

# Improved tuning method for Monte Carlo generators

**Fabian Klimpel**

38. IMPRS workshop 2017

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Technische Universität München



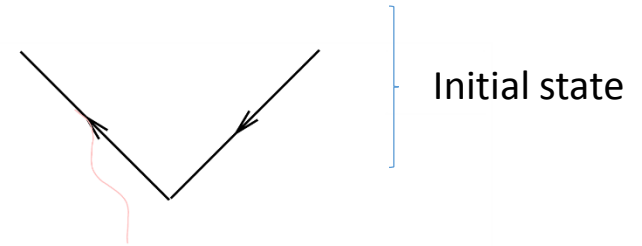
Max-Planck-Institut für Physik  
(Werner-Heisenberg-Institut)

# Overview

1. Introduction to parameter tuning
2. Reproduction of a previous tuning
3. Introducing new approaches for parameter tuning
4. Summary and outlook

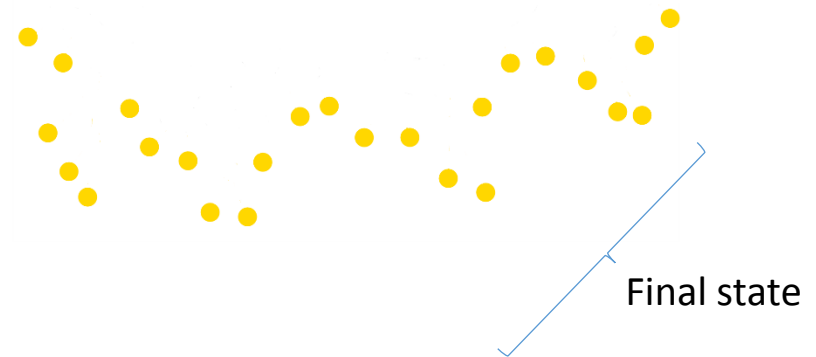
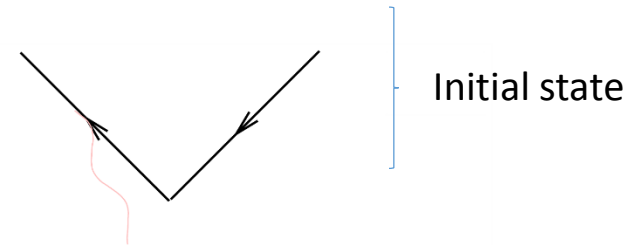
# What is parameter tuning?

- Experimental setup ( $e^+e^-$ ):
- Before the particle collision:
  - Initial state is (approximately) known



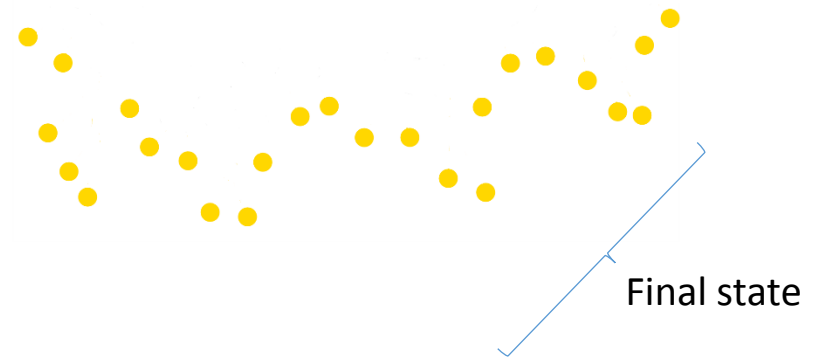
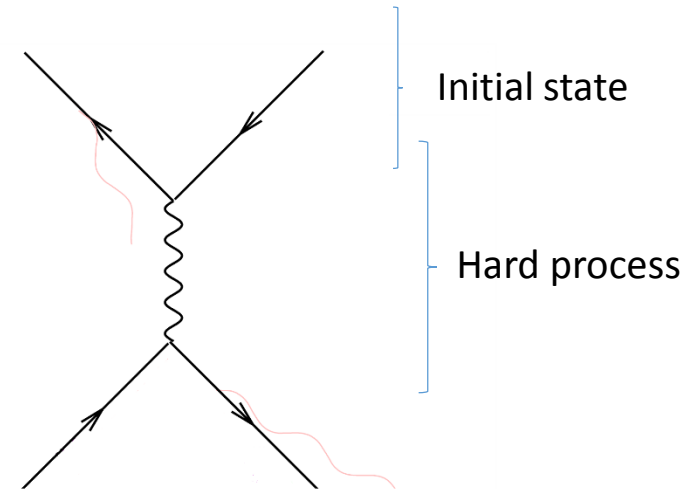
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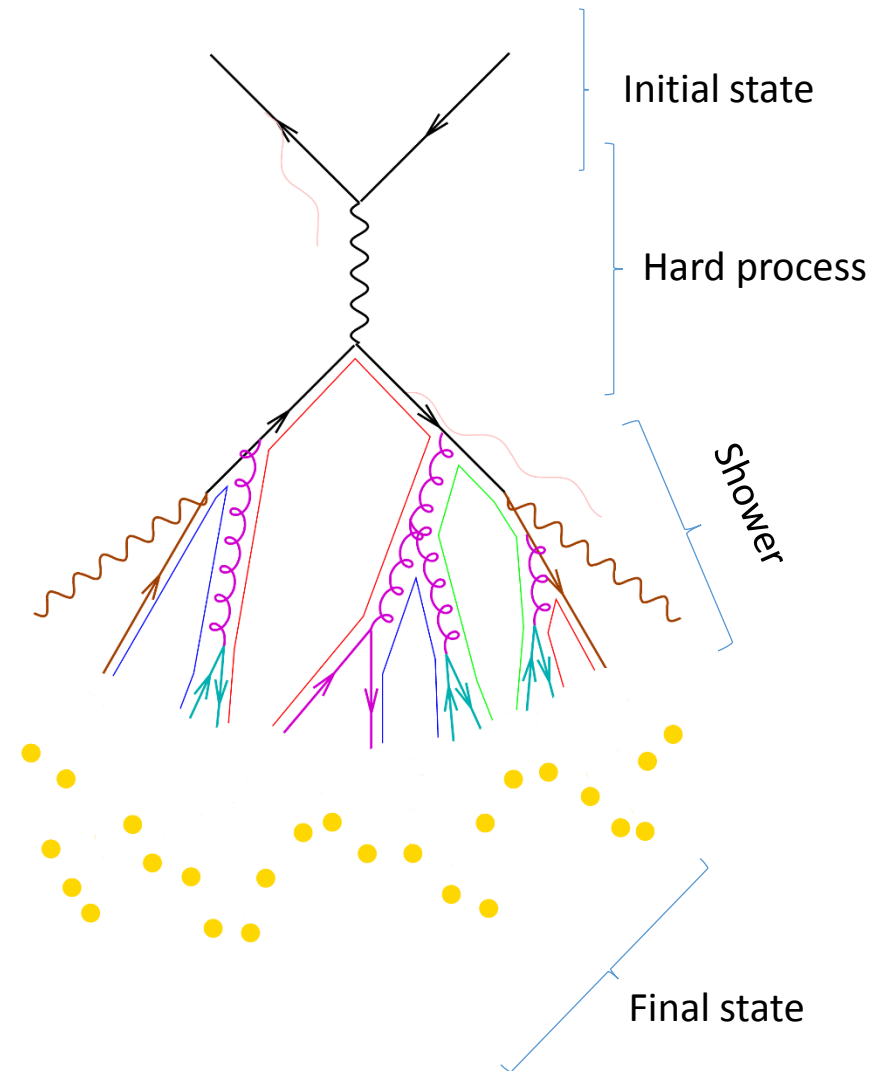
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- Hard process: calculable



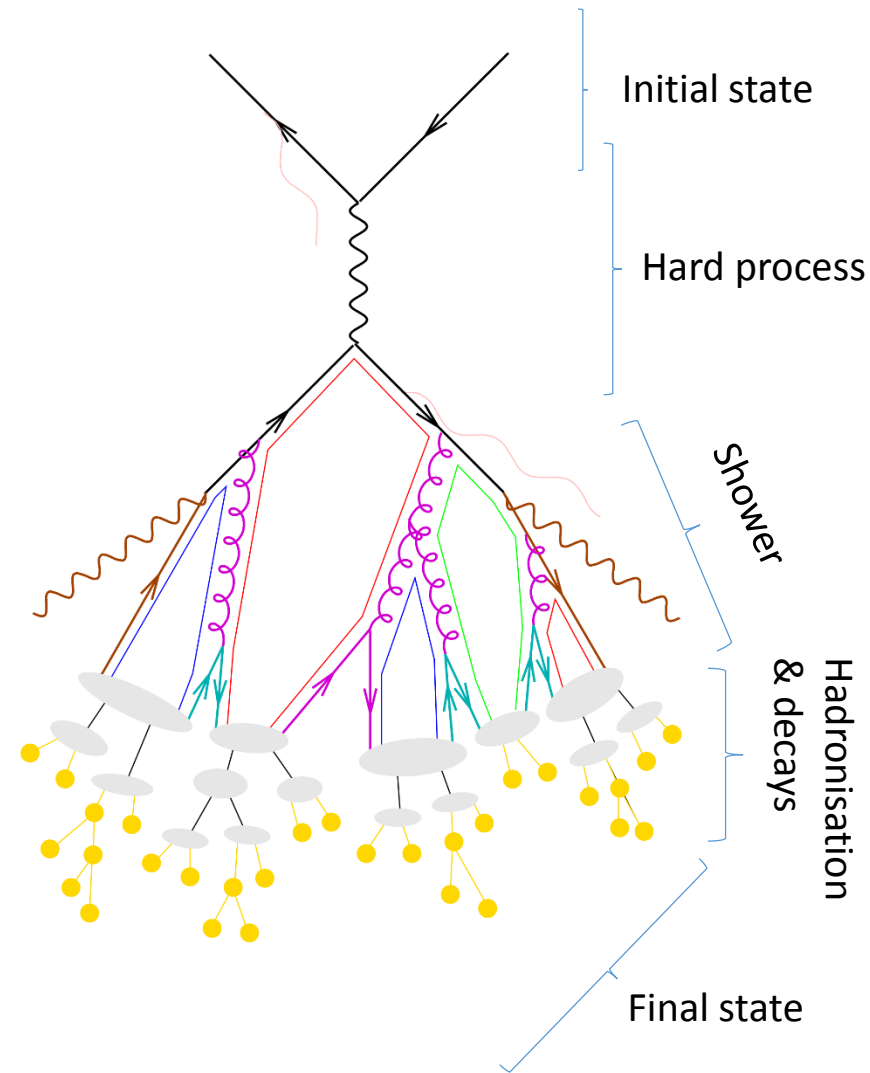
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- Parton shower: „modelled QCD“
- Hadronisation: modelled
- Adjust model parameters to optimize reproduction of measurement
- **But:** How to get their values?



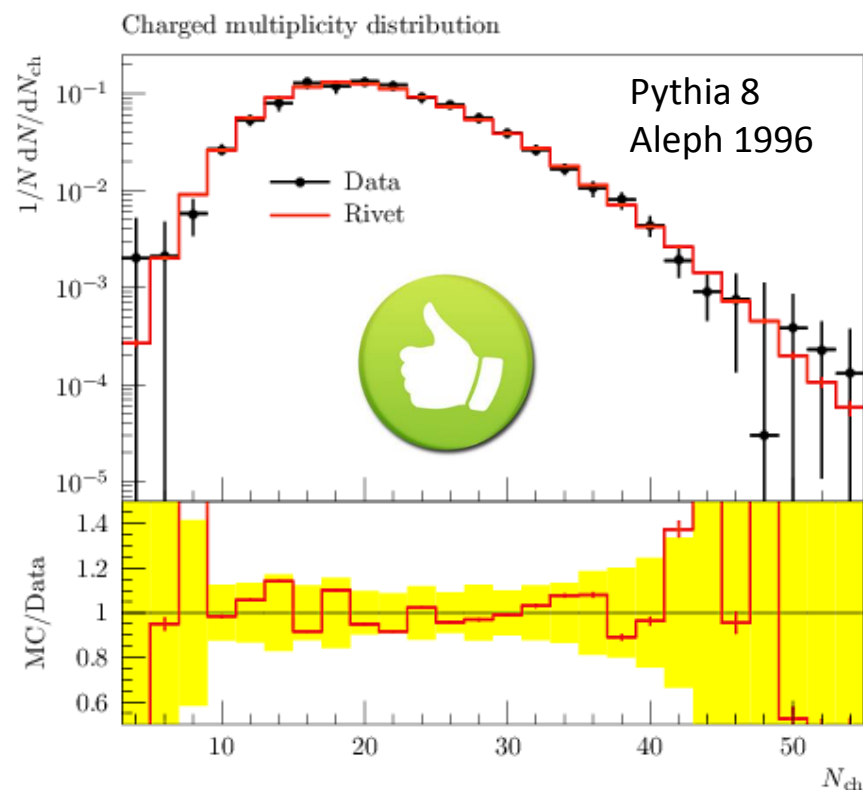
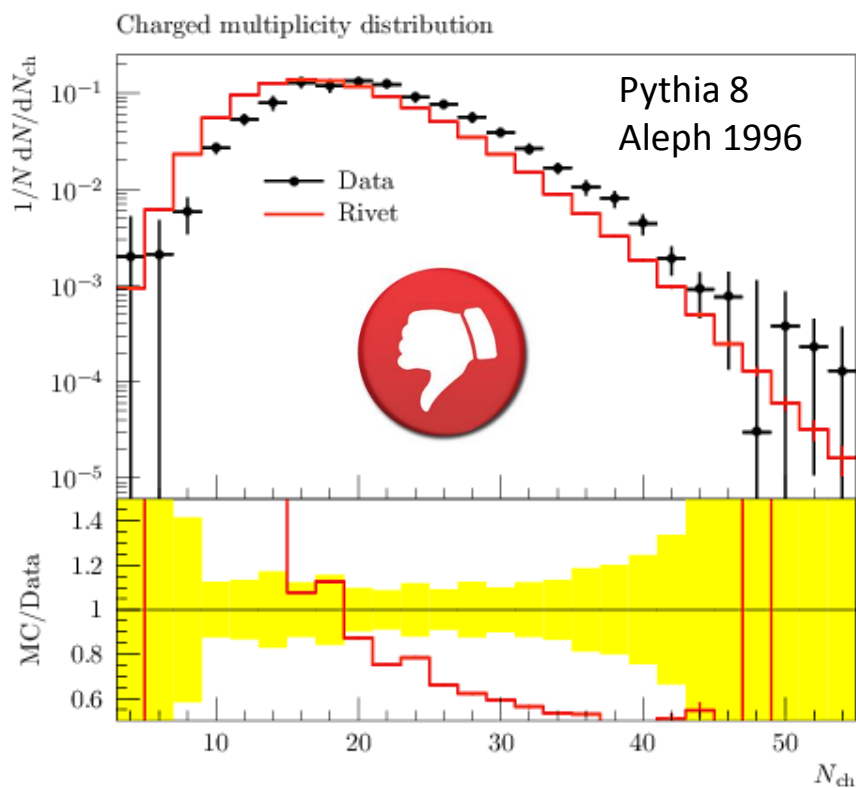
# Parameter tuning - general

