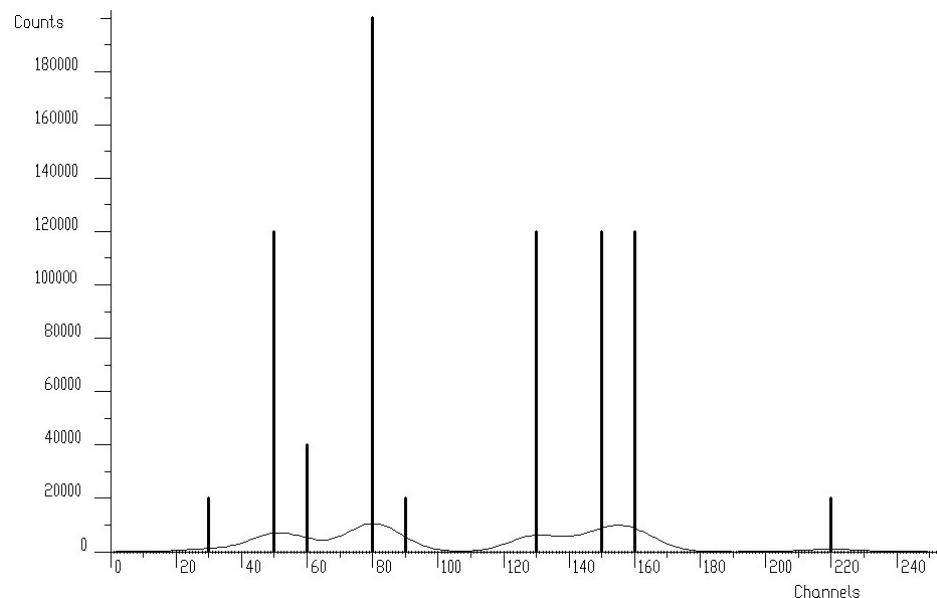
V. Matoušek and M. Morháč: Efficient Algorithms of Multidimensional γ Ray Spectra Compression/Deconvolution



- Extraction of the correct physics from experimental spectra:
- limited resolution: overlapping signals deconvolution and decomposition
- remove smearing effects using known resolution function

Data compressed,
e.g., with Walsh transform

proposed new high-resolution peak
searching algorithm based on
Gold deconvolution for one- and
two-dimensional spectra.



Wolfgang Rolke: Setting Limits in the Presence of Nuisance Parameters

How do we set limits on a signal rate ?

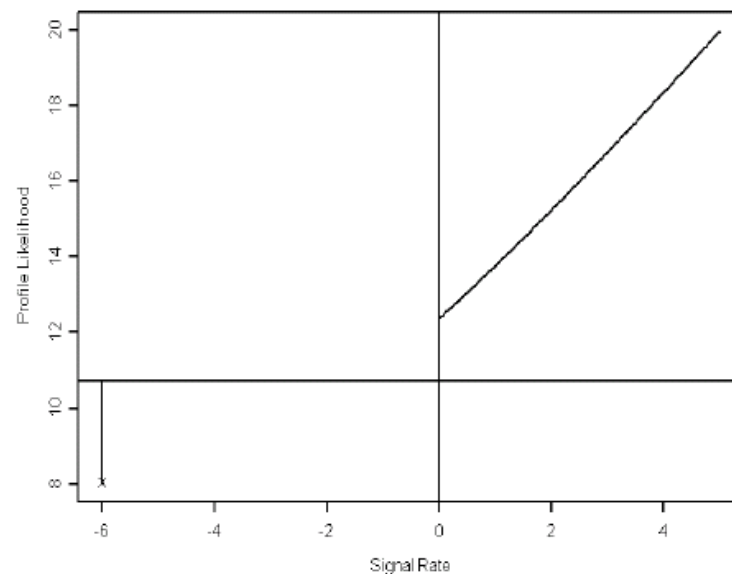
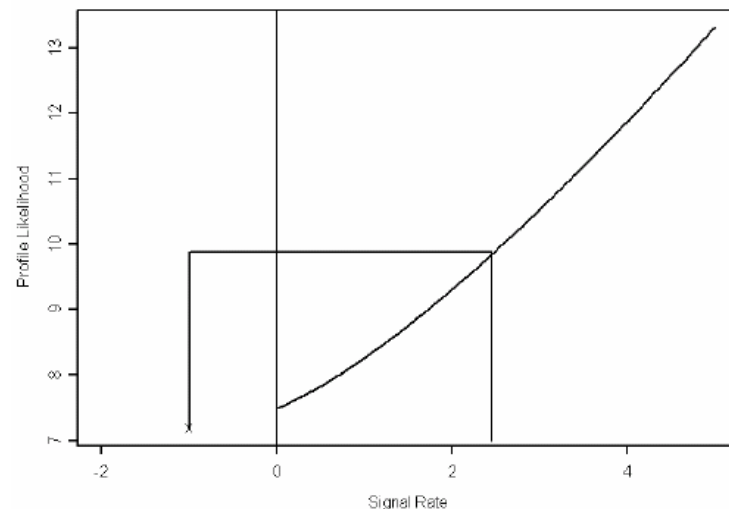
Generally: x in signal region
 $y \pm \Delta y$ in sidebands (background)
 $\varepsilon \pm \Delta\varepsilon$ (signal efficiency)

Problem already solved in MINUIT

BUT:
What if observed rate is below expected background ?

→ Profile Likelihood

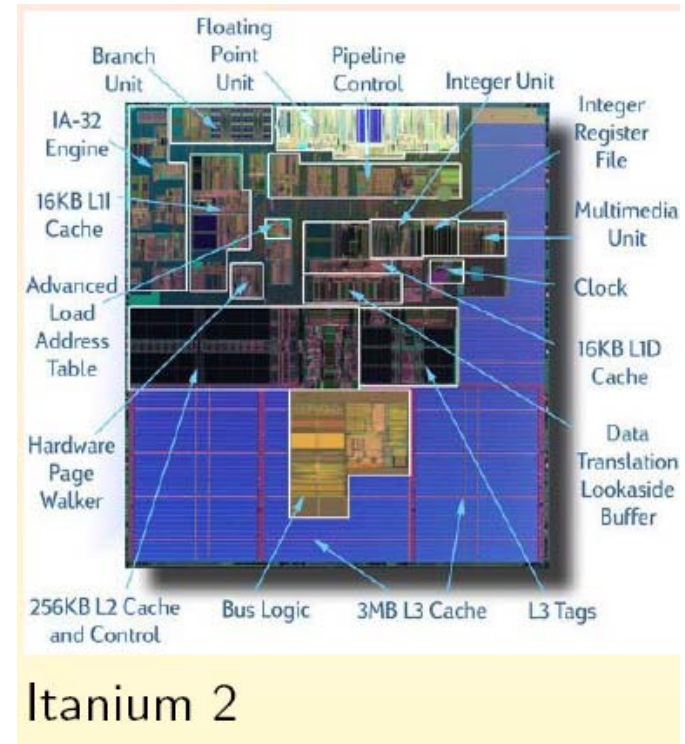
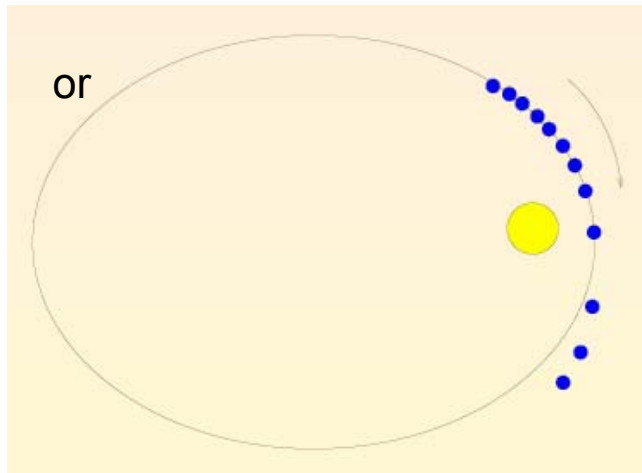
Method implemented as ROOT class



Florent de Dinechin: High Precision numerical Accuracy in Physics Research

Double Precision not enough?

Add more than 10^{15} numbers

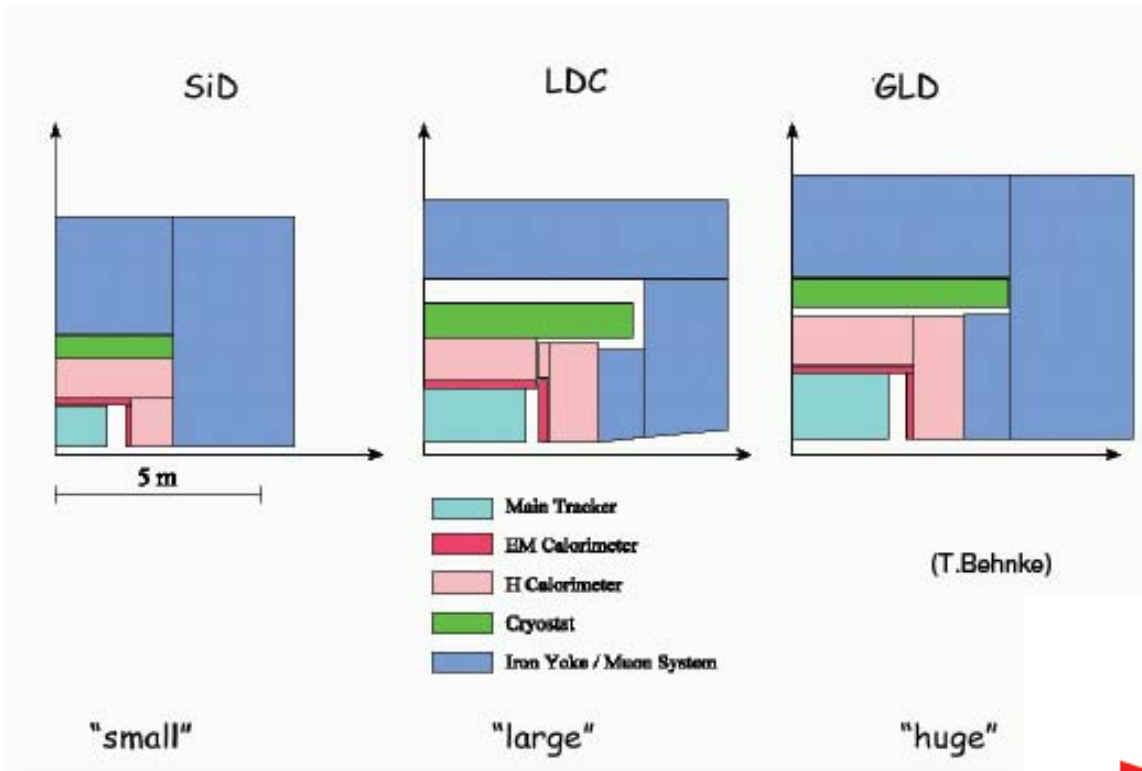


Implement Quad Precision in Software ?

Yes! More flexible (still double OK for most calculations)

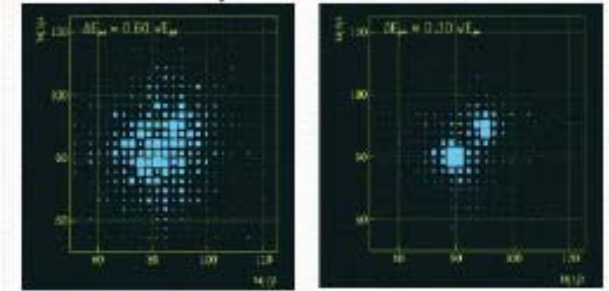
BUT: feasible also for very large codes ?