- Model parameters can be varied
  - parameters need values that describe the data best = tuning



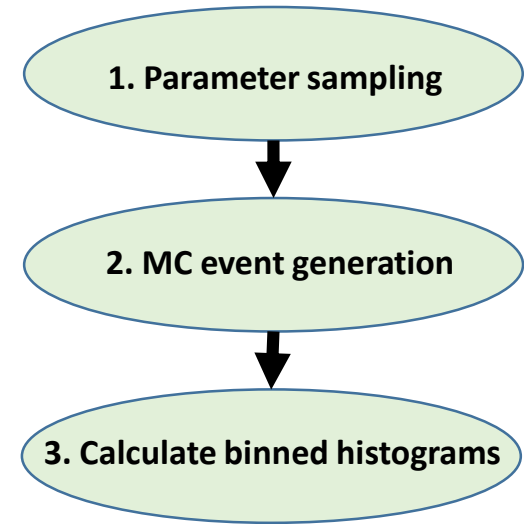
# Parameter tuning - general

- Model parameters can be varied
  - parameters need values that describe the data best = tuning
- Example:  $e^+e^-$  collisions at  $\sqrt{s} = 91.2$  GeV with two different parameter sets



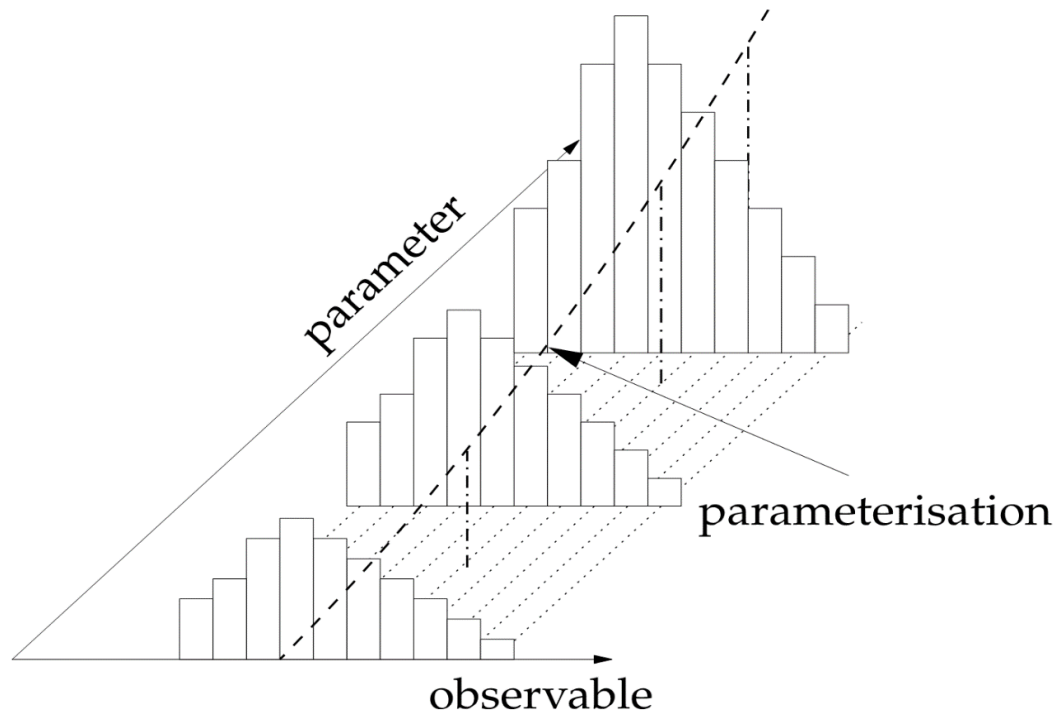
# How to tune? – general

1. Sample random model parameter vectors  $\mathbf{p}_i$  in predefined ranges
2. Use every  $\mathbf{p}_i$  (= „run“) as input for the MC generator
  - High CPU consumption
3. Extract observables from each run
  - binned histograms for each observable



# How to tune? – Interpolation

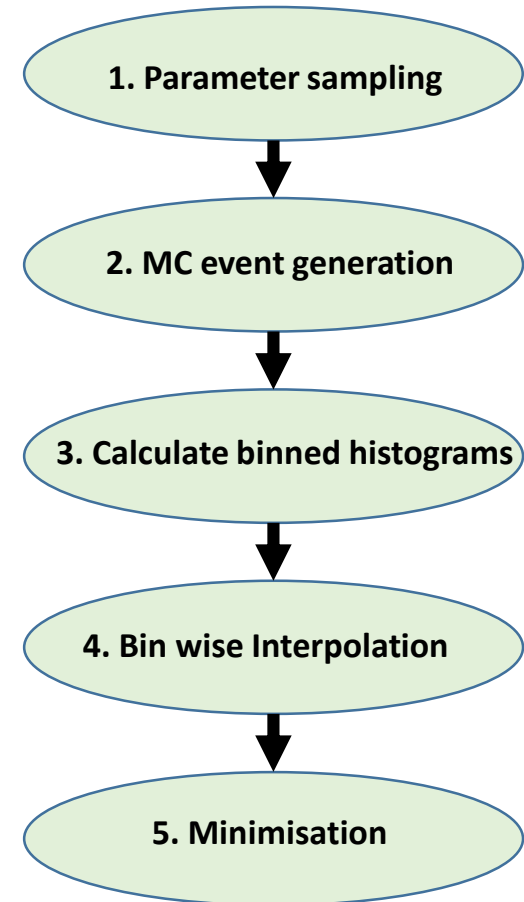
- Assumption: sufficiently smooth change in a bin  $b$  while changing the value of a parameter
- Each bin can be parametrised by a polynomial function  $f^{(b)}(\mathbf{p})$



Source: H. Schulz, Systematic Event Generator Tuning with Professor

# How to tune? – general

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3. Extract observables from each run
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4. Calculate  $f^{(b)}(\mathbf{p})$  as function of model parameters  $\mathbf{p}$
5. Minimise  $\chi^2(\mathbf{p})$



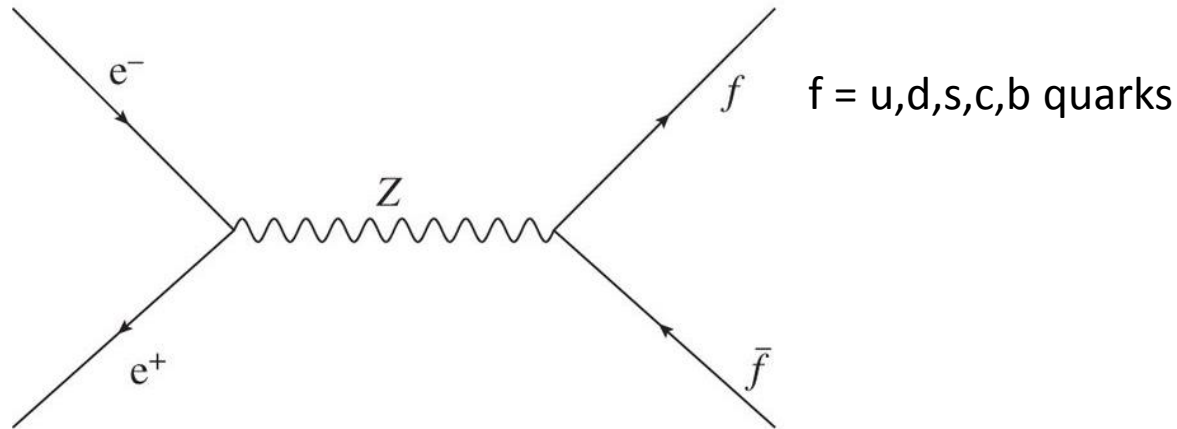
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# Tuning application

Source: N. Fischer, Angular Correlation and Soft Jets as Probes of Parton Showers

- Reproduced standard Pythia tune
- Hard process:

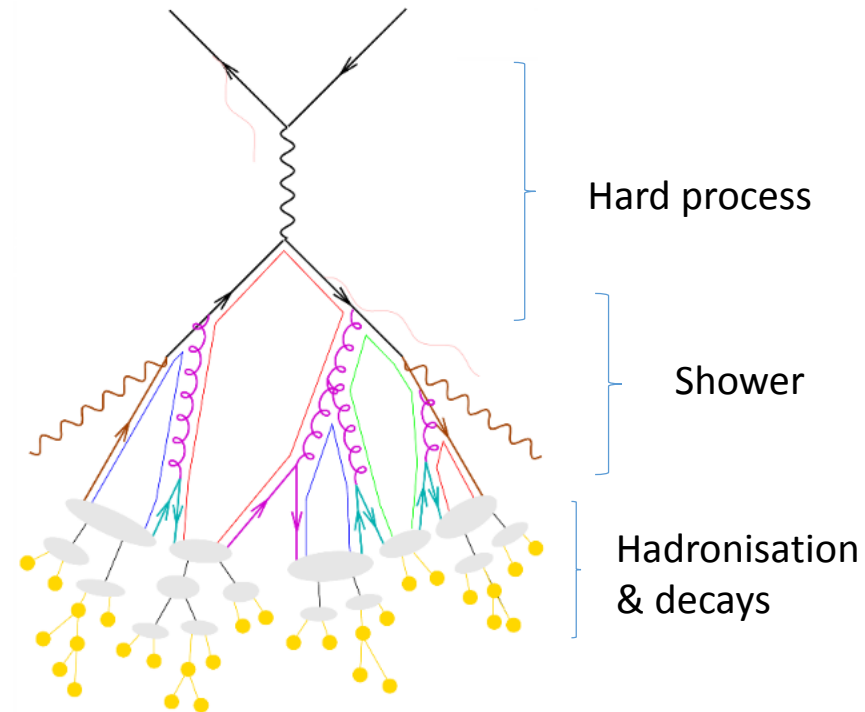


- Events simulated with Pythia 8 at  $\sqrt{s} = m(Z^0) = 91.2$  GeV, LO + LL
- Settings were extracted from standard tuning
- Data from LEP (Aleph, Opal, Delphi), PETRA (Jade) & PDG combinations
  - Phys. Rept., 294:1 (1998); PLB 512:30 (2001); ZP C73:11 (1996); EPJ C17:19 (2000); PLB 667:1 (2008)

# Which parameters to tune?

## 1. Parton shower model based on QCD:

- High energy partons radiate gluons with probability  $\sim \alpha_s \rightarrow$  shower
- Shower cutoff at  $p_{T,min}$ 
  - phase transition, confinement



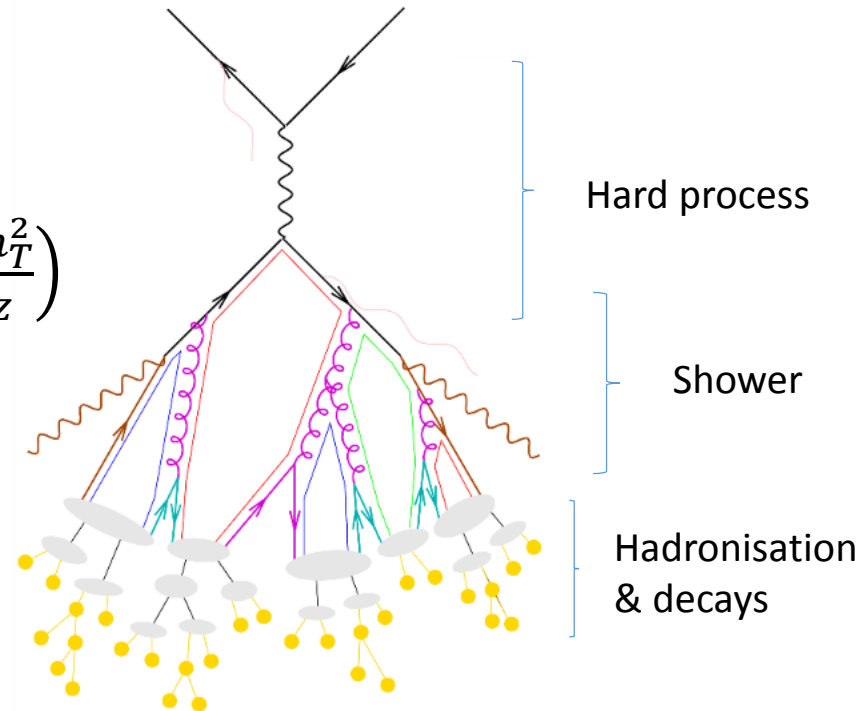
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## 2. Hadronisation (Lund-string model):

- $f(z) \propto \frac{1}{z} (1-z)^{a_{\text{Lund}}} \exp\left(-b_{\text{Lund}} \frac{m_T^2}{z}\right)$
- Baryons:  $a = a_{\text{Lund}} + a_{\text{ExtraDiquark}}$
- $P(p_T) \propto \exp\left(-\frac{1}{2} \frac{p_T^2}{\sigma^2}\right)$





# Which parameters to tune?

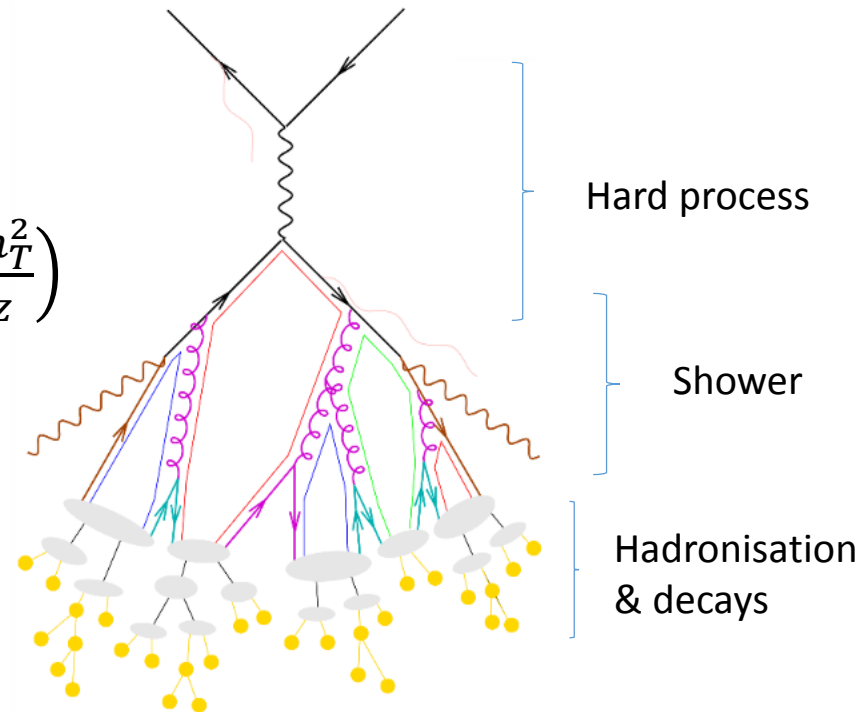
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## 3. Hadron decays from PDG tables

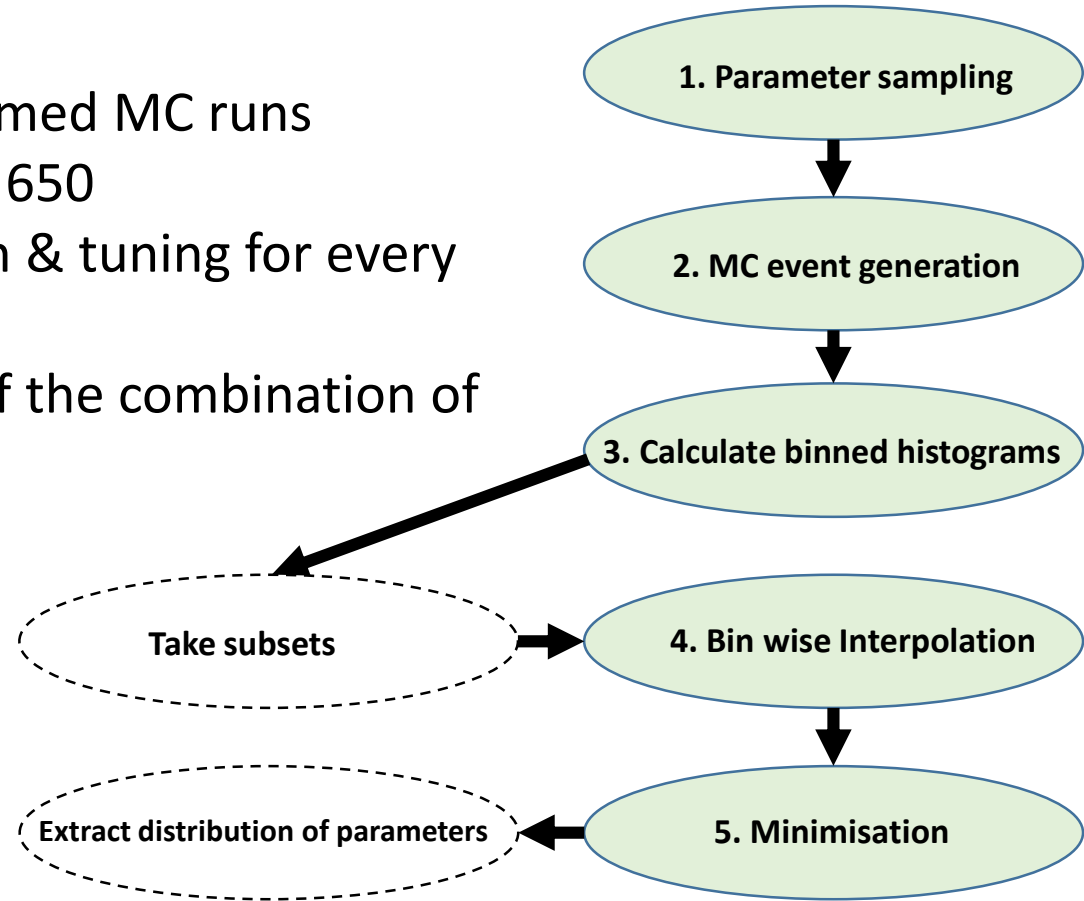


➤ overall 6 parameters to tune using the Professor framework

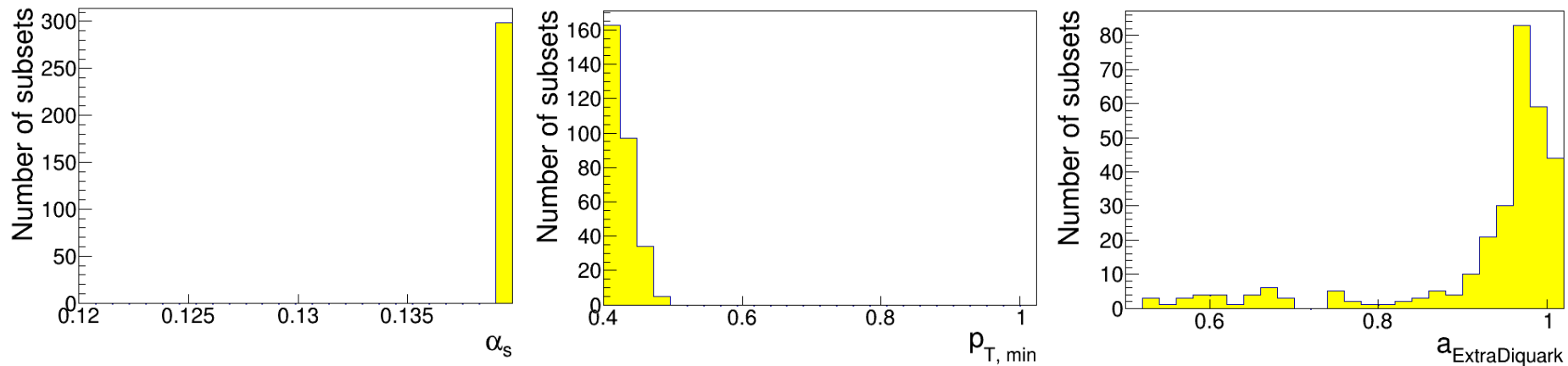
# How to tune? – bootstrapping

Known from previous studies:

- a) Take subsets of all performed MC runs
  - 300 times 500 out of 650
- b) Perform the interpolation & tuning for every subset independently
- c) Extract the distribution of the combination of tuned parameter values

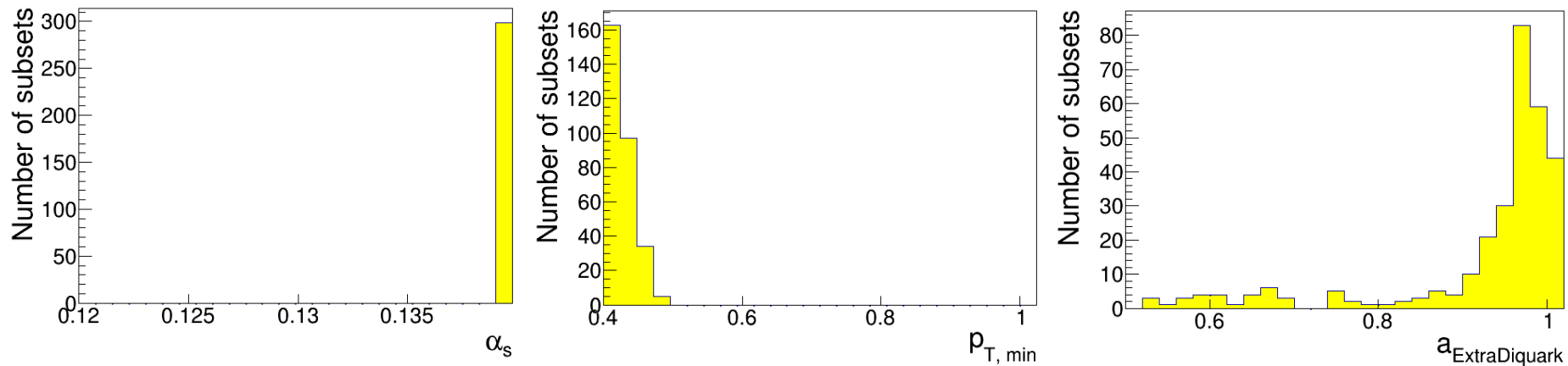


# Distribution of tuned parameters with fixed ranges



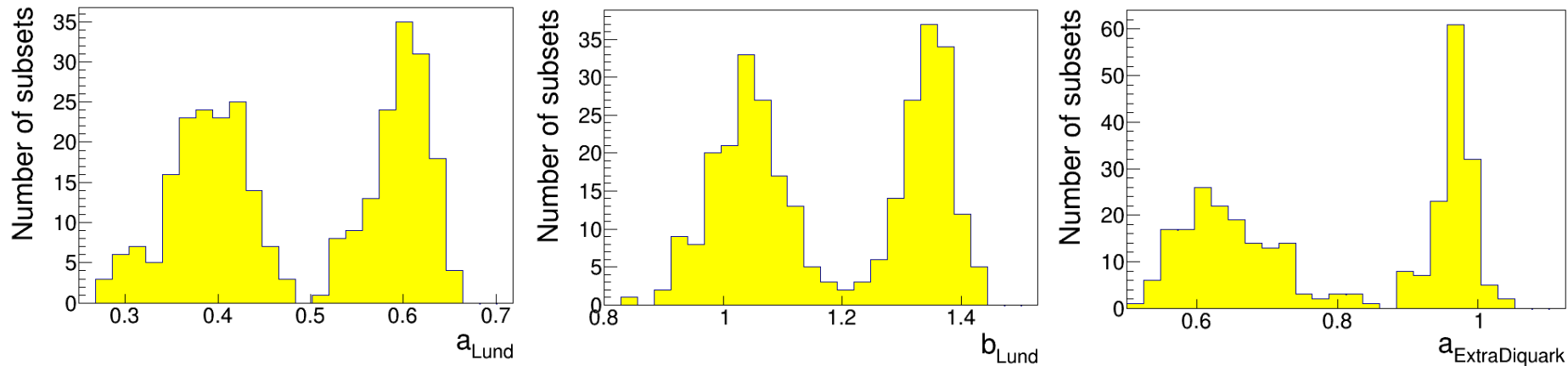
- Parameter values at fit-range limit
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# Distribution of tuned parameters with fixed ranges



- Parameter values at fit-range limit
- A better tune could lay outside the parameter ranges
- Need to extend parameter range
- Keep interpolation functions unchanged

# Distribution of tuned parameters without fixed ranges



- Extend parameter ranges, but no new MC samples
  - extrapolation in some parameters occurs
- Double peaks should not exist
  - result is sensitive to input set
- Is there a problem while minimising?
  - re-minimise by using another method

# Overview

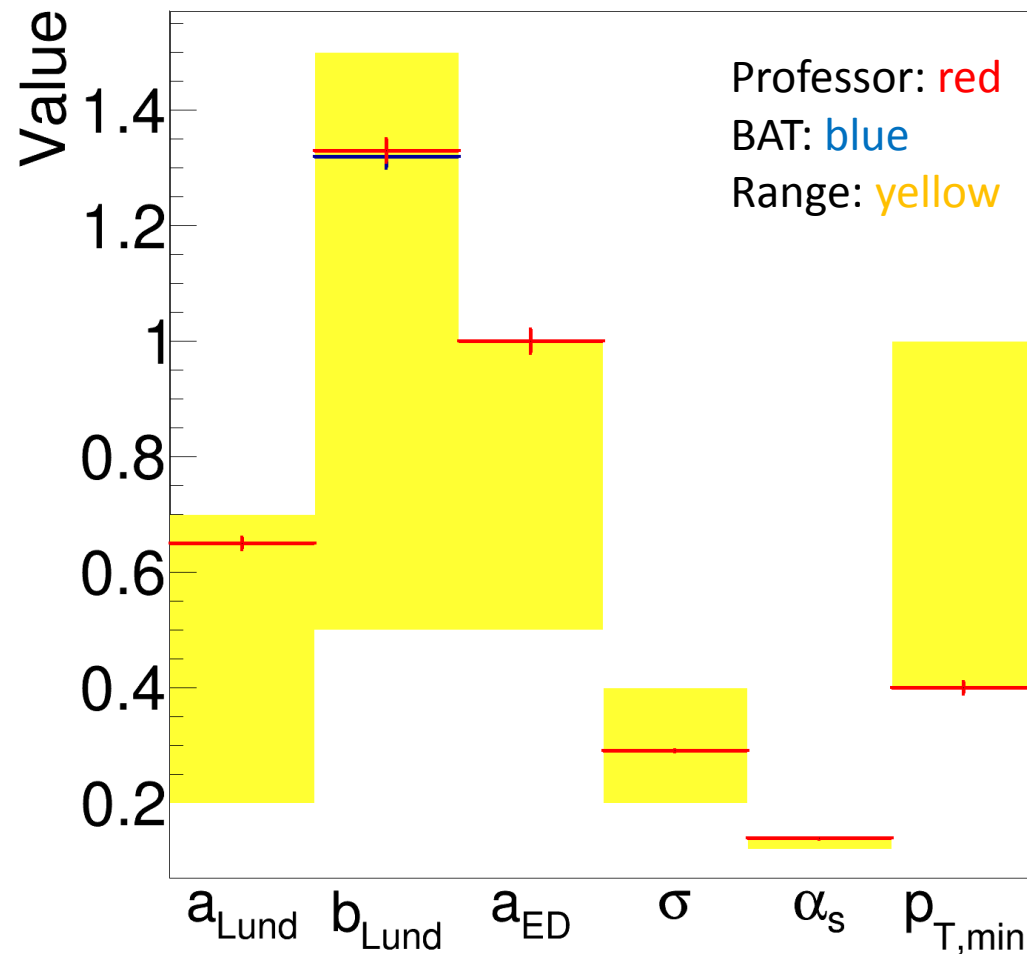
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# Bayesian Analysis Toolkit (BAT)

- Idea: Use BAT as control tune for Professor
- Working principle:
  - Based on self adapting Markov Chains
  - Steps determined by Metropolis-Hastings algorithm
  - Multiple Markov Chains should converge to same result
- Benefits of the algorithm:
  - Metropolis-Hastings algorithm reproduces a function
  - BAT collects information about the posterior likelihood
  - The algorithm can find the maximum posterior likelihood and thus optimal parameters



# BAT - results



➤ The problem is not the minimisation!