Frank Gaede: Simulation and Reconstruction Software for the ILC



three interregional
detector concept
studies ongoing

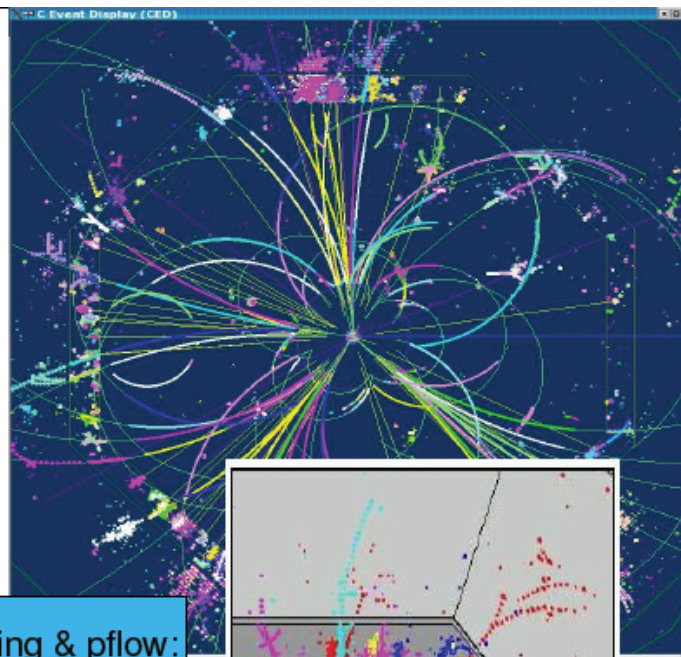
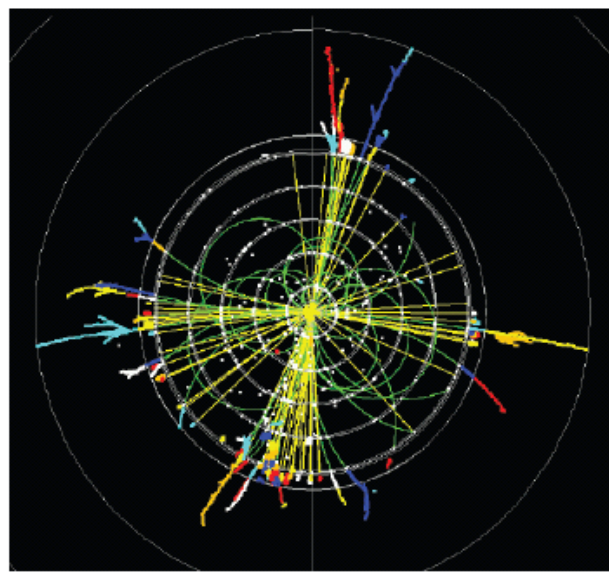
WW-ZZ separation



Need common **Simulation and Reconstruction**
software to study detector concepts' performance !

Particle Flow

- reconstruct all single particles
- use tracker for charged particles
- use Ecal for photons
- use Hcal for neutral hadrons



Need software tools to improve clustering & pflow:

- detailed hadronic shower simulation (**Geant4**)
- framework for developing and comparing pflow algorithms

A Common Software Framework for the ILC ?

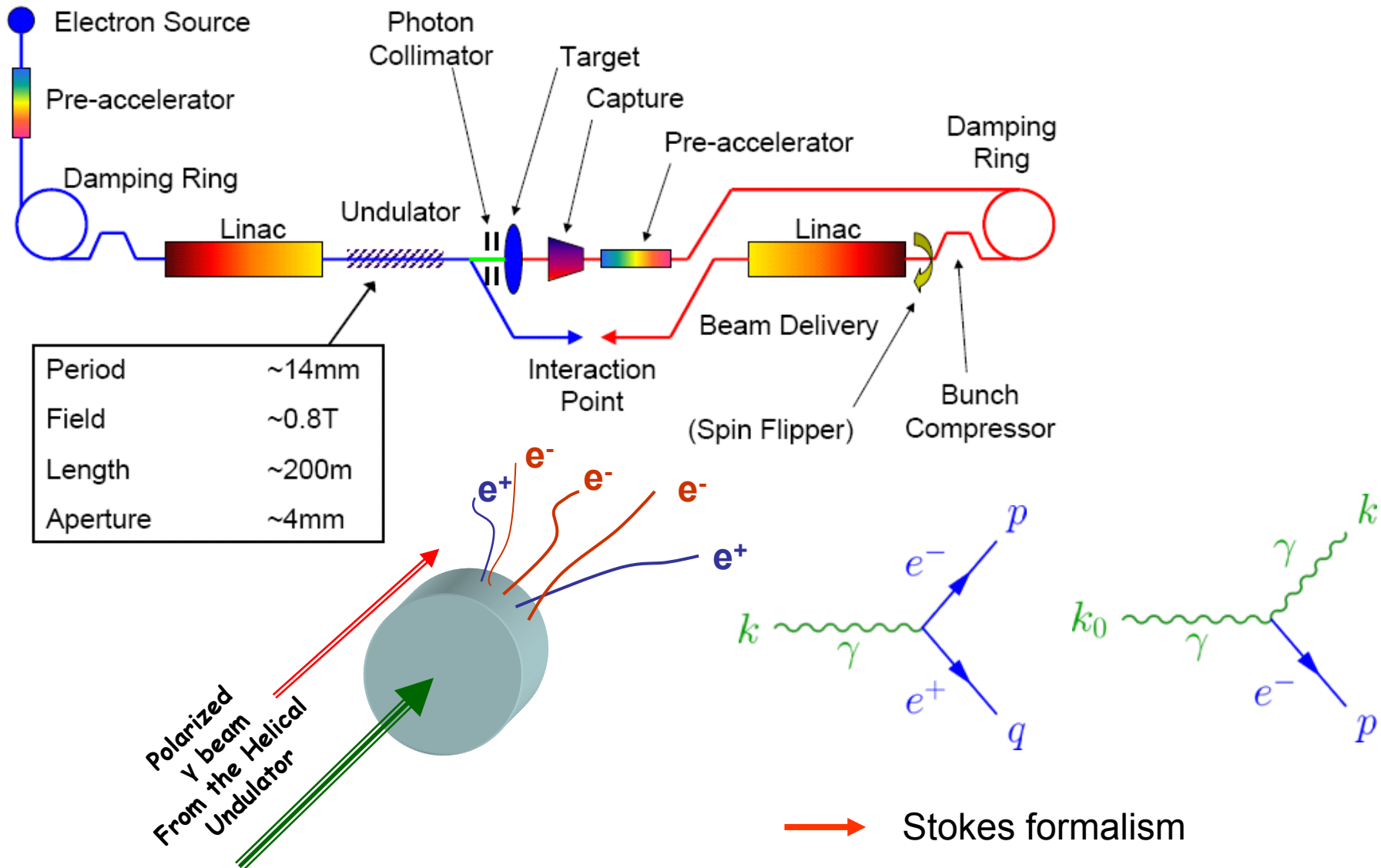
→ **M**odular **A**nalysis & **R**econstruction for the **LIN**ear Collider

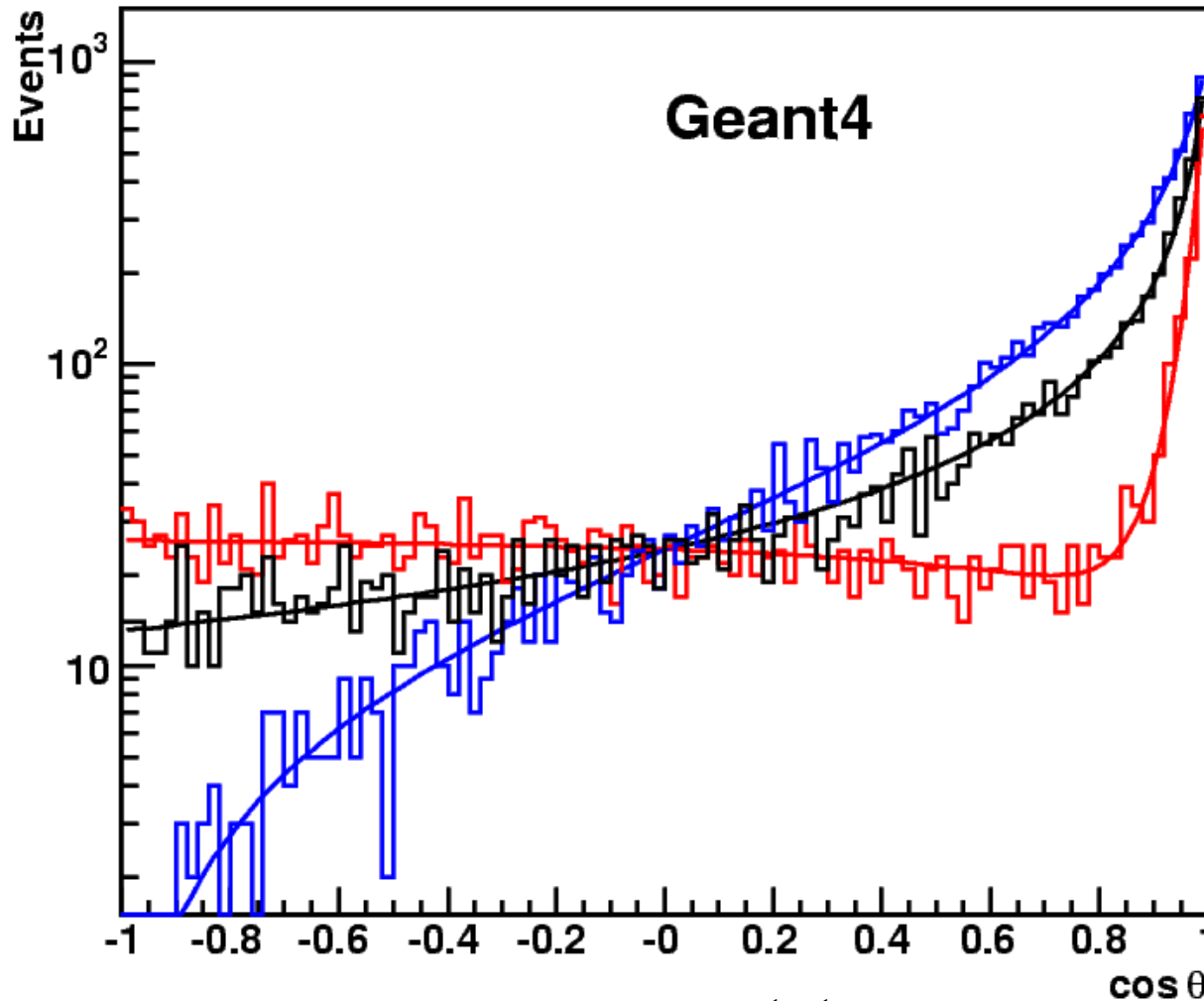
C++, Java

Holy grail: have an internationally used common software framework for the ILC that is used to support R&D and the detector concept studies !

	Description
Simdet	fast Monte Carlo
SGV	fast Monte Carlo
Lelaps	fast Monte Carlo
Mokka	full simulation – Geant4
Brahms-Sim	Geant3 – full simulation
SLIC	full simulation – Geant4
LCDG4	full simulation – Geant4
Jupiter	full simulation – Geant4
Brahms-Reco	reconstruction framework (most complete)
Marlin	reconstruction and analysis application framework
hep.lcd	reconstruction framework
org.lcsim	reconstruction framework (under development)
Jupiter-Satelite	reconstruction and analysis
LCCD	Conditions Data Toolkit
LCIO	Persistency and datamodel
JAS3/WIRED	Analysis Tool / Event Display

Andreas Schälicke: Monte Carlo based studies of polarized positrons source for the International Linear Collider (ILC)





Polarized:

← $P_e = +1$
 ← $P_\gamma = +1$

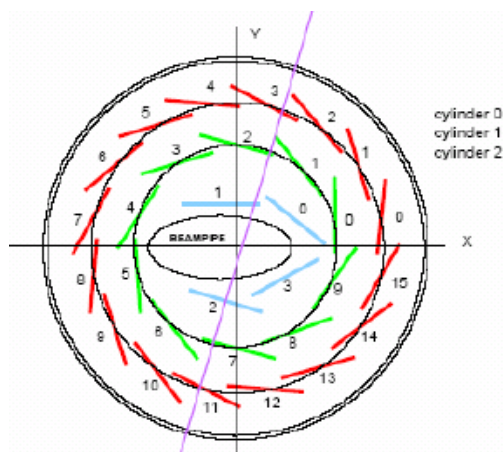
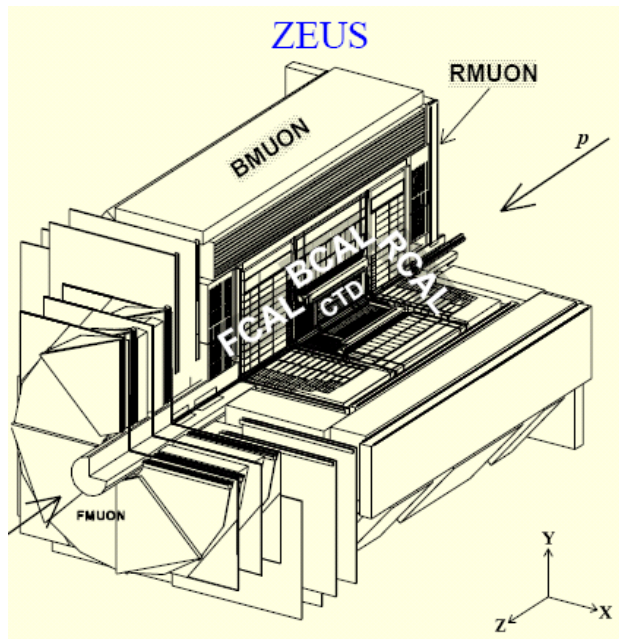
→ $P_e = -1$
 ← $P_\gamma = +1$

Unpolarized:

← $P_e = 0$
 → $P_\gamma = 0$
 ← $P_e = 0$
 → $P_\gamma = 0$

→ next steps:
 compare with EGS4, experimental results (E166)

Takanori Kohno: Alignment of the ZEUS MVD with Cosmic Rays



determine:

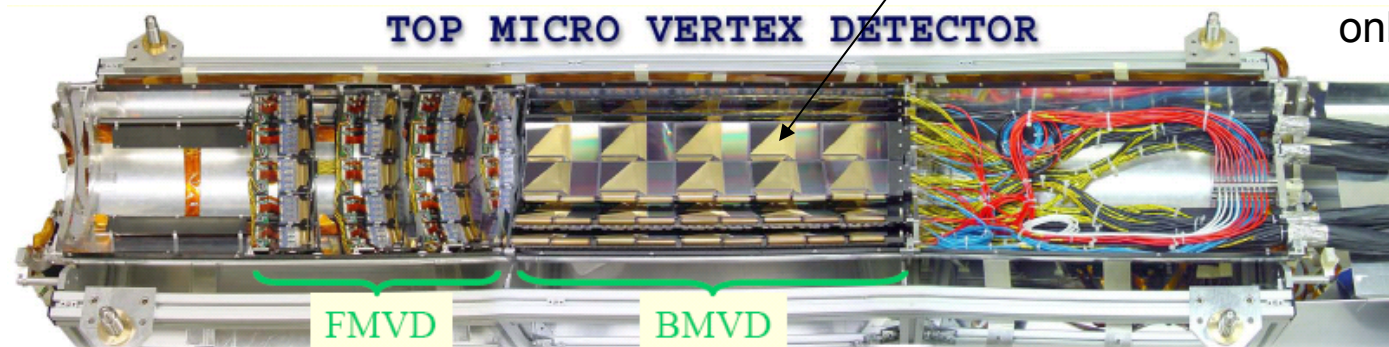
- relative position of ladders
- absolute position in ZEUS

Goal:

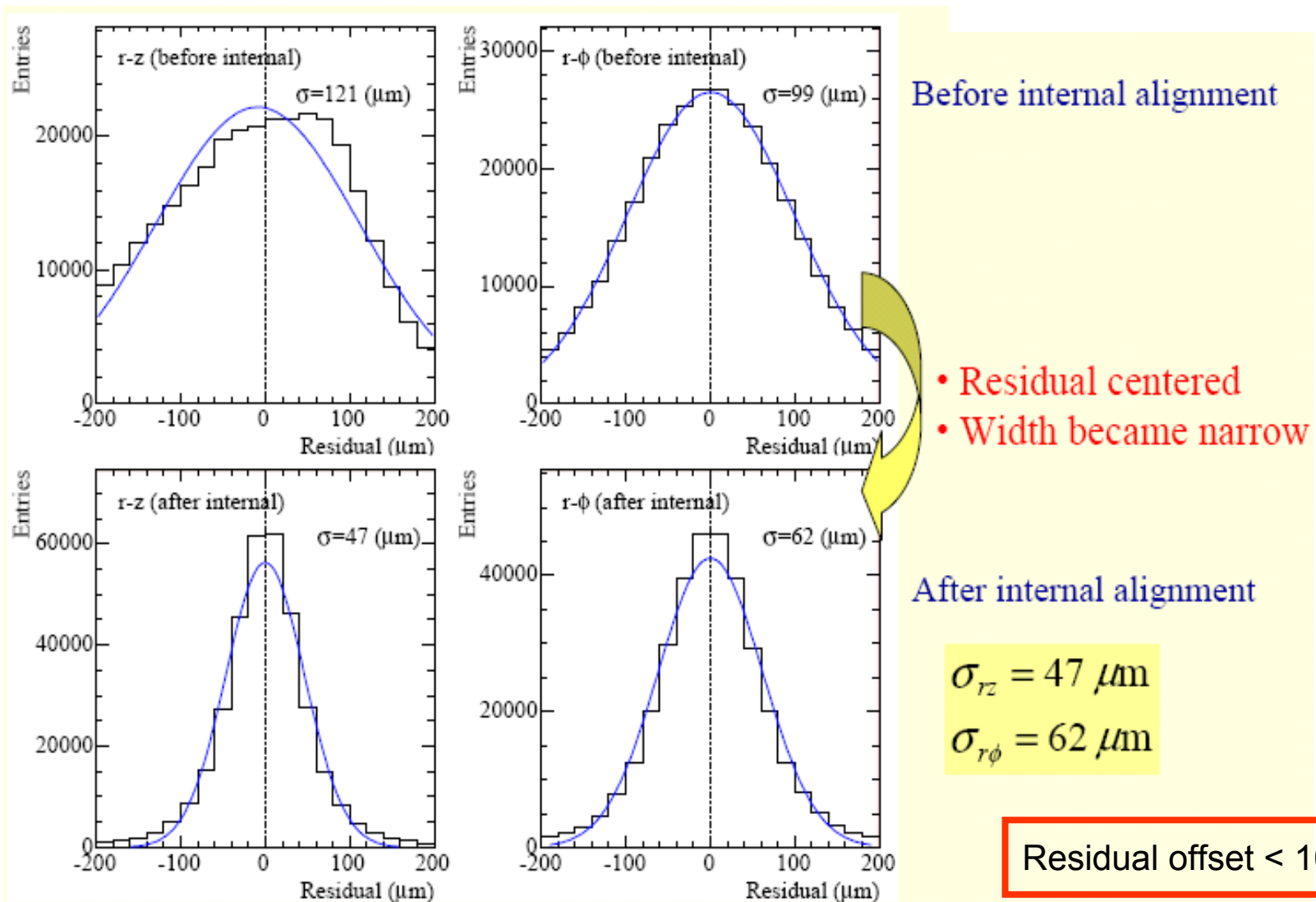
alignment precision $< 10 \mu\text{m}$

„ladders“

Cosmics:
only useful for
barrel



Effect of alignment procedure on residuals:
(local χ^2 minimation with linear approximation)



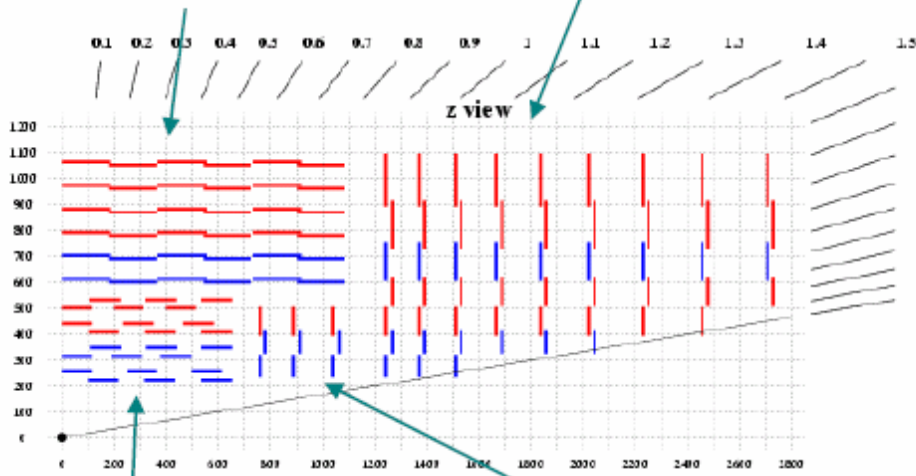
Thomas Speer: Track Reconstruction in the CMS Detector

Outer Barrel (TOB): 6 layers

- Thick (500 μm) sensors
- Long Strips

Endcap (TEC): 9 disks pairs

- $r < 60\text{cm}$: Thin sensors
- $r > 60\text{cm}$: Thick sensors

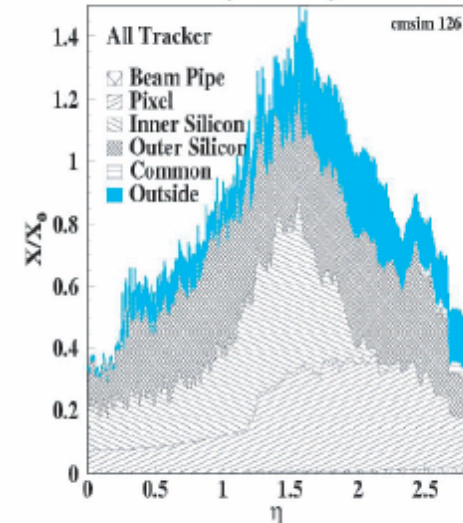


Inner Barrel (TIB): 4 layers

- Thin (320 μm) sensors
- Short Strips

Inner Disks (TID): 3 disks pairs

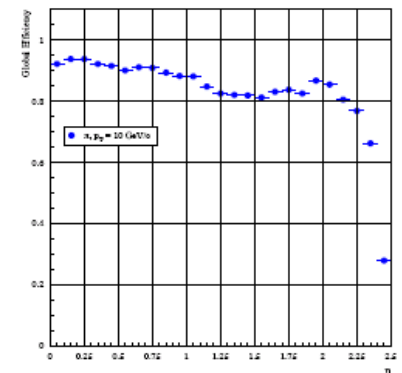
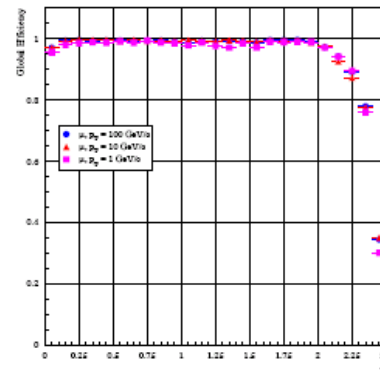
- Thin sensors



Material budget of the tracker

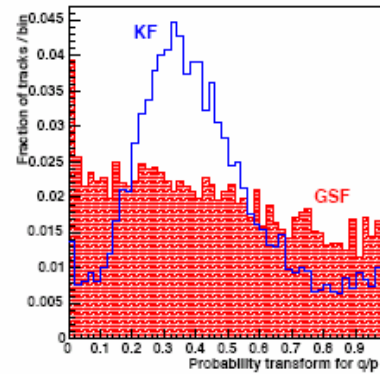
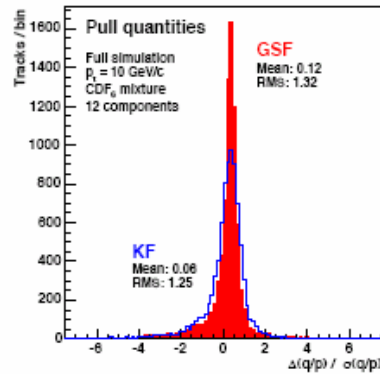
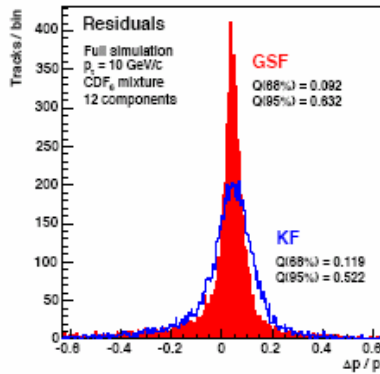
muons, $p_T = 1, 10, 100 \text{ GeV}/c$

pions, $p_T = 10 \text{ GeV}/c$



→ Combinatorial Kalman Filter
(equivalent to least squares fit)
efficient even for non-Gaussian errors

The Gaussian-sum Filter (non-linear generalization of KF)



non-Gaussian tails in hit residuals (multiple Coulomb scat.)

can improve core of distributions, little improvement in tails (→ first layer radiation)