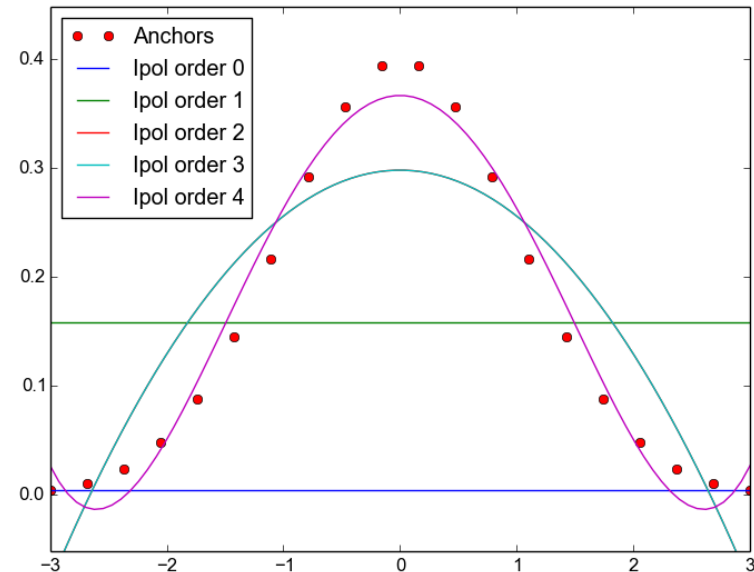


# Interpolation

- The problem could be produced while interpolating

- a) Professor uses a fixed order polynomial function for interpolation
- possible over-/underfitting?

Simplified example of underfitting:



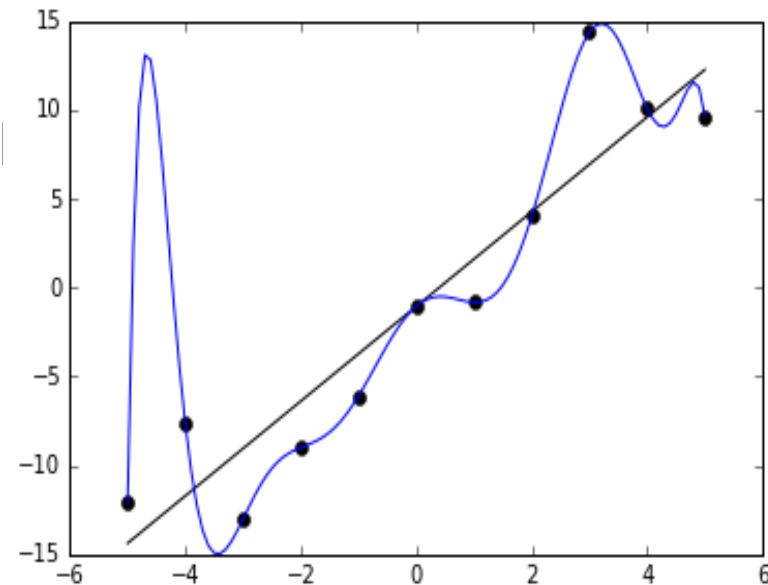
Underlying function: Gauss distribution

# Interpolation

- The problem could be produced while interpolating
- a) Professor uses a fixed order polynomial function for interpolation
  - possible over-/underfitting?
- b) The quality of the fit should not be judged upon  $\chi^2$  only
  - Small  $\chi^2 \nrightarrow$  good fit

➤ another approach is needed to avoid this

Simplified example of overfitting:



Source:

[https://en.wikipedia.org/wiki/Overfitting#/media/File:Overfitted\\_Data.png](https://en.wikipedia.org/wiki/Overfitting#/media/File:Overfitted_Data.png)

# New Interpolation

## a) Avoid under-/overfitting

- Iteratively increase the number of terms in polynomial
- until interpolation „is good“

Construction based on:  
IEEE Transactions on Pattern Analysis and  
Machine Intelligence, vol. 32, 561 (2010)

# New Interpolation

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## b) Improved quality criterion:

- Introduce shape dependent parameter:

$$D_{Smooth} = \frac{1}{N} \sum_{i=1}^N \mathbf{n}_{Simulation\ data,i} \cdot \mathbf{n}_{Interpolation,i}$$

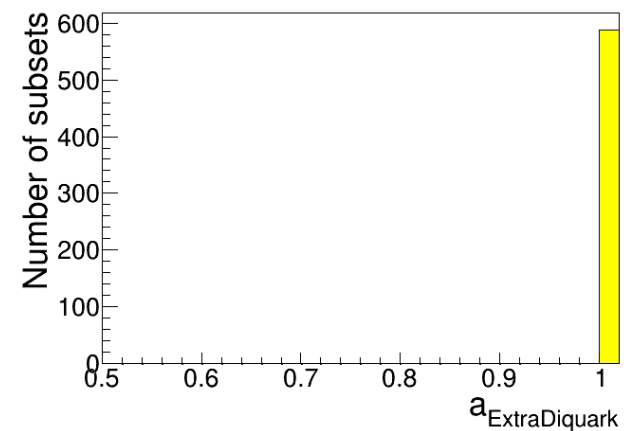
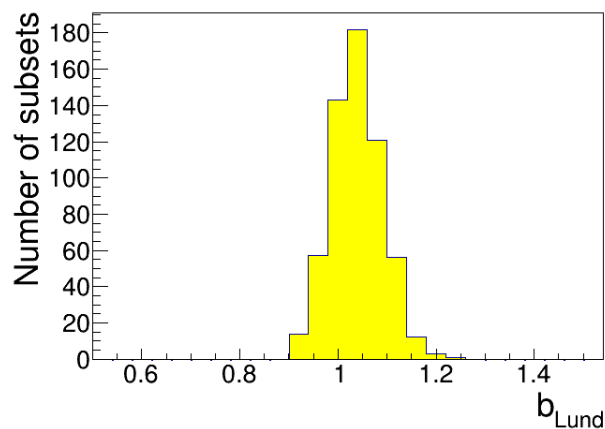
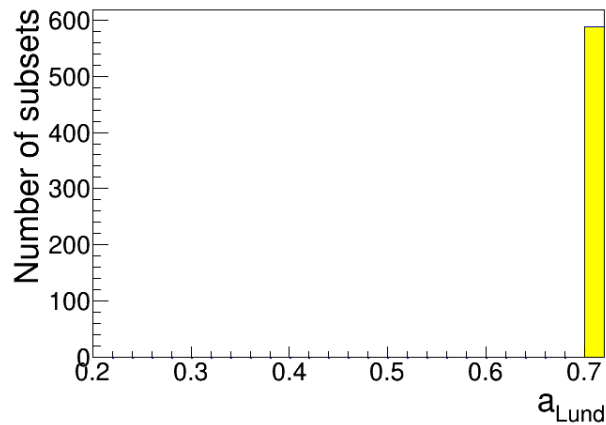
Normalised gradient of the simulated data

Normalised gradient of the interpolation

➤ Minimise new criterion:  $f = \chi^2 \frac{(1 - D_{Smooth})}{(1 + D_{Smooth})}$

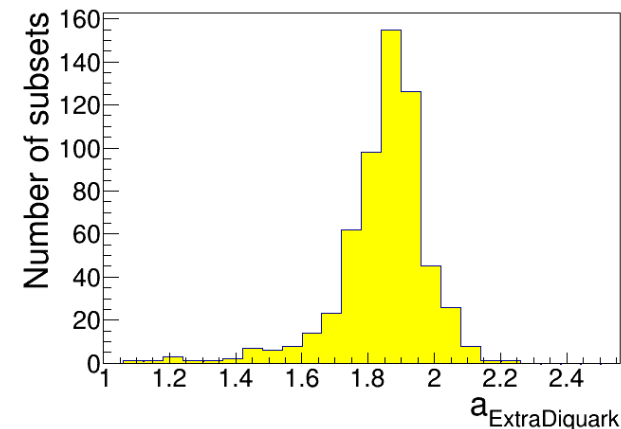
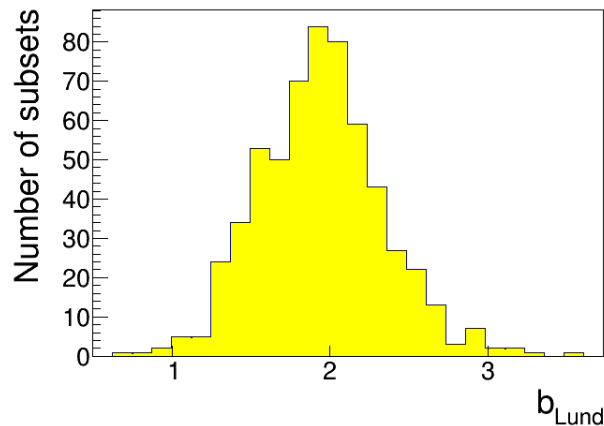
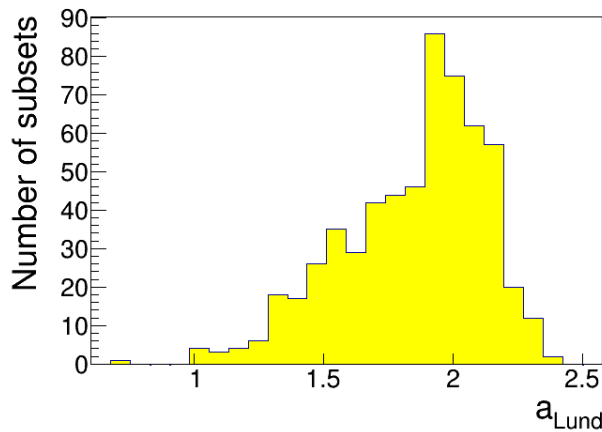
# Distribution of tuned parameters

- Fixed ranges:
  - Parameter values at the limit
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# Distribution of tuned parameters

- Fixed ranges:
  - Parameter values at the limit
    - Allowing extrapolation
- Without fixed ranges:
  - Parameter values distributed around a single centre
    - Final values can be extracted



# Error propagation of interpolation

• Until now: 
$$\begin{pmatrix} \sigma_a^2 & \sigma_{ab} & \sigma_{ac} \\ \sigma_{ab} & \sigma_b^2 & \sigma_{bc} \\ \sigma_{ac} & \sigma_{bc} & \sigma_c^2 \end{pmatrix}$$

➤ Consider the correlation between the fit parameters

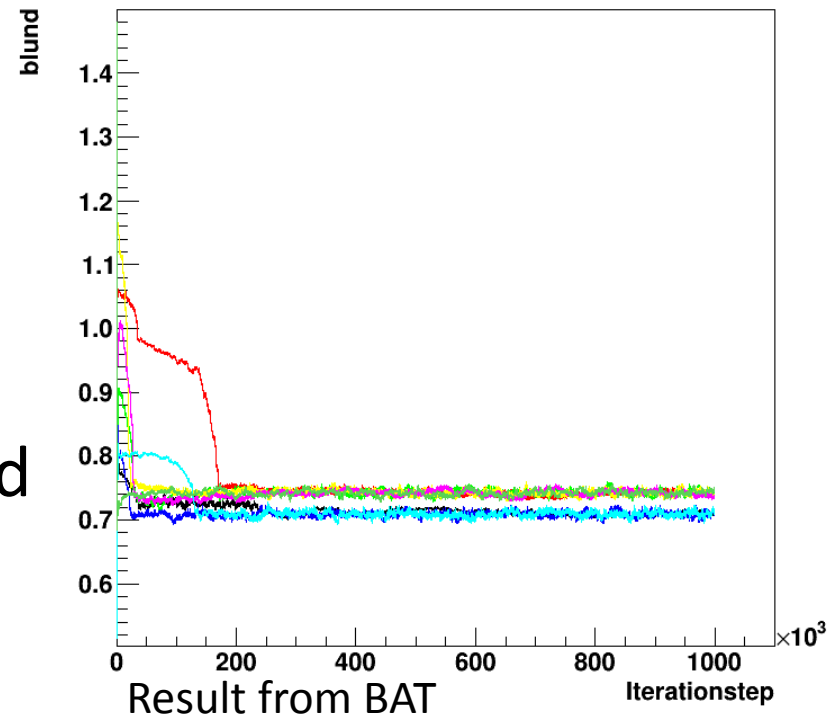
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➤ Consider the correlation between the fit parameters

- But: Complicated likelihood & multiple attractors appear

➤ further investigations are needed





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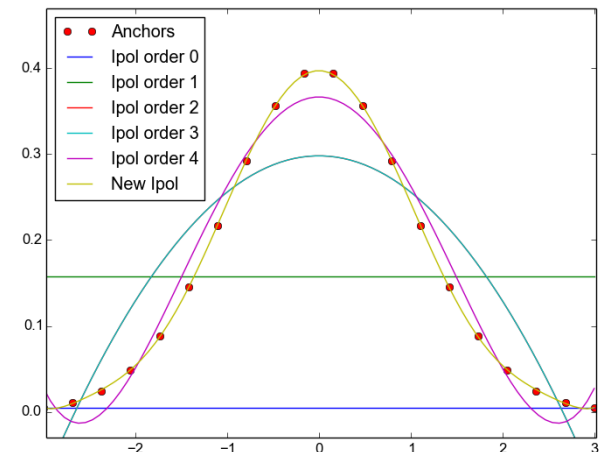
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# Summary

- Professor tuning maybe unstable
- Problem caused by the interpolation algorithm

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- Problem caused by the interpolation algorithm
- Using new approach to increase stability of interpolation with
  1. An iterative construction that increases the number of terms
  2. A new quality criterion  $f = \chi^2 \frac{(1 - D_{\text{Smooth}})}{(1 + D_{\text{Smooth}})}$
- Using covariances of fit parameters is statistically consistent but causes further problems