Adaptive Filters:

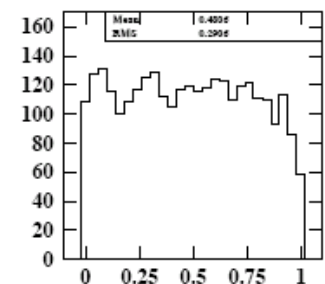
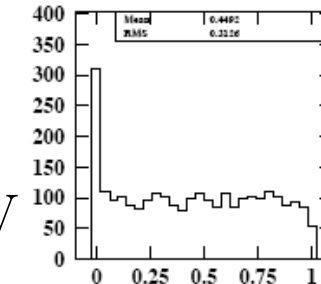
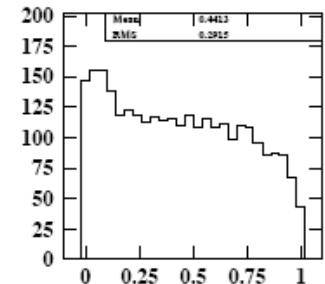
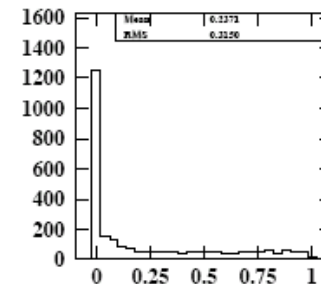
- Deterministic Annealing Filter (DAF)
- Multi-track fit (MTF)

→ both need hit collection and track seeds

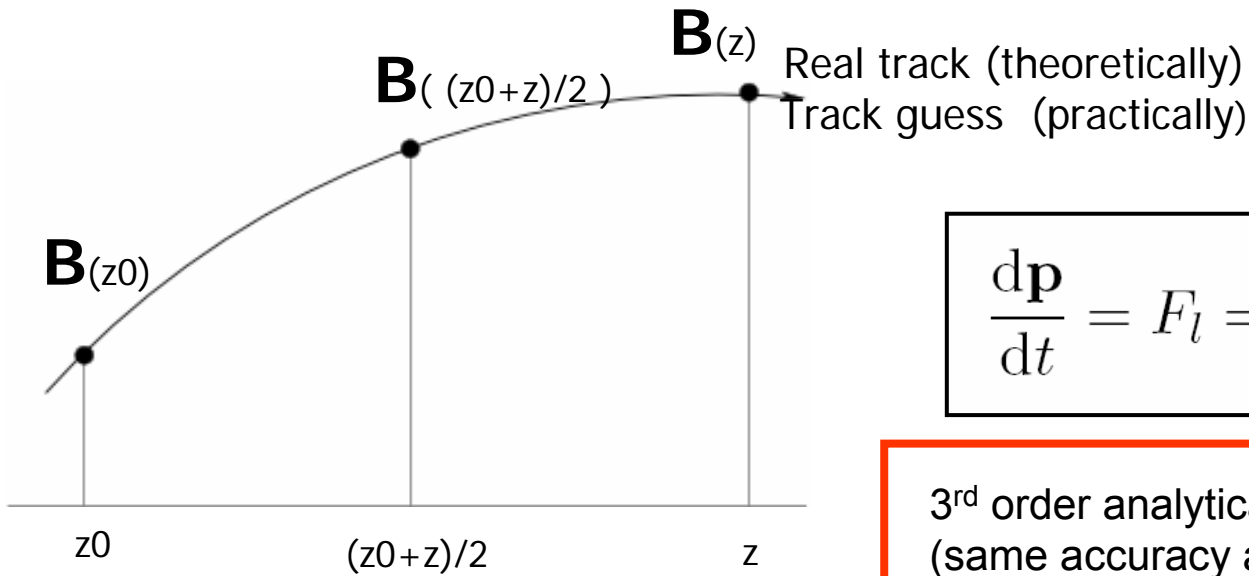
Bench mark : $H \rightarrow \tau^+ \tau^-$ $M(H) = 500$ GeV

→ Improvement in high track density

χ^2 probability

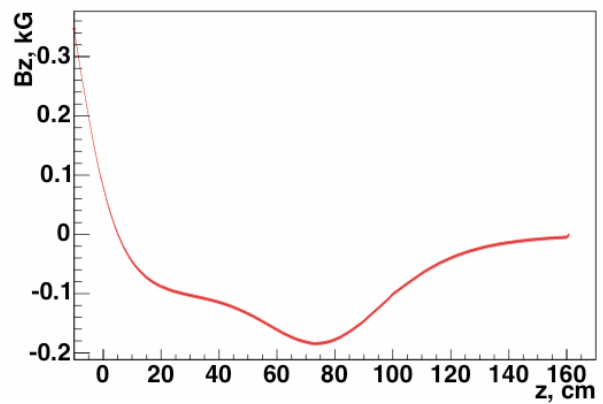
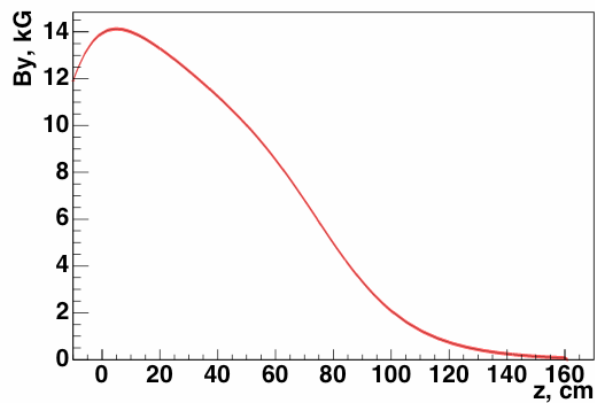
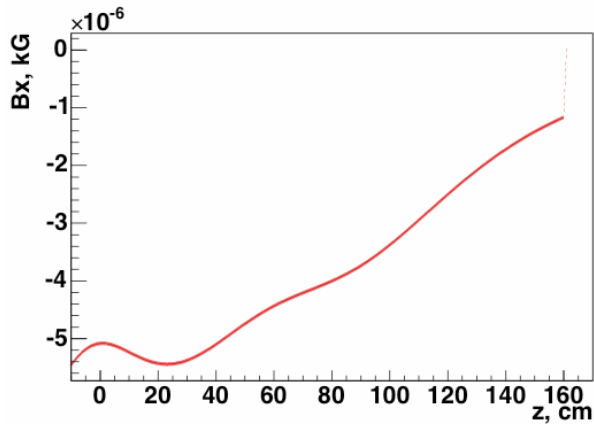


Sergey Gorbunov: Analytical Formula for Track Extrapolation in an Inhomogeneous Magnetic Field

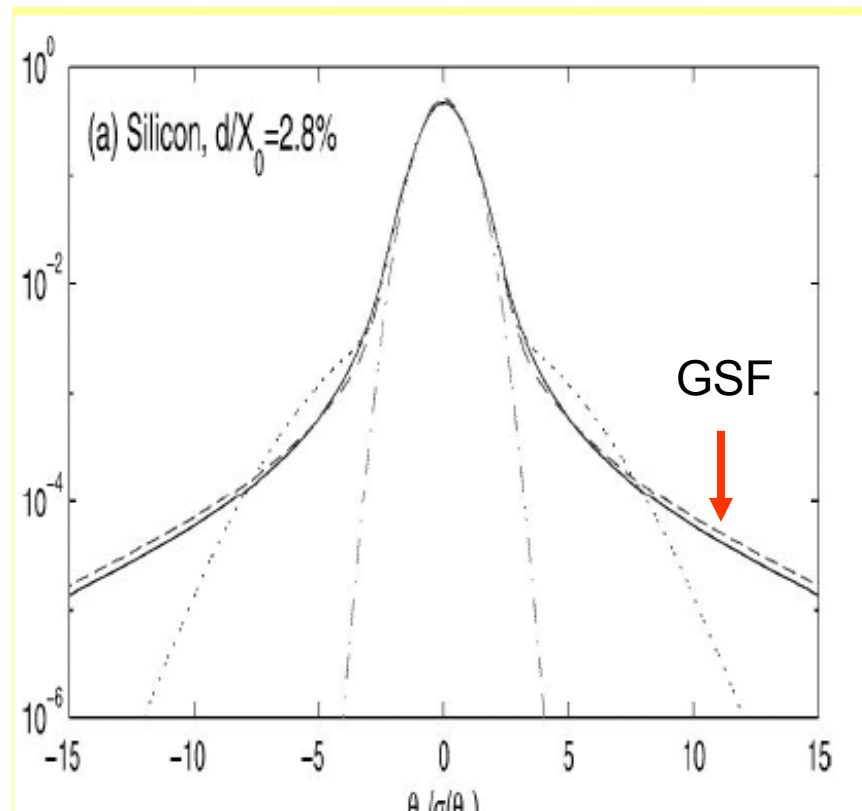
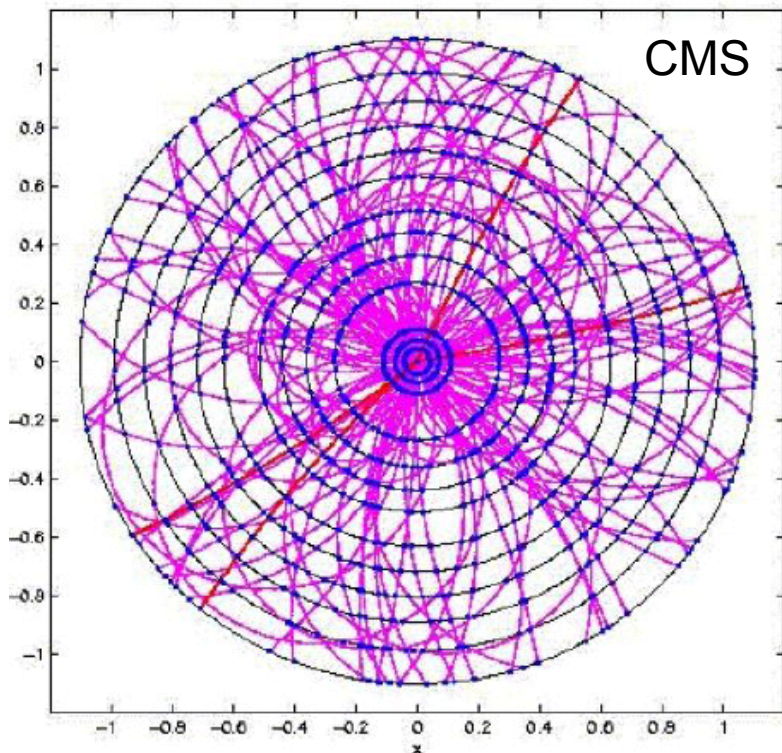


$$\frac{d\mathbf{p}}{dt} = F_l = \kappa \cdot q \cdot \mathbf{v} \times \mathbf{B}$$

3rd order analytical formula
 (same accuracy as 4th order Runge-Kutta)



Are Strandlie: Modeling non-Gaussian Tails of Multiple Coulomb Scattering in Track Fitting with GS-Filter



Treatment of non-Gaussian tails implemented in simple detector geometry

Standard method: Kalman Filter

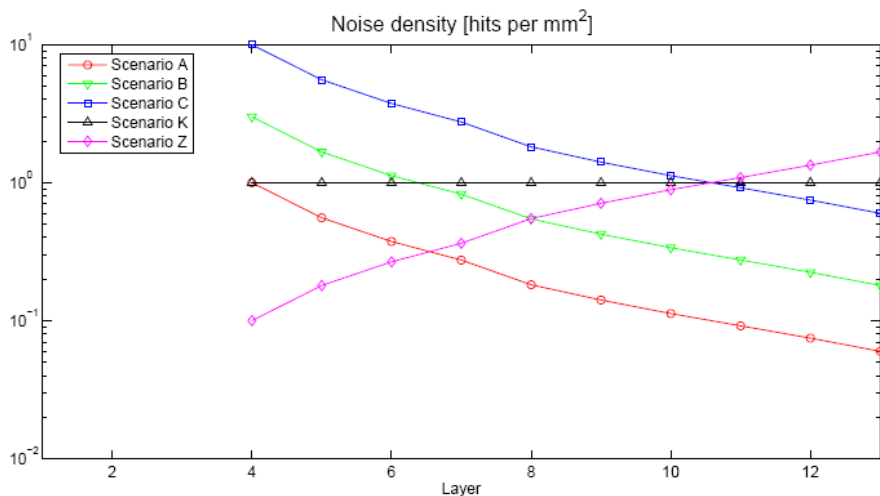
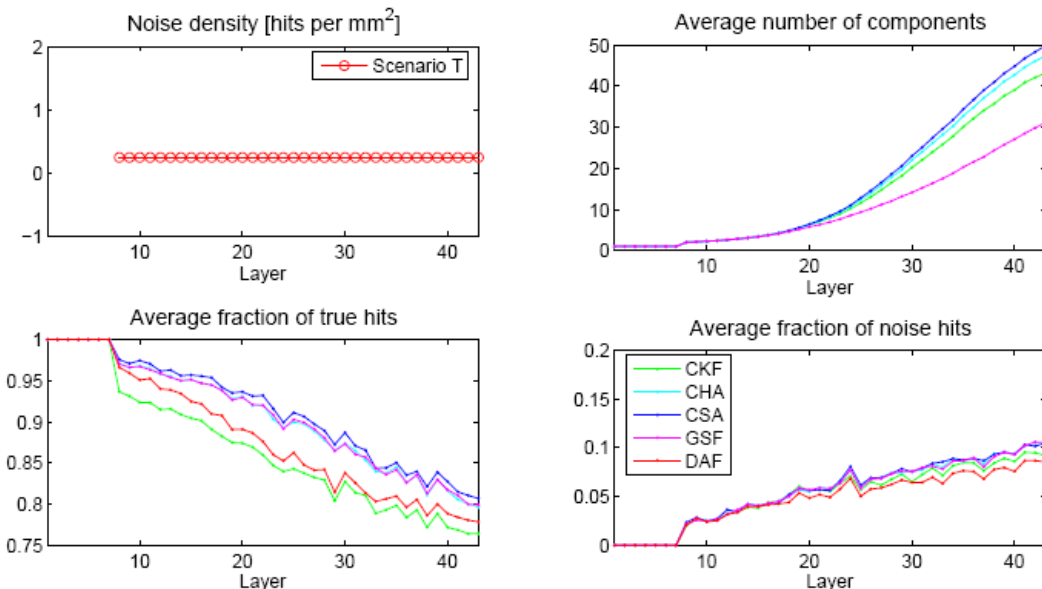
Gaussian Sum Filter slightly more precise than KF

Are Strandlie: Adaptive Filters for Track Finding

Filters studied:

- Combinatorial Kalman Filter („standard filter“ with seeds)
- Competition with hard/soft assignment
- Gaussian Sum Filter
- Deterministic Annealing Filter

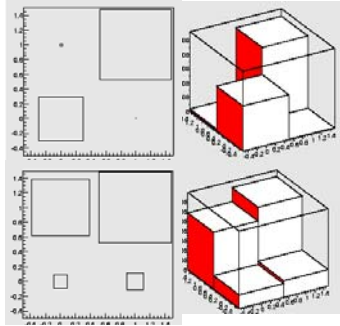
Example: ATLAS tracker



Method	CKF	CHA	CSA	GSF	DAF
Avg. true hits	37.4	39.1	39.4	39.1	38.0
Avg. noise hits	2.23	2.36	2.39	2.35	2.04
Avg. missg hits	3.40	1.56	1.25	1.56	2.97
Efficiency	0.97	0.99	1.00	0.99	1.00
Time per seed ¹	1.00	1.10	1.18	0.33	0.06
Fake rate	0.01	0.03	0.54	0.03	0.02
Time per seed ²	0.14	0.16	0.64	0.08	0.06

Scenario T

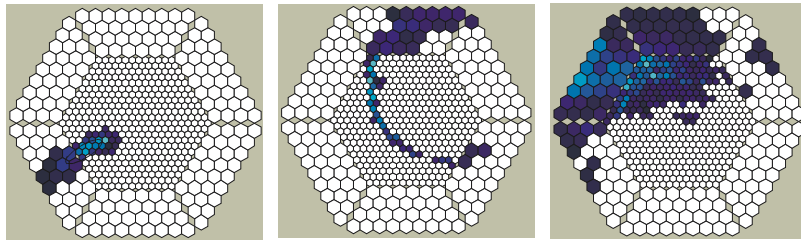
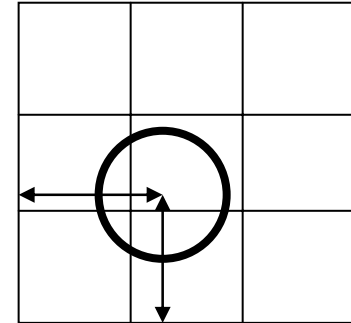
Jens Zimmermann: Statistical Learning Methods



Pileup vs. Single photon



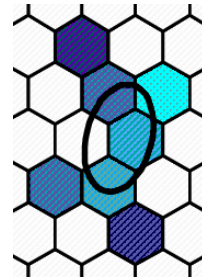
Reconstruction of the incident position with subpixel resolution



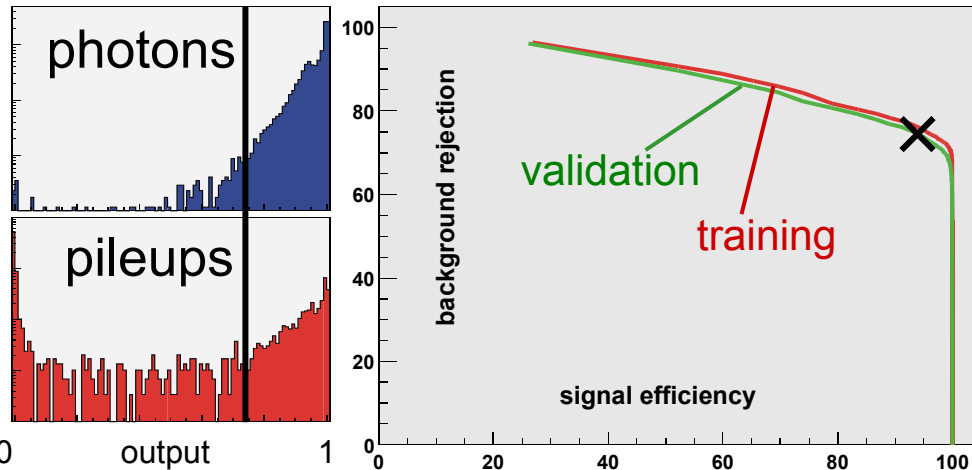
Gamma vs. Myon vs. Hadron event



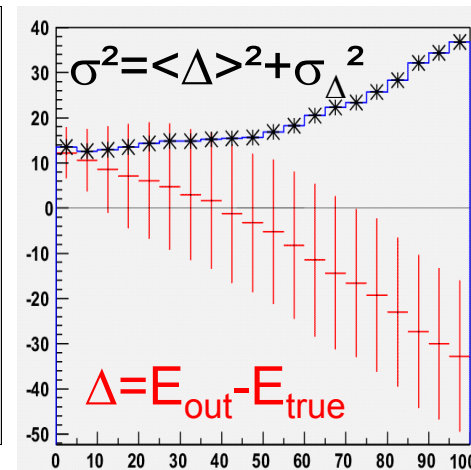
Reconstruction of the primary photon energy



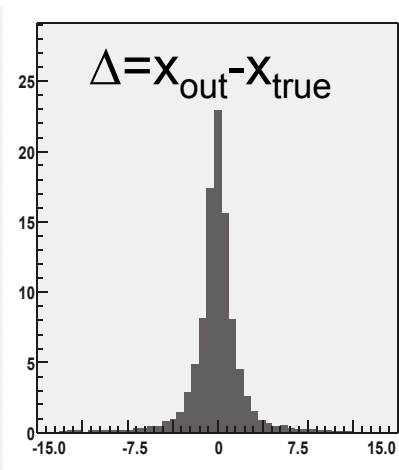
XEUS – Photon recognition



MAGIC – E[GeV]



XEUS – x[μm]

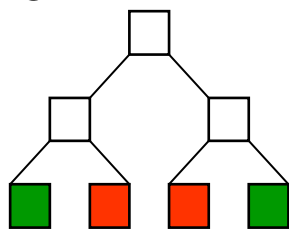


Decision Trees

C4.5

CAL5

CART



Local Density Estimators

k-Nearest Neighbours

Naïve Bayes
"Maximum Likelihood"

Linear Separation

Linear
Discriminant
Analysis

Support Vector Machine

Neural Network

Meta Learning Strategies

Bagging

Boosting

Random
Subspace

implemented in unified system

Systematic Uncertainties: Comparison of the Performance of Statistical Learning Methods

NN: 96.5% vs. SVM: 95.7%

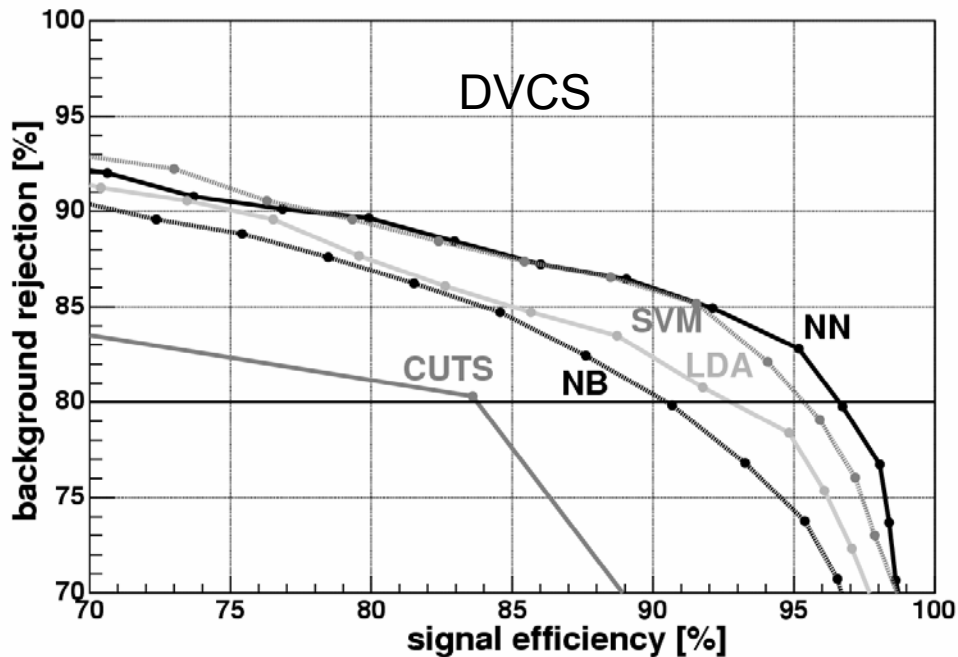
Statistically significant?