# Outlook

- Work on uncertainty calculation:
  - Investigation of the source the problems (e.g. parameter ranges, selected observables or weights)

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- Implementation of the new interpolation algorithm into the Professor framework

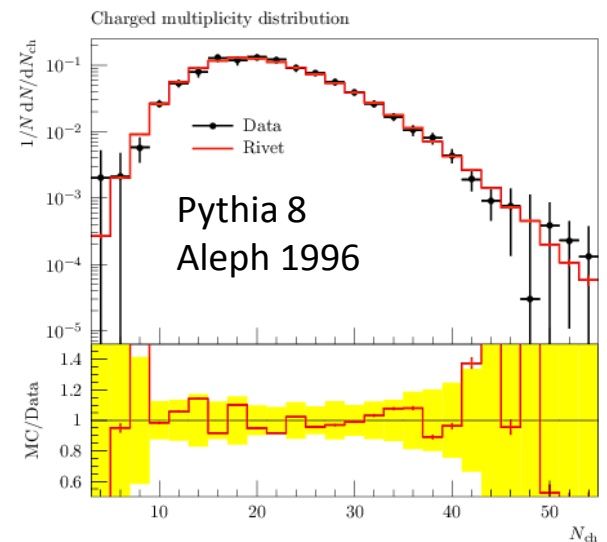
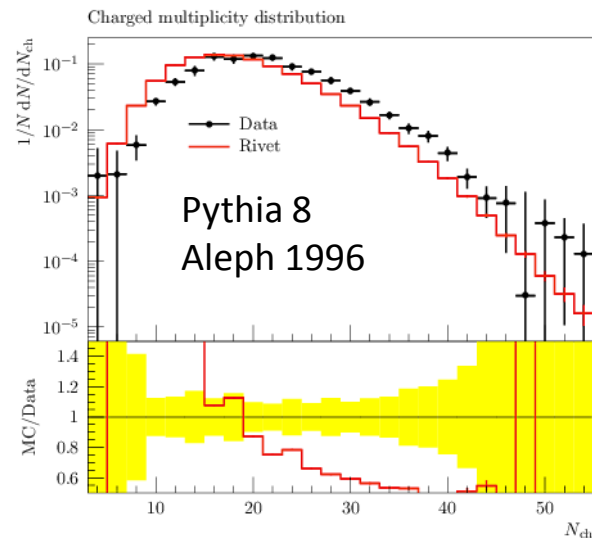
Thank you for your attention



# Backup

# Backup: Parameter sets of example distributions

Parameter	Left Set	Right Set
$a_{\text{Lund}}$	0.42	0.56
$b_{\text{Lund}} [\text{GeV}^{-2}]$	0.82	1.00
$a_{\text{ExtraDiquark}}$	0.99	0.93
$\sigma [\text{GeV}]$	0.259	0.399
$\alpha_S$	0.120	0.126
$p_{T,\text{min}} [\text{GeV}]$	0.42	0.95



# Backup: gof

Sum over every observable and bin

Interpolation function

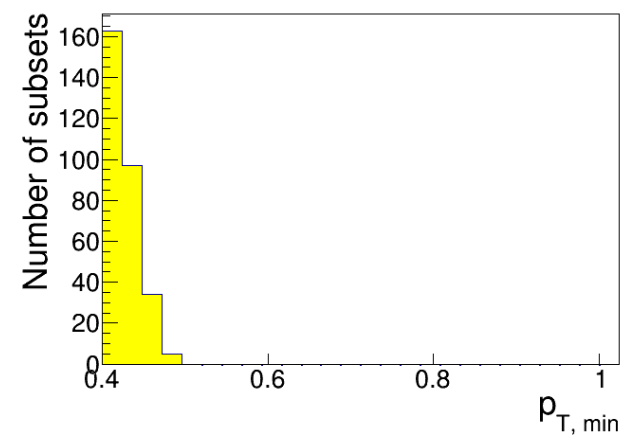
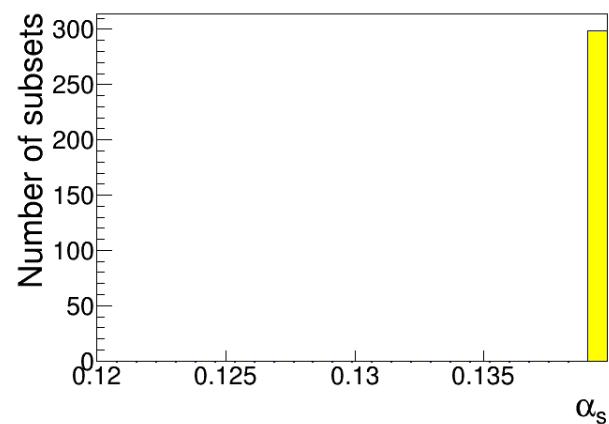
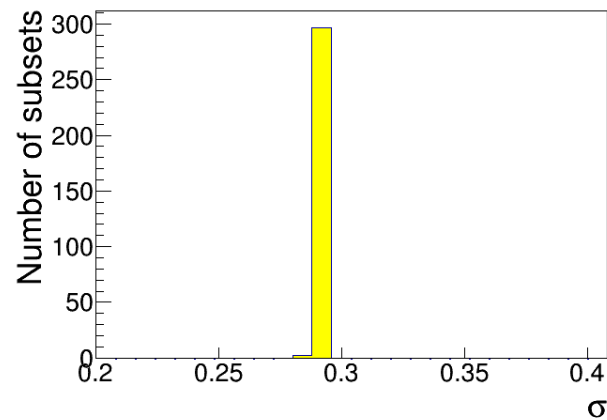
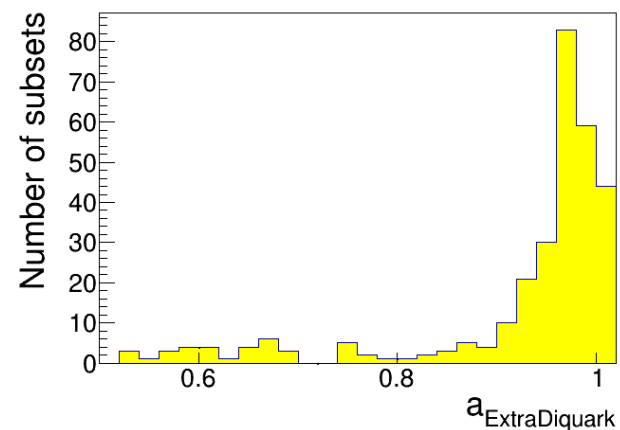
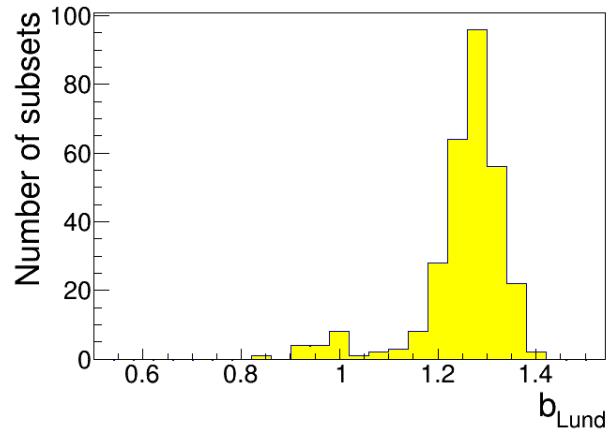
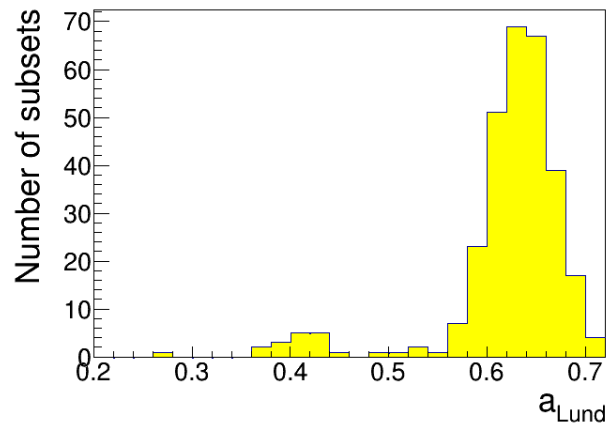
Measurement

$$\chi^2(\mathbf{p}) = \sum_O \sum_{b \in O} w_b \frac{(f^{(b)}(\mathbf{p}) - R_b)^2}{\Delta_b^2}$$