Build 95% confidence interval!

$$[\mu - z\sigma_\mu, \mu + z\sigma_\mu]$$

σ_μ is the variation over different parts of the test set

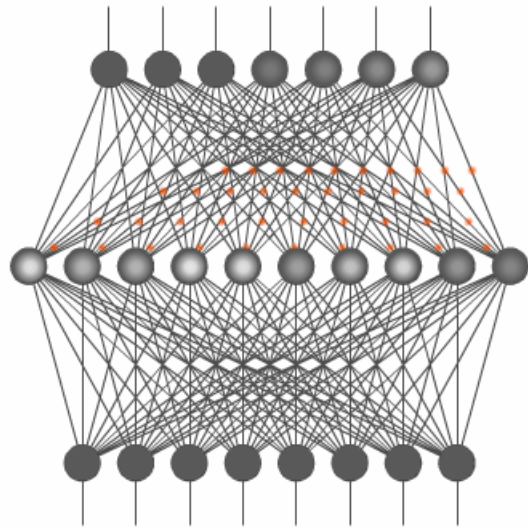
n	3	4	5	6	7	8	9	10	11	12	13	14	15
z	2.39	2.64	2.81	2.94	3.04	3.14	3.20	3.26	3.32	3.37	3.41	3.45	3.49



Neural Network	96.5%
$\Delta = 0.7\% \pm 0.9\%$	
Support Vector Machine	95.7%
$\Delta = 3.3\% \pm 1.5\% (!)$	
Linear Discriminant Analysis	92.5%
$\Delta = 2.2\% \pm 2.1\% (!)$	
Naive Bayes	90.5%
$\Delta = 6.8\% \pm 2.5\% (!)$	
Cuts	83.6%

efficiencies for fixed rejection of 80%

Ulrich Kerzel: The NeuroBayes Neural Network Package

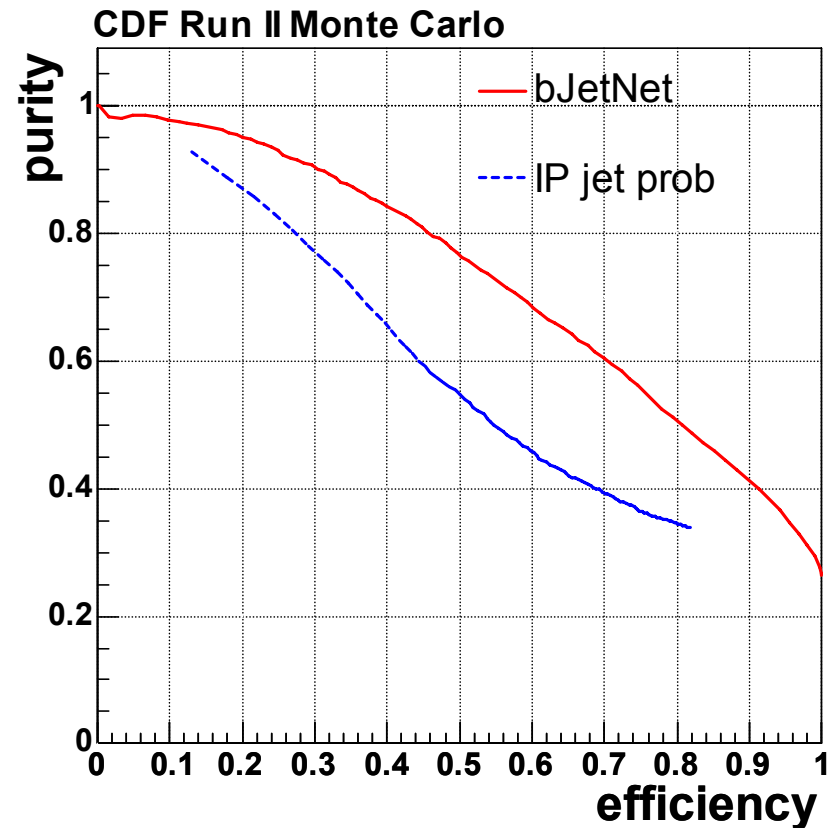


Outputs („probabilities“)

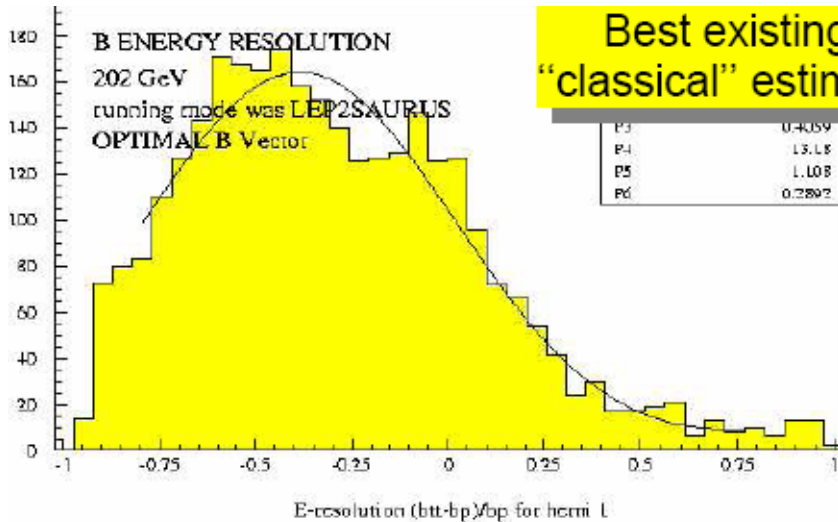
Inputs
(preprocessing)

Input: „intelligent“ variables,
e.g. jet variables

- Bayesian regularization
- Simple networks, small weights
- Remove non-significant nodes during training

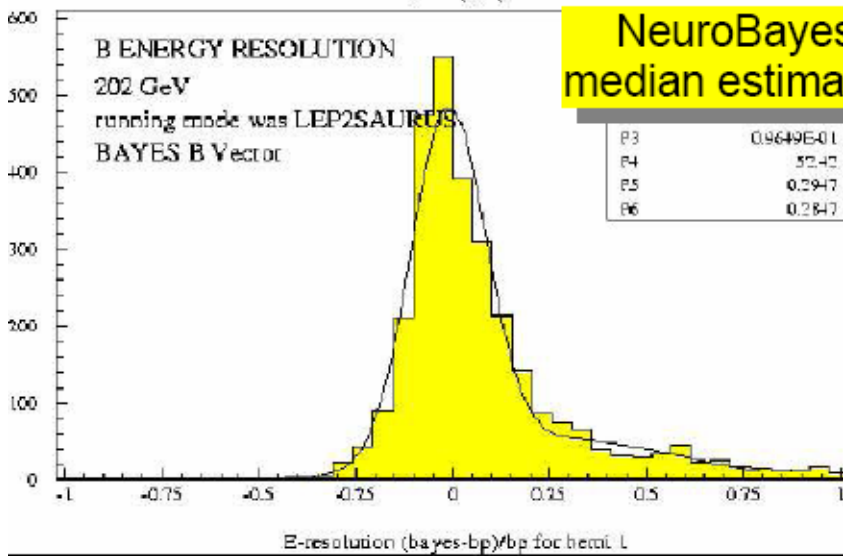


Recent real world application



Best existing
"classical" estimator

Relative resolution of reconstructed B hadron energy in DELPHI at LEP II at 202 GeV energy
(completely inclusive)



NeuroBayes
median estimator

core resolution
40% -> 10%

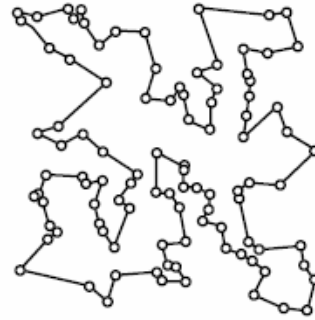
Spin-off: commercial applications
Company founded:
medicine, insurances, banks, ...

Sergey Gorbunov: Elastic Neural Net for Standalone Rich Ring Finding

→ collective selforganization networks (unsupervised learning + neighbor relations)

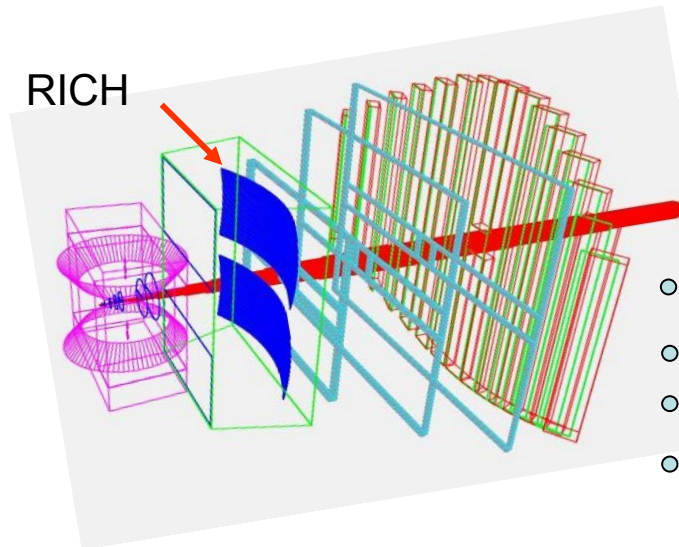


travelling salesman problem



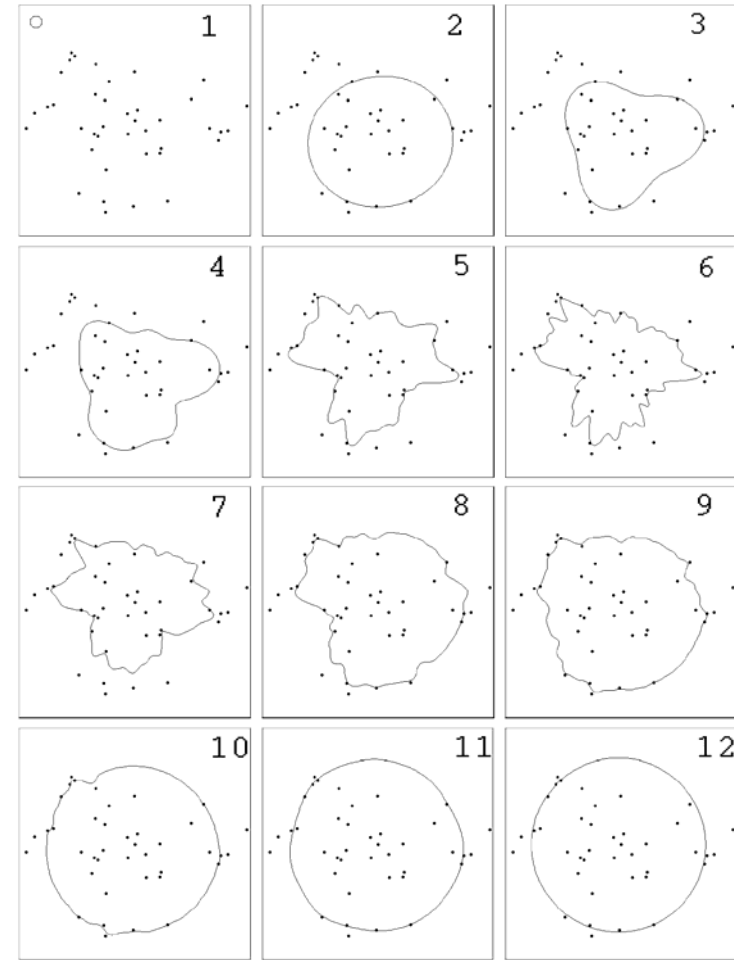
CBM-experiment (GSI)

RICH

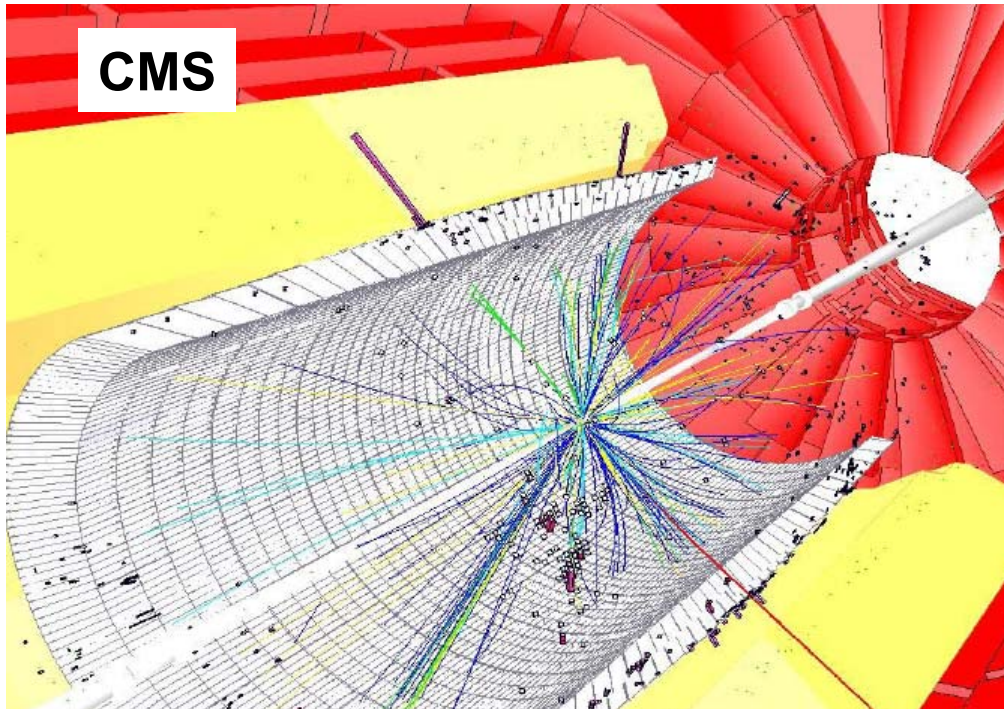


Few iterations
necessary to
find solution

- standalone
- simple
- efficient (92 %)
- Fast (1ms)