Weights

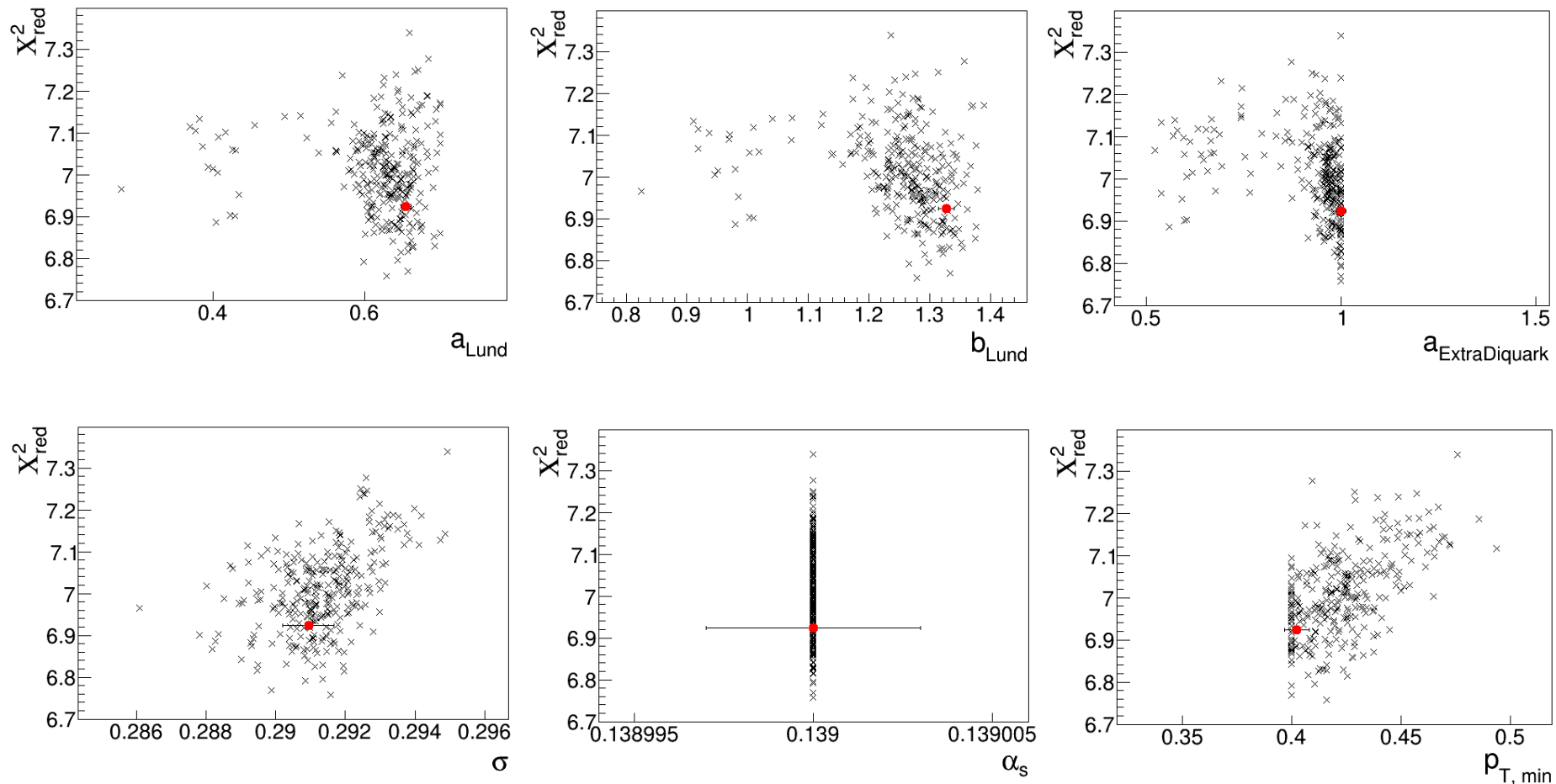
Sum of variances

# Backup: Professor with parameter limits I



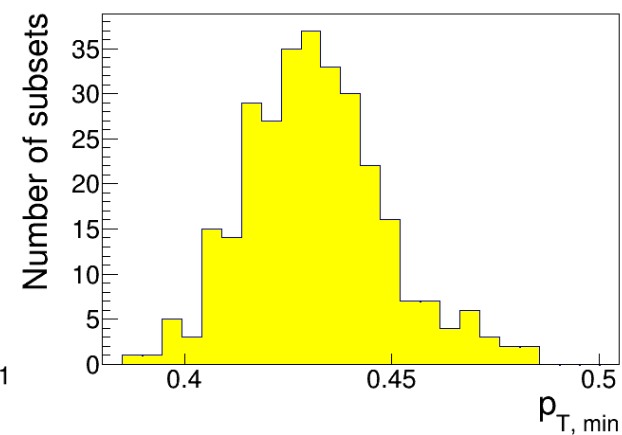
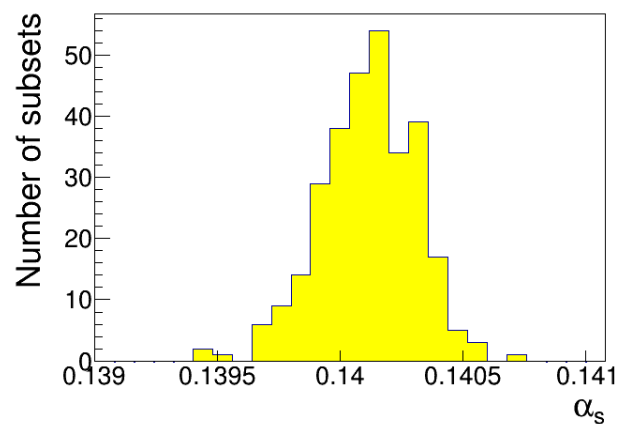
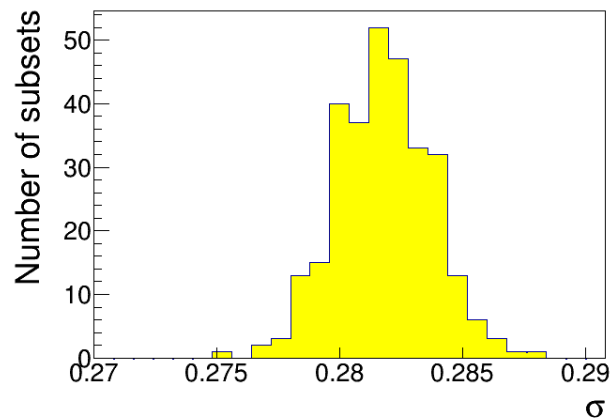
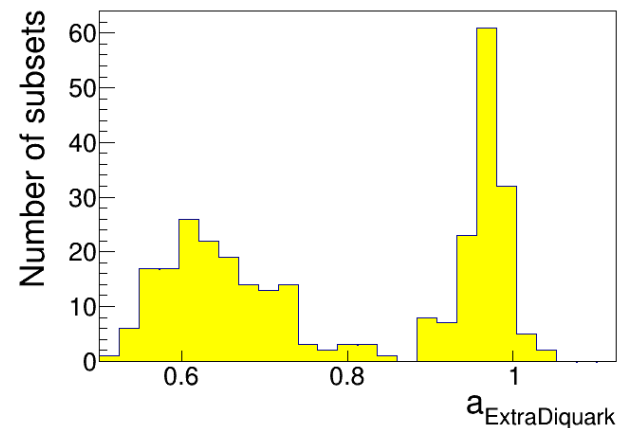
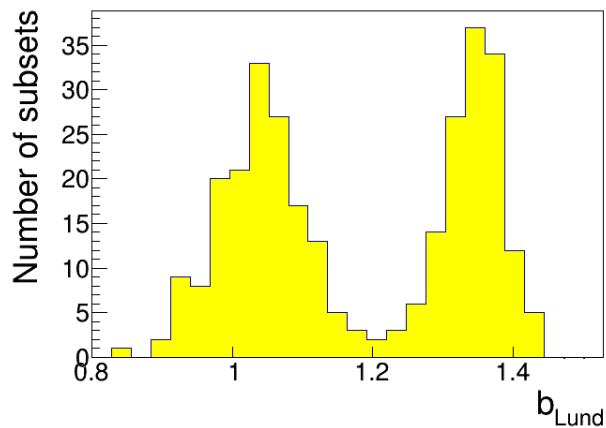
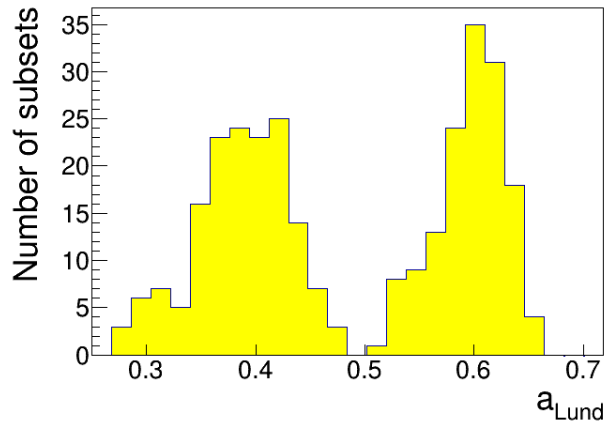
650 samples

# Backup: Professor with parameter limits II



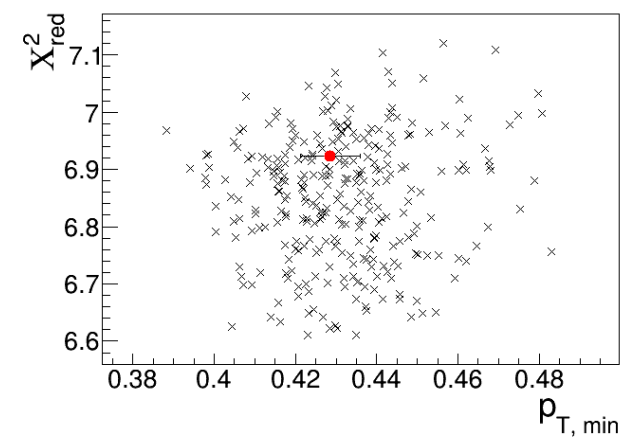
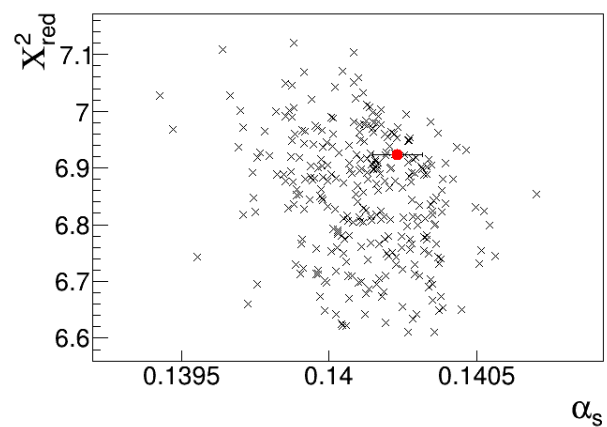
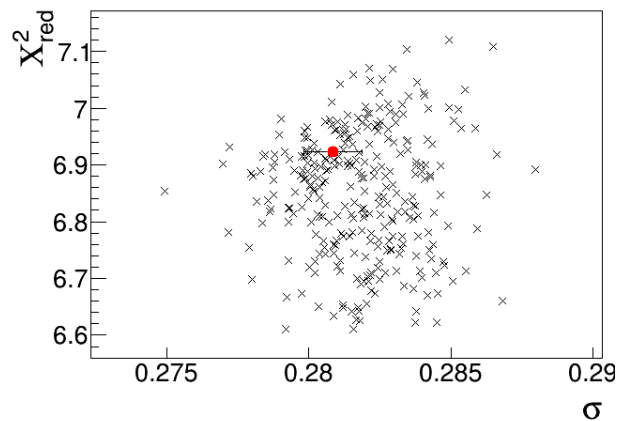
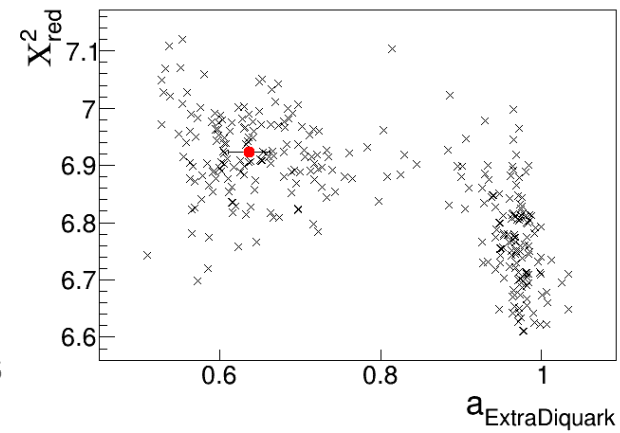
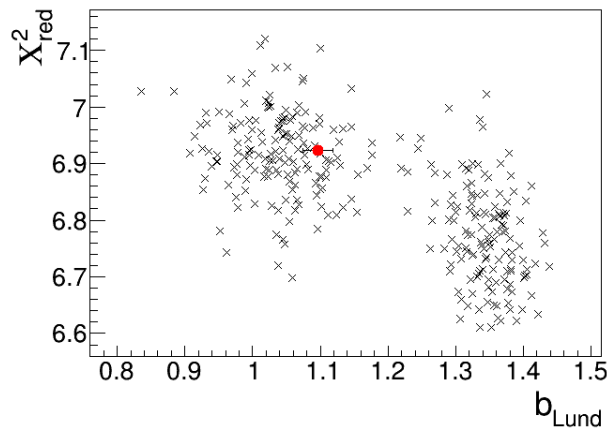
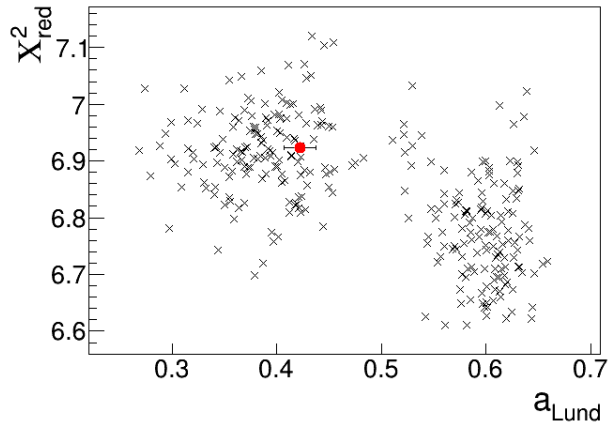
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# Backup: Professor without parameter limits I



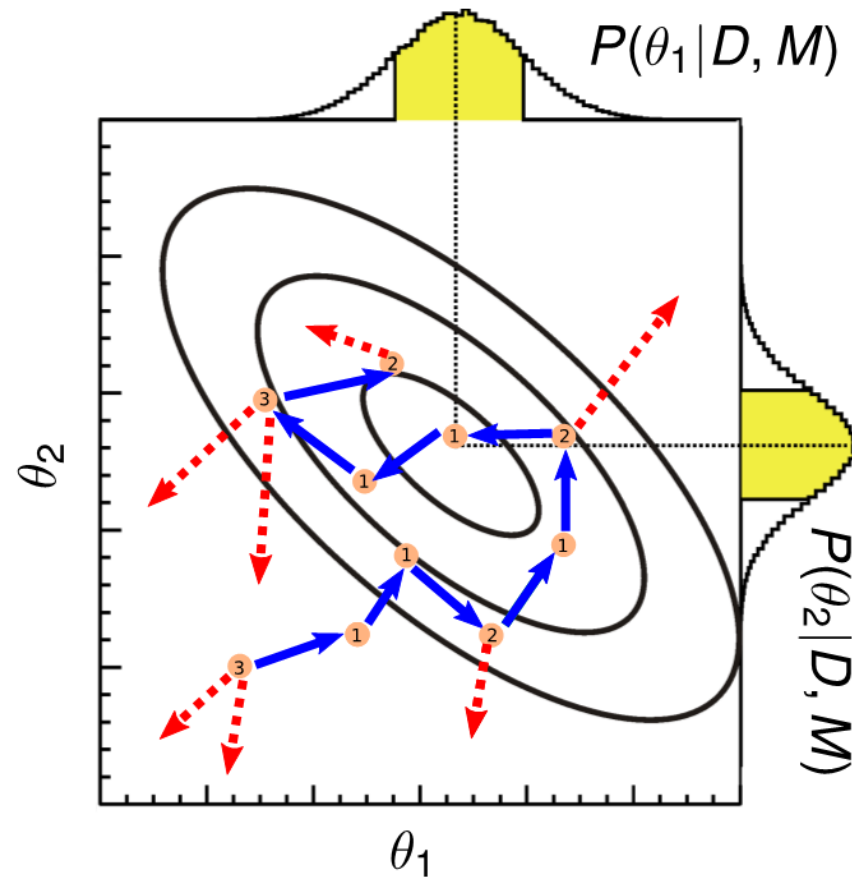
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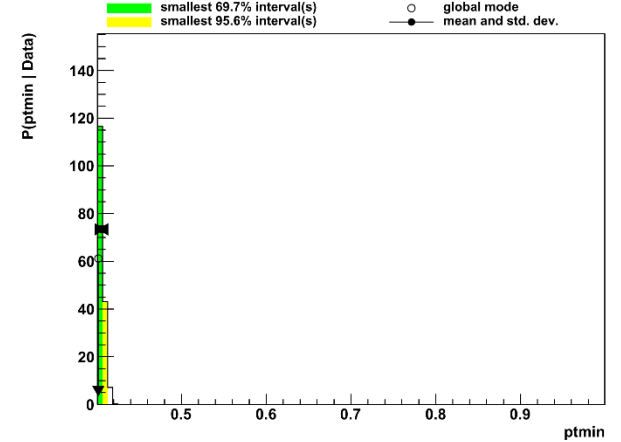
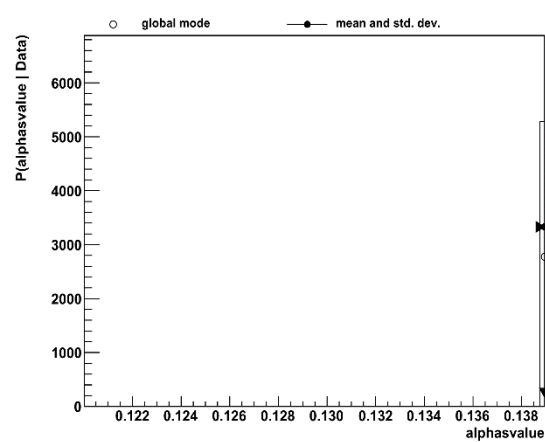
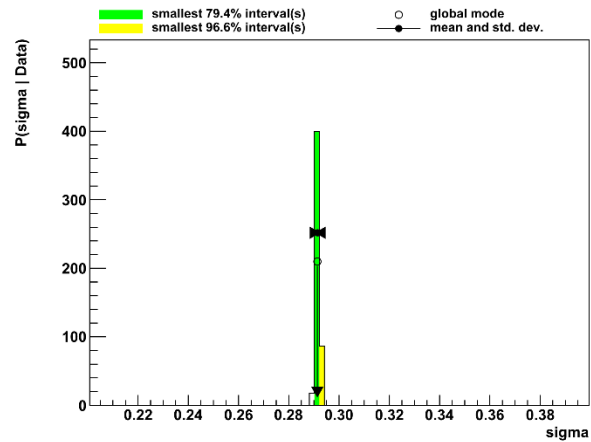
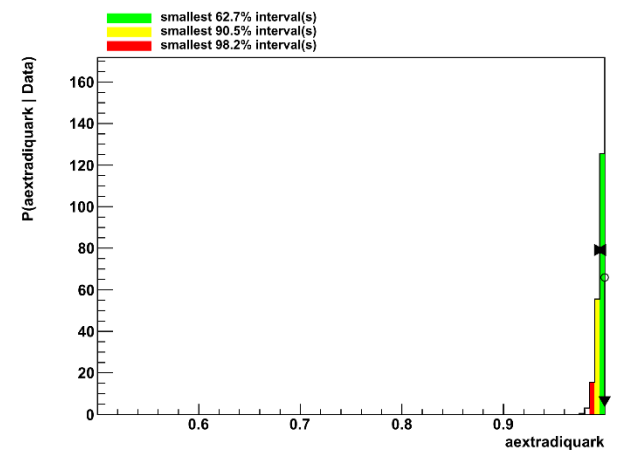
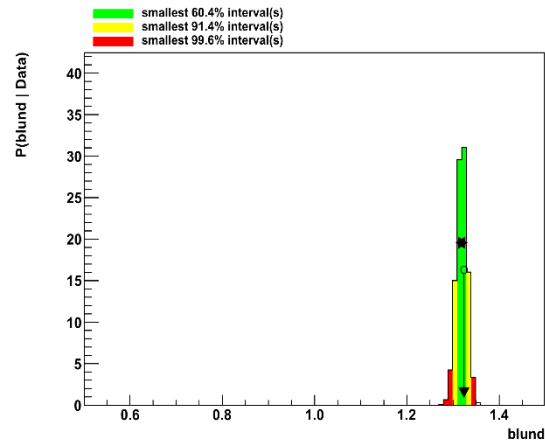
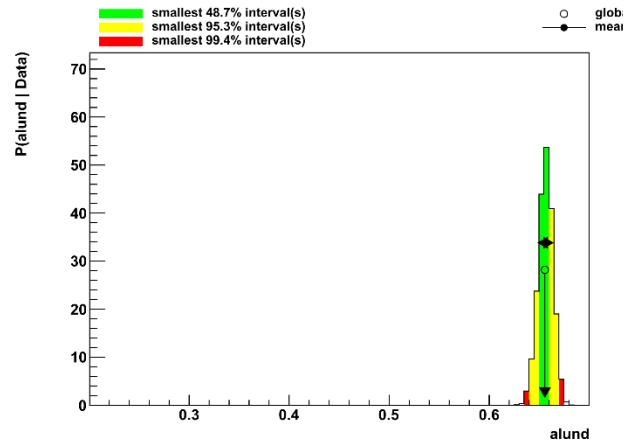
650 samples