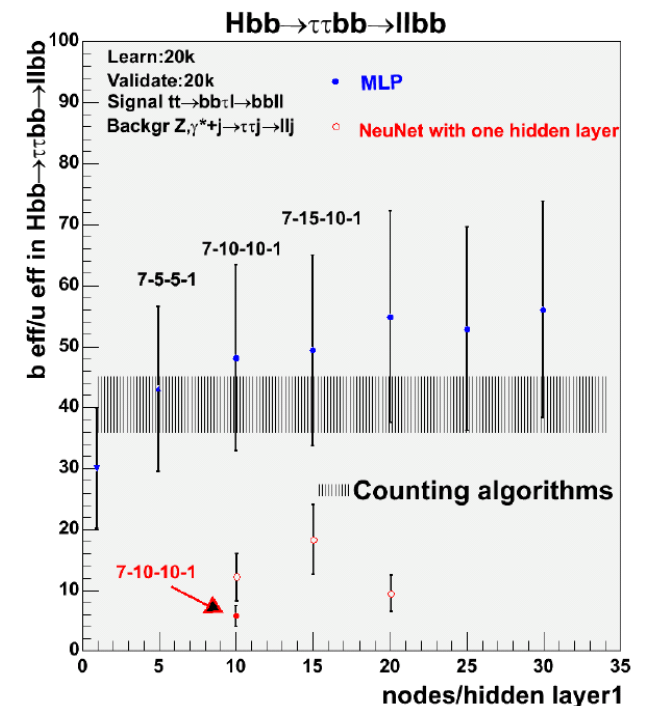
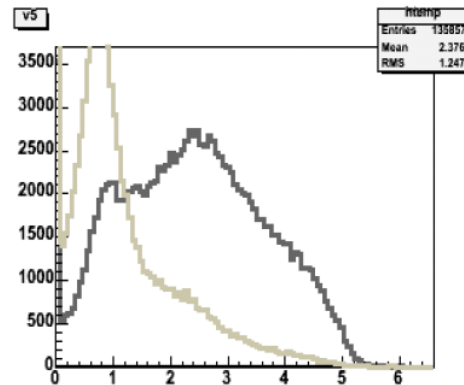
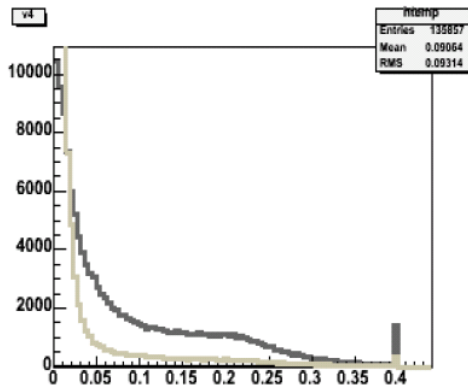
Aatos Heikkinen: Tagging b Jets Associated with Heavy Neutral MSSM Higgs Bosons



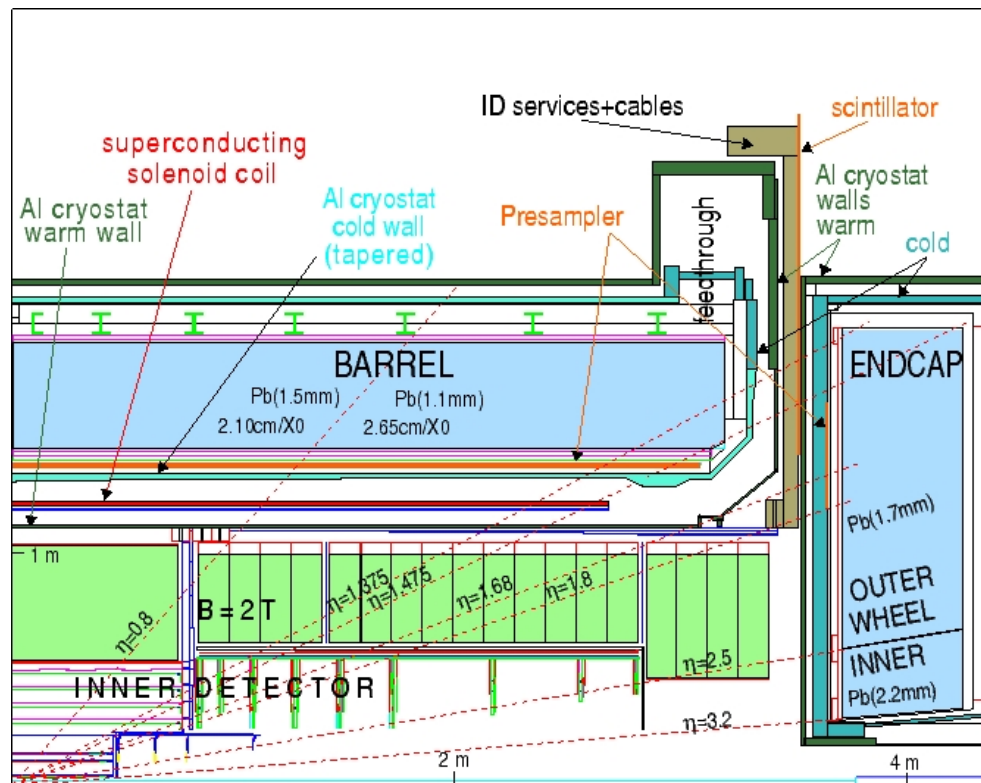
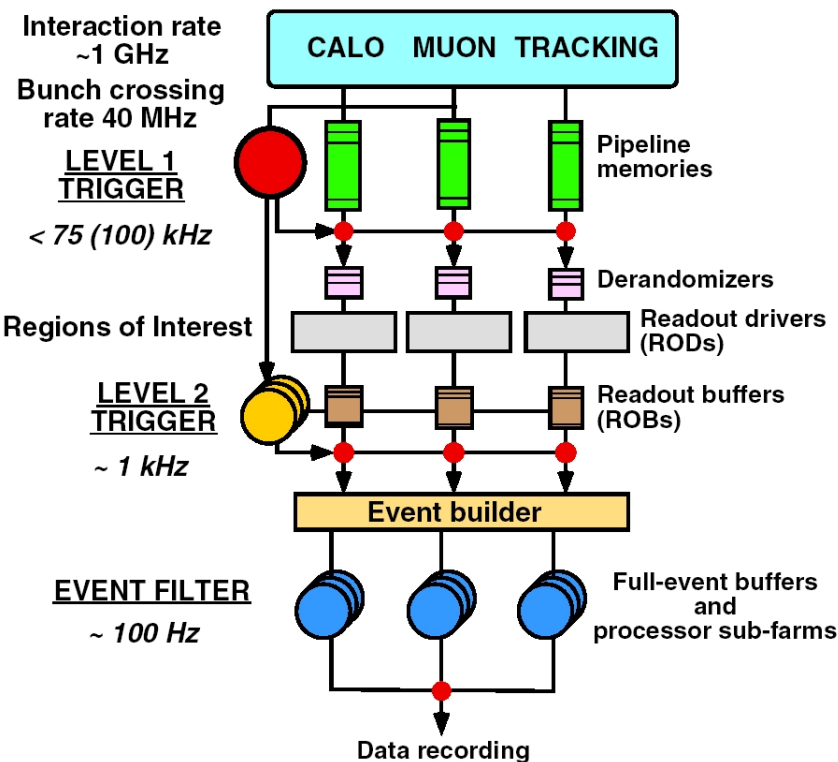
Standard method vs neural approach to solve pattern recognition problem:

find Higgs candidates in QCD background environment

use available packages:
ROOT, NeuNet (MLP's)
SOM-PAK, LVQ-PAK

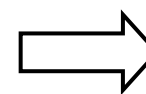
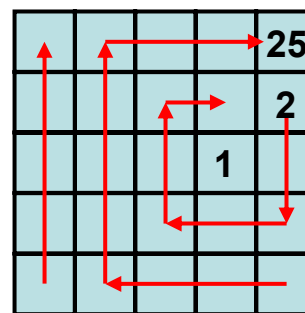


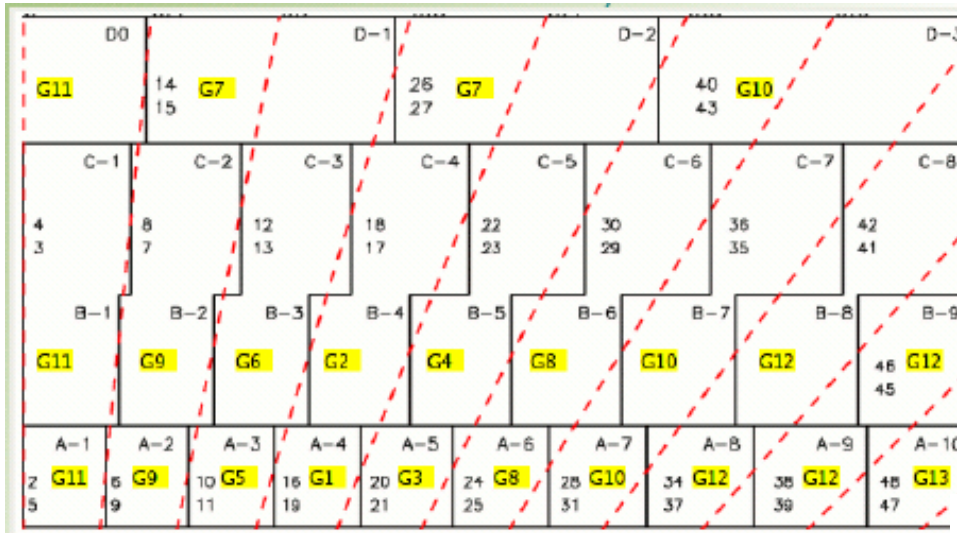
José M de Seixas: A Segmented Principal Component Analysis Applied to Calorimetry Information at ATLAS



Preprocessing of neural inputs:

Principal component extraction





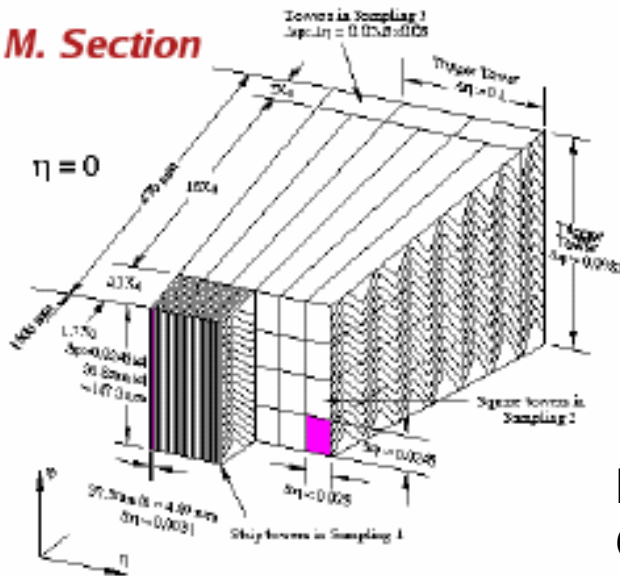
Neural Net for e/π separation:

Nr. of inputs/nodes depending on detail of detector information

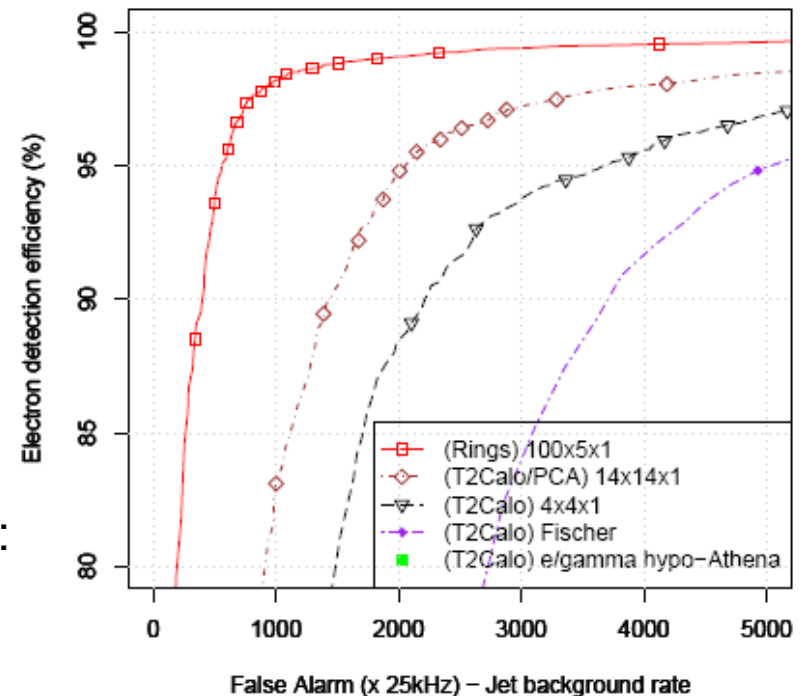


R.O.C. for e/jet discrimination

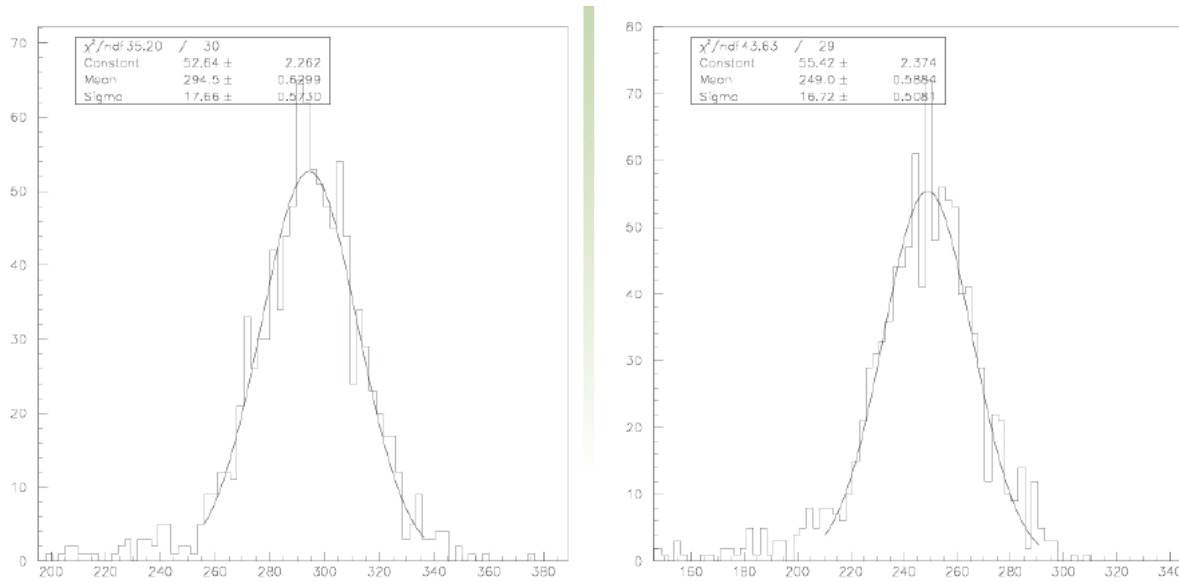
E.M. Section



NN on DSP:
O(10 μs)



Paulo Vitor Magacho da Silva: Energy Reconstruction for a Hadronic Calorimeter Using Neural Networks



Energy Resolution

Network with 2 hidden layers

NNoutput, $\frac{\sigma}{\mu} = 6.0\%$

Raw data, $\frac{\sigma}{\mu} = 6.7\%$

Network also improves linearity

	<i>Non-linearity (%)</i>
Raw	2.2
H1	1.3
Neural Net.	0.42

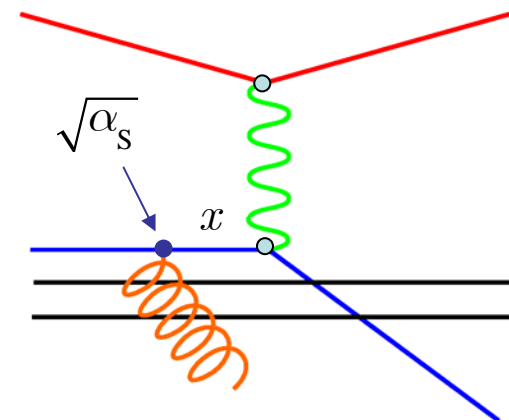
Andrea Piccione: Neural Networks Approach to Parton Distribution Fitting

- ▶ The cross section

$$\frac{d^2\sigma}{dx dQ^2} = \frac{4\pi\alpha^2}{Q^4} \left[[1 + (1-y)^2] F_1 + \frac{1-y}{x} (F_2 - 2xF_1) \right]$$

- ▶ The structure function (QCD + parton model)

$$F_2(x, Q^2) = x \left[\sum_{q=1}^{n_f} e_q^2 C^q \otimes q_q(x, Q^2) + 2n_f C^g \otimes g(x, Q^2) \right]$$



Traditional method: polynomial ansatz for parton distribution functions at some low Q_0

$$xq(x, Q_0) = Ax^B(1-x)^C [1 + D\sqrt{x} + Ex]$$

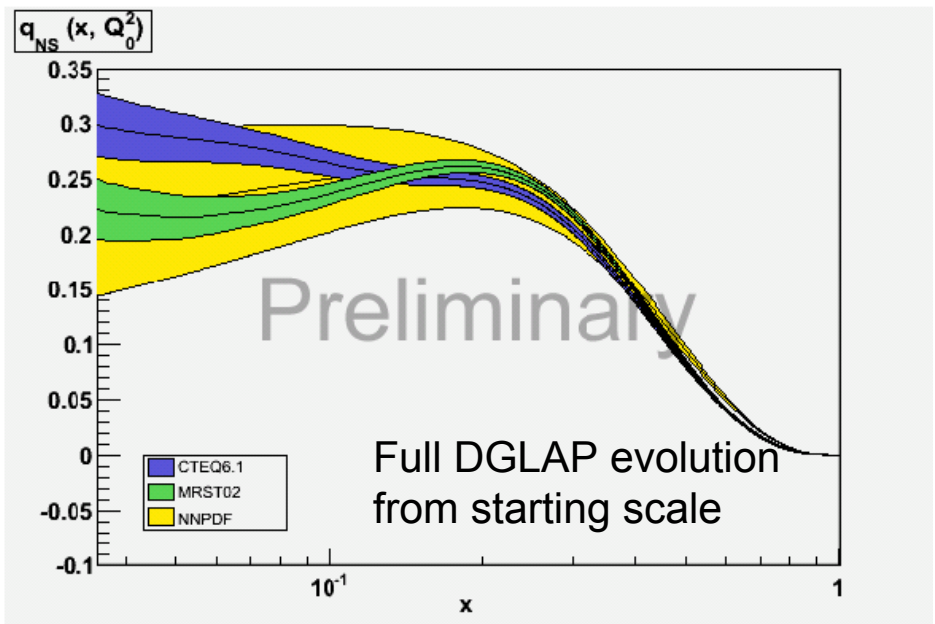
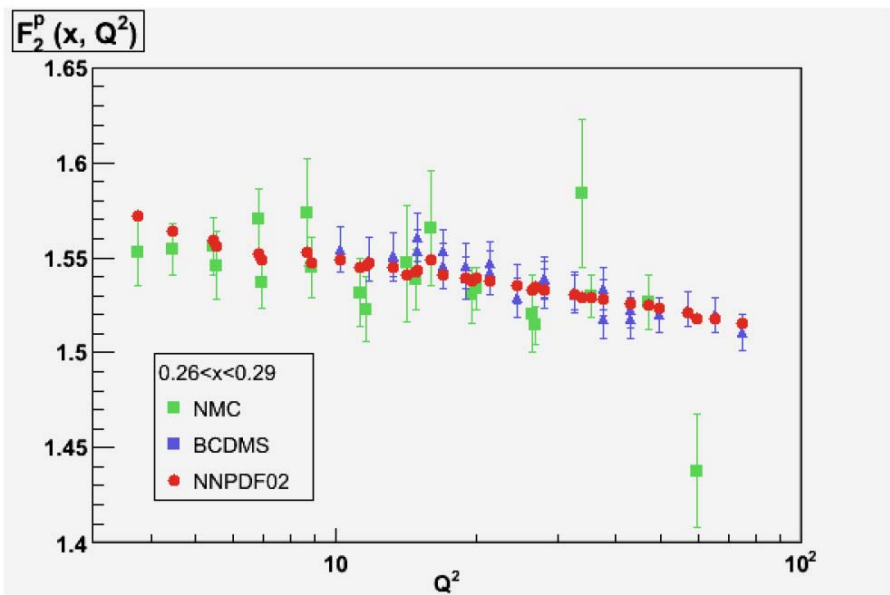
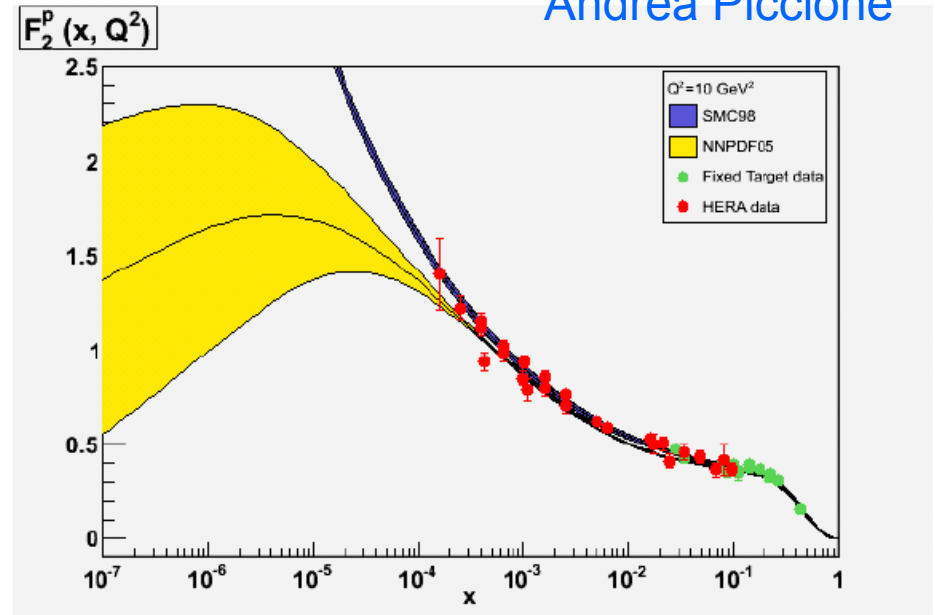
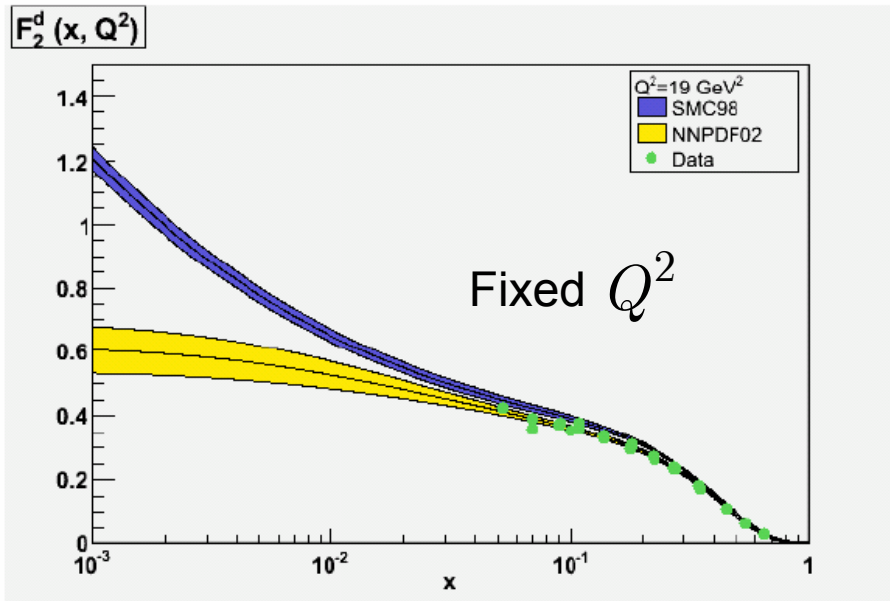
Neural approach: functional form „chosen“ by data

inputs: $x, Q^2, \ln x, \ln Q^2$

▶ Architecture: 4-5-3-1

output: $F_2(x, Q^2)$

Train net with data set (replicas)



Conclusions

- Session 2 was quite lively, good attendance
- Good workshop atmosphere
- In general high quality talks, showing originality in the spirit of the workshop
- Contributions of non-statistical and statistical (neural) algorithms in balance
- Personal opinion (maybe also shared by others): More time discussions („workshop“)
- Looking forward for the next workshop !