# Backup: Markov Chains





# Backup: BAT results for Professor Ipol



# Backup: Comparison BAT $\leftrightarrow$ runcombs

Prof

BAT

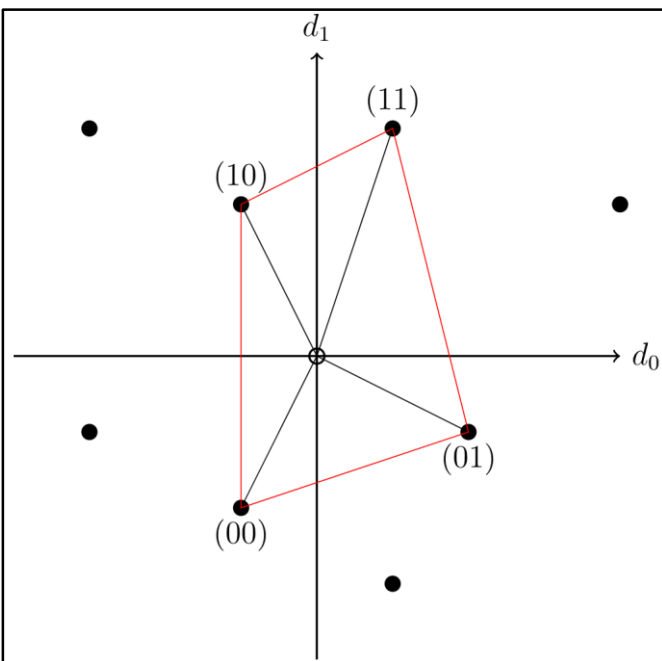
Parameter	Value	Error
$a_{\text{Lund}}$	0.622	0.064
$b_{\text{Lund}}[\text{GeV}^{-2}]$	1.253	0.090
$a_{\text{ExtraDiquark}}$	0.928	0.113
$\sigma$ [GeV]	0.292	0.001
$\alpha_s$	0.139	0.001
$p_{\text{T,min}}$ [GeV]	0.426	0.019

Parameter	Value	Error
$a_{\text{Lund}}$	0.655	0.008
$b_{\text{Lund}}[\text{GeV}^{-2}]$	1.324	0.014
$a_{\text{ExtraDiquark}}$	1.000	0.008
$\sigma$ [GeV]	0.291	0.001
$\alpha_s$	0.139	0.001
$p_{\text{T,min}}$ [GeV]	0.402	0.009

Uncertainty calculation unreliable because parameters at edges

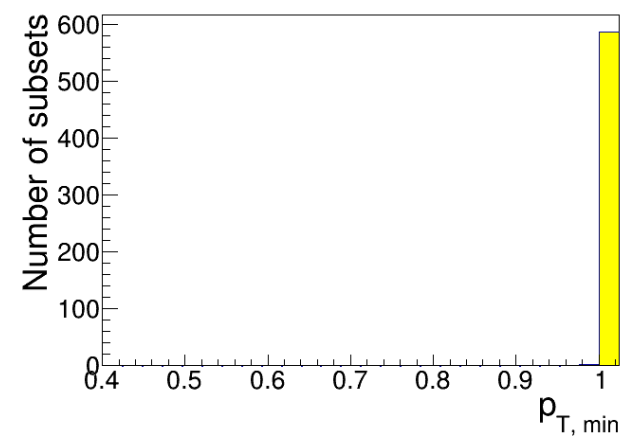
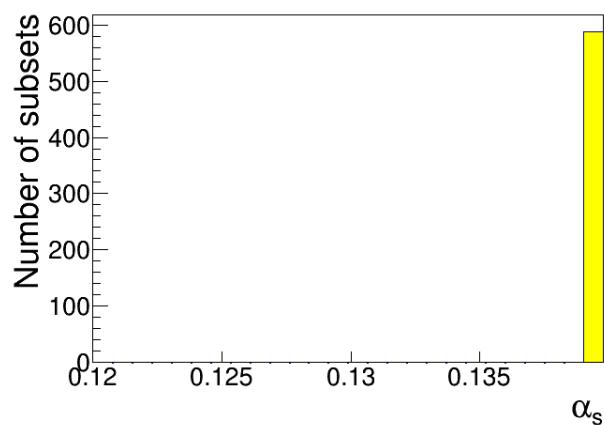
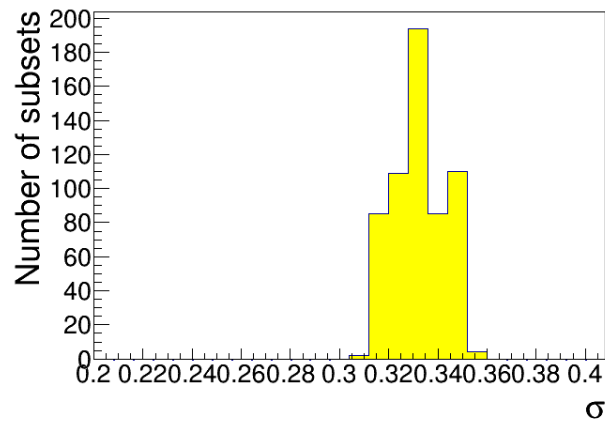
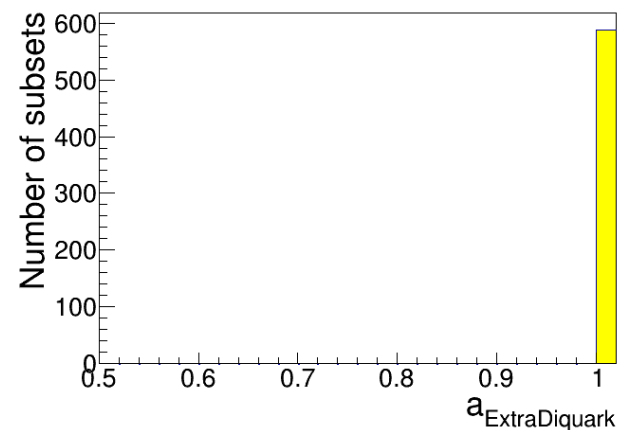
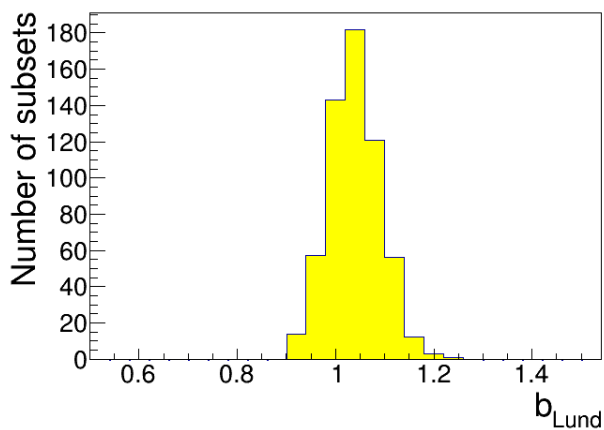
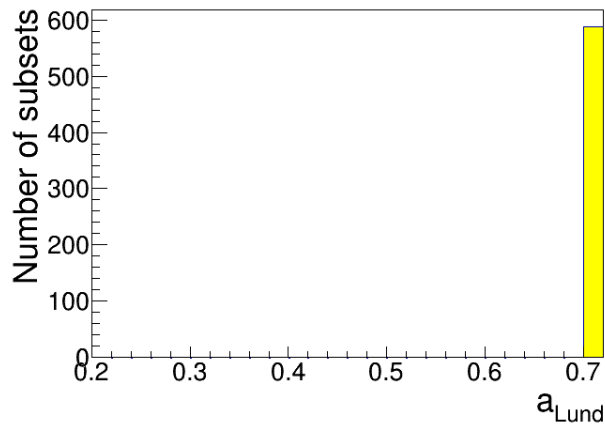
# Backup: New Interpolation: Gradients

- $\mathbf{n}_{\text{Interpolation},i} = \frac{1}{\|\nabla f_{\text{Interpolation}}\|} \nabla f_{\text{Interpolation}} \big|_{x_i}$ 
  - Polynomial function  $\rightarrow$  analytical gradient
- $\mathbf{n}_{\text{Simulation data},i} = \frac{1}{\|\nabla f_{\text{Simulation data}}\|} \nabla f_{\text{Simulation data}} \big|_{x_i}$



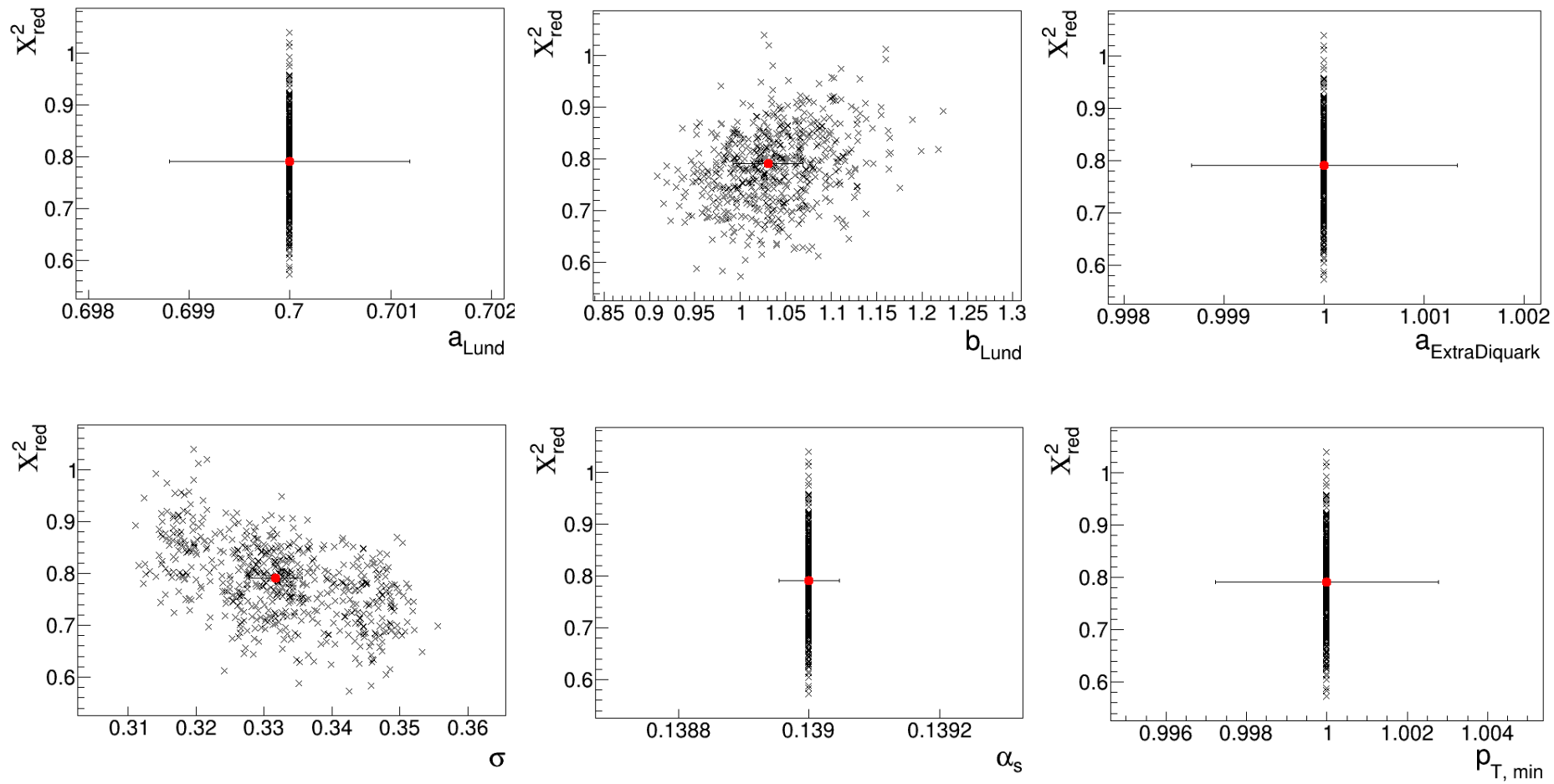
- Approach:
- Select 2<sup>dimension</sup> closest points
- Re-weight using the distance to center
- Interpolate with first order polynomial
- Calculate gradient analytically

# Backup: New Ipol with parameter limits I



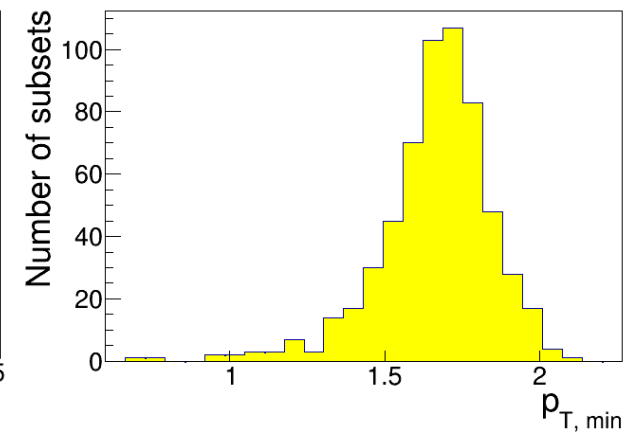
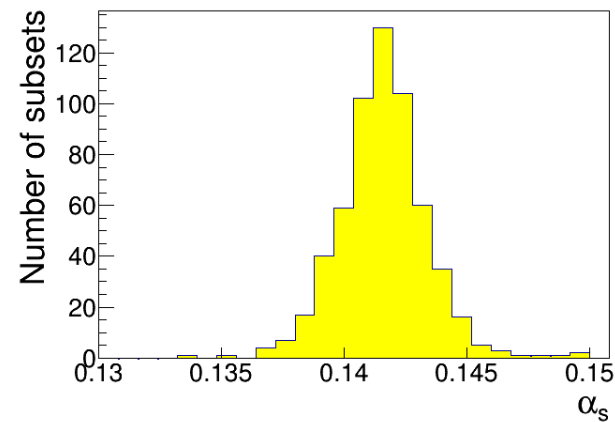
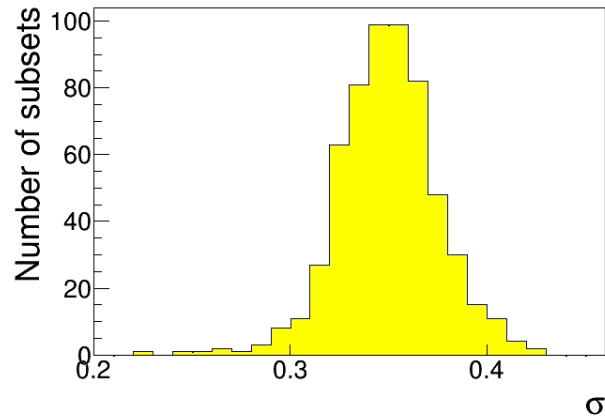
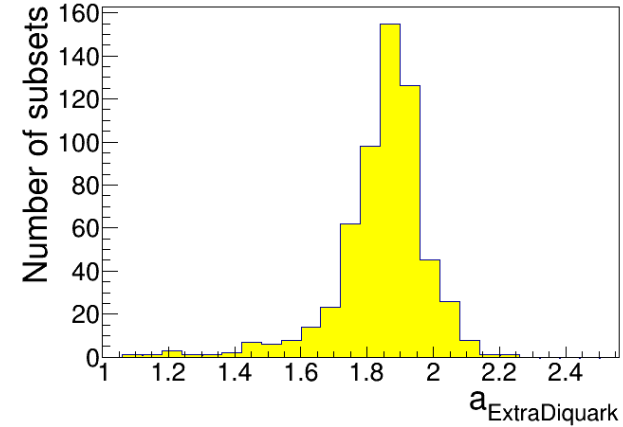
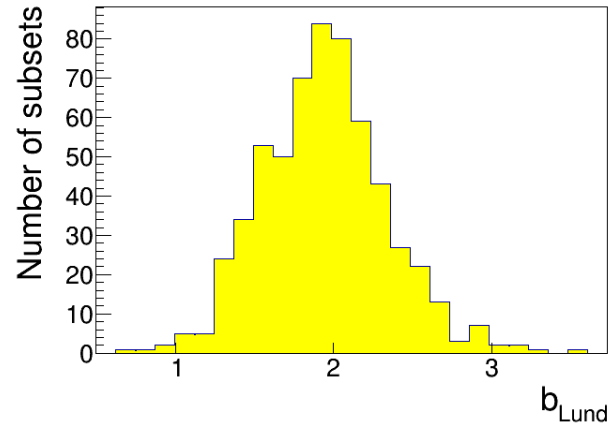
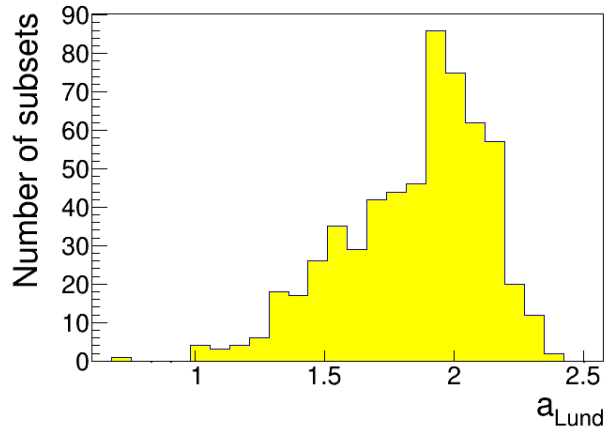
1500 samples

# Backup: New Ipol with parameter limits II



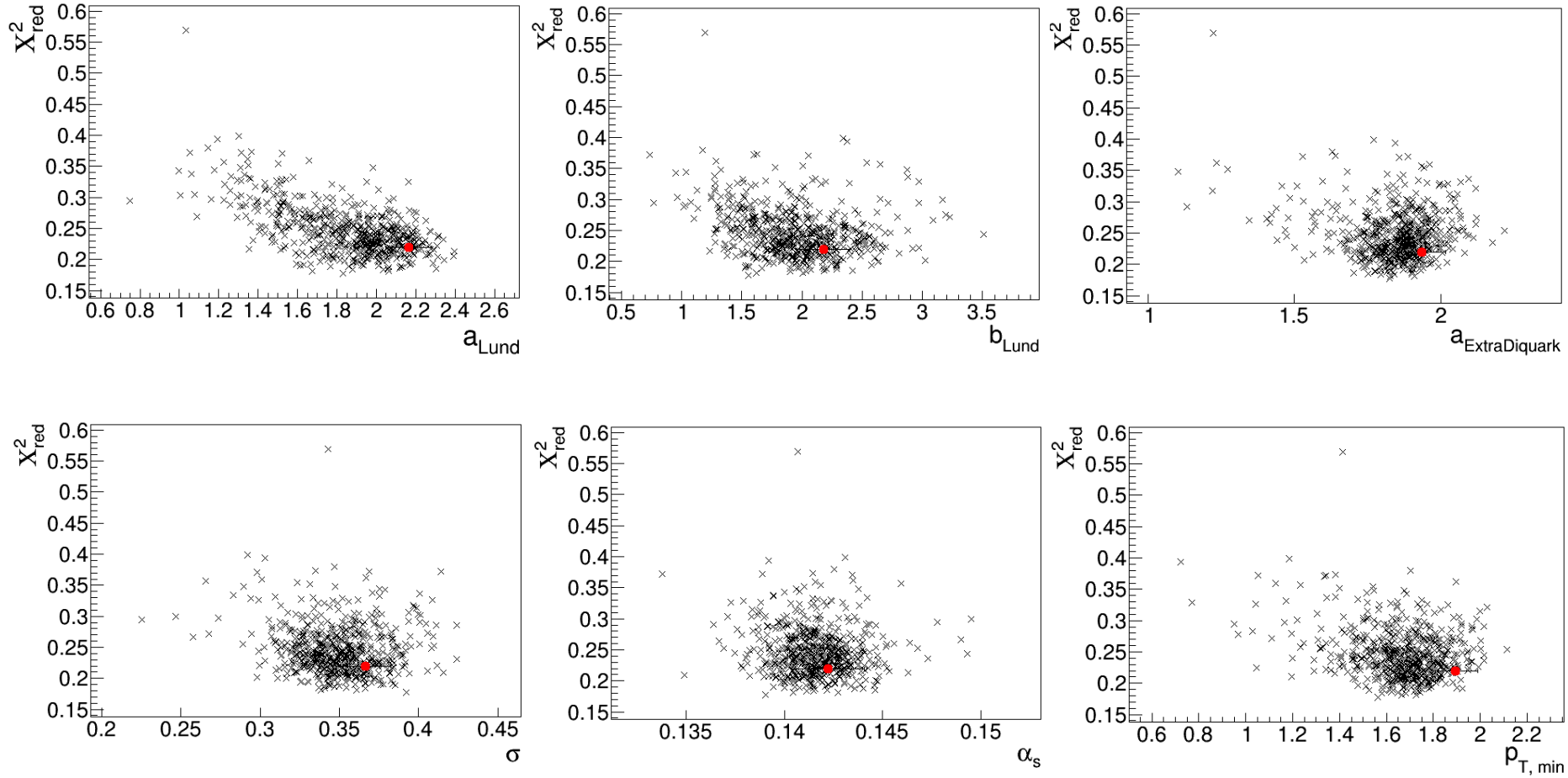
1500 samples

# Backup: New Ipol without parameter limits I



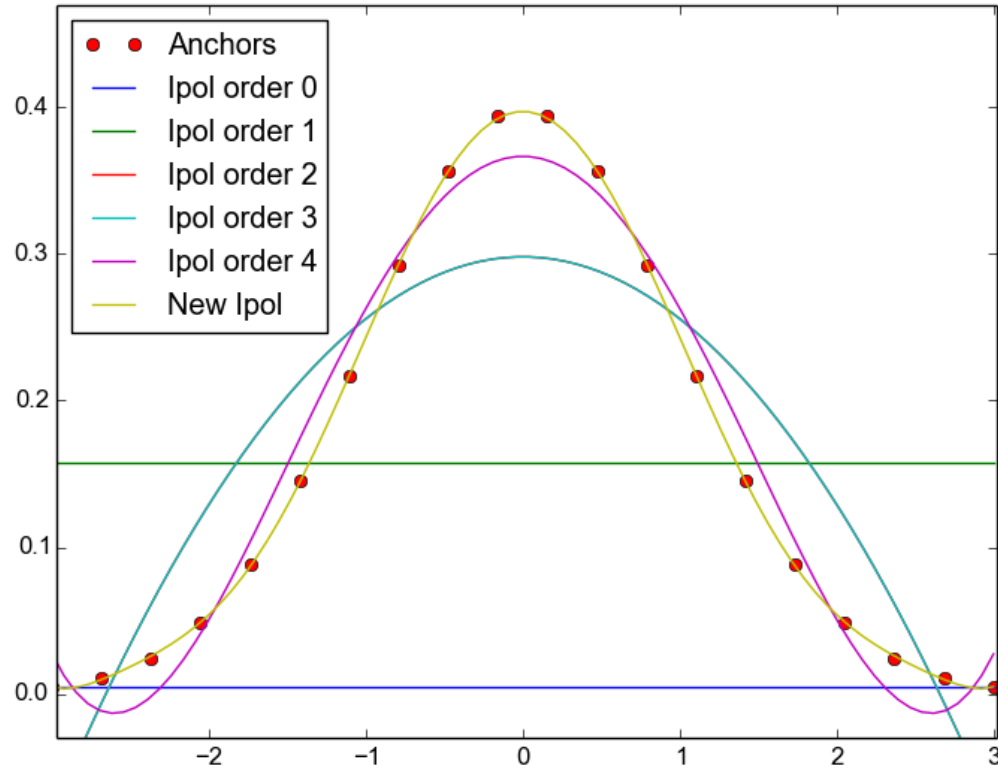
1500 samples

# Backup: New Ipol without parameter limits II



1500 samples

# Backup: Fitting the normal distribution

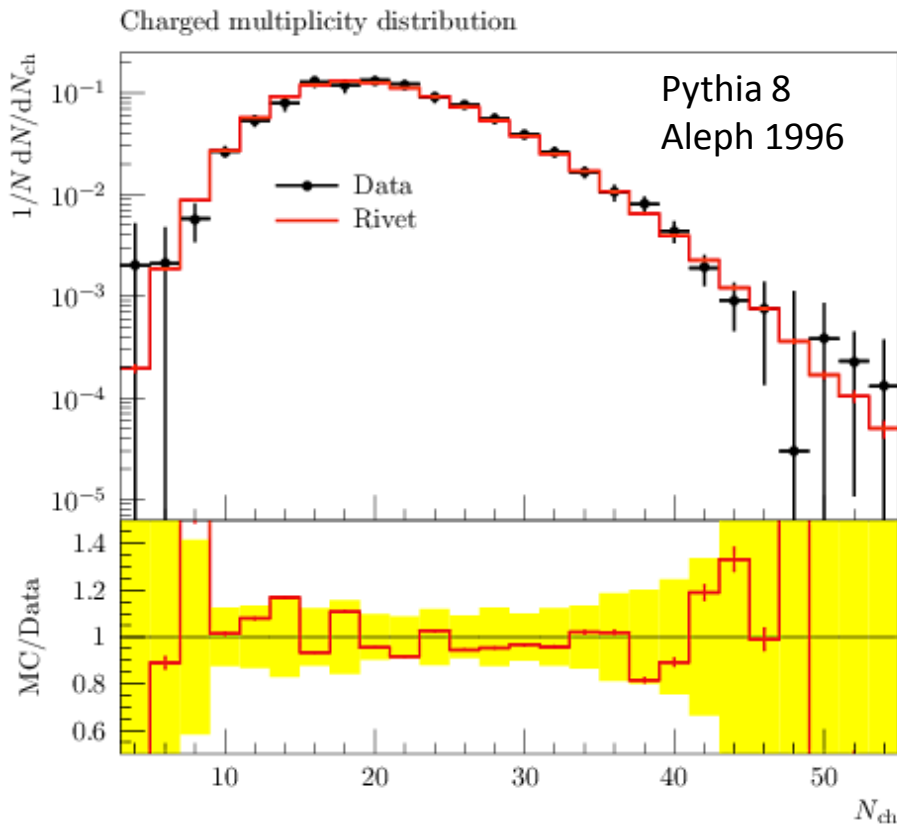




# Backup: Comparison by re-simulating

- Simulation with tuned parameter set with limits

Professor:



New interpolation:

