

MONTE CARLO TUNING AT THE LHC

Holger Schulz¹ (HU Berlin)

Hadron-Hadron & Cosmic-Ray Interactions at multi-TeV Energies

November 30, 2010

Trento



¹on behalf of the Professor and the Rivet collaborations

INTRODUCTION

- LHC is a QCD-machine in a new energy regime
- QCD well known where perturbation theory applies
- 'Soft effects' (Underlying event (UE), hadronisation...) need to be modelled
- Use Monte-Carlo generators to do that
- Models often phenomenological \Rightarrow tuneable parameters (a priori unknown)
- MC predictions used to
 - estimate experimental efficiencies, uncertainties
 - test theories
- \Rightarrow generator tuning essential to simulate events that look like real data

TYPICAL TUNEABLES

- **Intrinsic** k_T : a dirty little MC secret, important for first 5 GeV of boson p_\perp (peak)
- **(FSR)**: assume universality \rightarrow tune to e^+e^- data (eventshapes). Parameters: α_s , cutoff, starting scale fudge factors; different shower evolutions (Q^2, p_\perp, \dots) \rightarrow different tunings
- **Hadronisation**: model dependent! String or cluster constants, many parameters, separate heavy quark fragmentation. Tune to (e^+e^-) identified particle spectra
- **(ISR)**: similar to FSR, tune to hadron collider data. Inter-jet data e.g. $Z p_\perp$ and dijet angular decorrelation – but jet shapes now considered important. For PYTHIA, fitting jet shapes means more **semi-dirty tricks**: vary α_s in FSR of ISR particles! (Perugia 2010)
- **Underlying Event (UE)**: Tune to hadron collider data, sensitive to PDF choice. Parameters: beam particle matter distribution, cutoff for Multiple Parton Interactions (MPI)

TUNING THROUGH THE AGES (AND AT LHC)

- Manual tunes: lots of time and manpower or tuning experience of a life-time
 - Brute-force grid-scans: tough in higher dimensions of parameter space
 - Genetic algorithm (GAMPI, Sami Kama): burns a LOT of CPU
 - **systematically:**
 - Bin-wise interpolation of MC generator response and χ^2 minimization (DELPHI 1995, Hamacher et al.)
- but:**
- 2nd order polynomials account for parameter correlations
 - Code (fortran) not sufficiently flexible
 - Restricted to 2nd order polynomial for bin-wise interpolation

Professor ([arXiv:0907.2973](https://arxiv.org/abs/0907.2973), [arXiv:0906.0075](https://arxiv.org/abs/0906.0075), [arXiv:0902.4403](https://arxiv.org/abs/0902.4403))

“PROCEDURE FOR ESTIMATING SYSTEMATIC ERRORS”

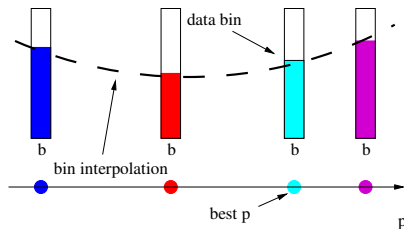
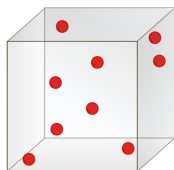


- Pick up DELPHI idea, much more functionality
- Implemented as a Python package and set of scripts:
- Actively being developed



TUNING PROCEDURE IN PROFESSOR (1D, 1BIN)

- 1 Random sampling: N parameter points in n -dimensional space
- 2 Run generator and fill histograms
- 3 For each bin: use N points to fit interpolation (2nd or 3rd order polynomial)
- 4 Construct overall (now trivial) $\chi^2 \approx \sum_{bins} \frac{(interpolation - data)^2}{error^2}$
- 5 and Numerically *minimize* `pyMinuit`, `SciPy`



PROFESSOR NEWS

- Version 1.0.0 just released, version 1.0.1 out soon
- Focus on usability, user friendliness
- Have setup scripts now
- Extensive documentation (SPHINX)
- Command lines unified, simplified
- Can assign weights bin-wise now
- More exploitation of covariance matrices ("Eigentunes")
- Readily available on AFS

```
/afs/cern.ch/sw/lcg/external/MCGenerators/professor/1.0.0
```

- Started a YouTube channel for screencasts

```
http://www.youtube.com/user/ProfessorRivet
```



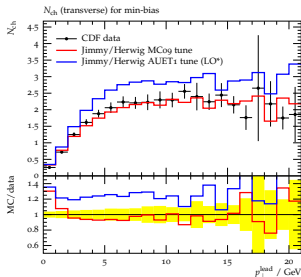
OBSERVABLES AND WEIGHTS

- This is what Professor minimises: $\chi^2(\vec{p}) = \sum_{\mathcal{O}} \sum_{b \in \mathcal{O}} w_b \frac{(f^{(b)}(\vec{p}) - \mathcal{R}_b)^2}{\Delta_b^2}$
- Slightly more art than science
- Garbage in, garbage out
- Use weights w_b to:
 - emphasize certain observables
 - emphasize certain bins of an observable
 - switch off single bins (e.g. MinBias region for Jimmy Herwig)



OBSERVABLES AND WEIGHTS

- This is what Professor minimises: $\chi^2(\vec{p}) = \sum_{\mathcal{O}} \sum_{b \in \mathcal{O}} w_b \frac{(f^{(b)}(\vec{p}) - \mathcal{R}_b)^2}{\Delta_b^2}$
- Slightly more art than science
- Garbage in, garbage out
- Use weights w_b to:
 - emphasize certain observables
 - emphasize certain bins of an observable
 - switch off single bins (e.g. MinBias region for Jimmy Herwig)
- No MinBias physics in Jimmy Herwig
- Cannot get first 3 bins or so right
- Transition from MinBias to UE type physics
- \Rightarrow Exclude these bins from Professor minimisation



OBSERVABLE SELECTION

How do we select, which (existing) data to tune to?



OBSERVABLE SELECTION

How do we select, which (existing) data to tune to?

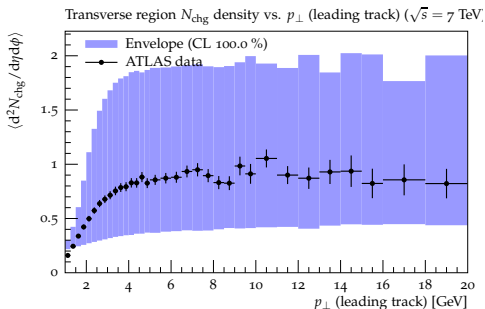
- Lots of thinking, reading and consultation of generator authors.



OBSERVABLE SELECTION

How do we select, which (existing) data to tune to?

- Lots of thinking, reading and consultation of generator authors.
- Checking production (envelopes) \rightarrow helps identify problematic regions.



OBSERVABLE SELECTION

How do we select, which (existing) data to tune to?

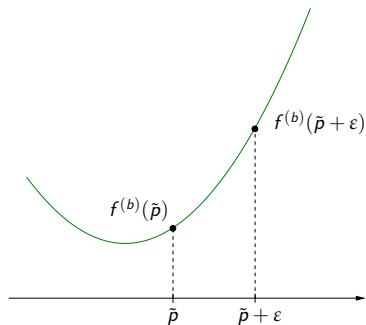
- Lots of thinking, reading and consultation of generator authors.
- Checking production (envelopes) → helps identify problematic regions.
- Analysing sensitivity of observables to shifts in parameter space:
“How much does the bin content change if I vary parameter i ?”



OBSERVABLE SELECTION

How do we select, which (existing) data to tune to?

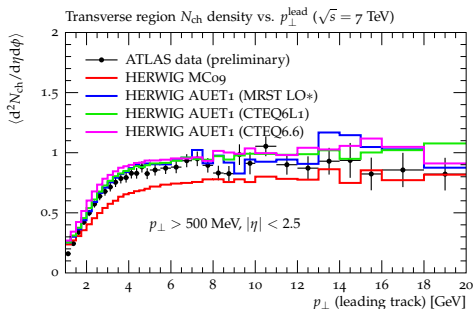
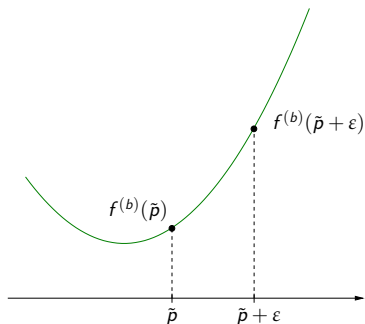
- Lots of thinking, reading and consultation of generator authors.
- Checking production (envelopes) \rightarrow helps identify problematic regions.
- Analysing sensitivity of observables to shifts in parameter space:
“How much does the bin content change if I vary parameter i ?”



OBSERVABLE SELECTION

How do we select, which (existing) data to tune to?

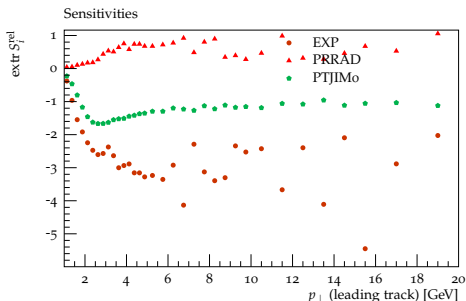
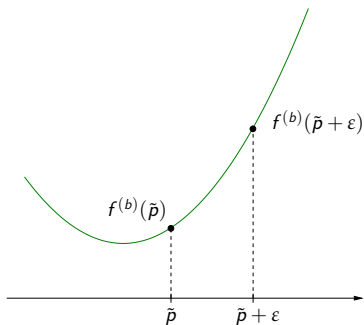
- Lots of thinking, reading and consultation of generator authors.
- Checking production (envelopes) \rightarrow helps identify problematic regions.
- Analysing sensitivity of observables to shifts in parameter space:
“How much does the bin content change if I vary parameter i ?”



OBSERVABLE SELECTION

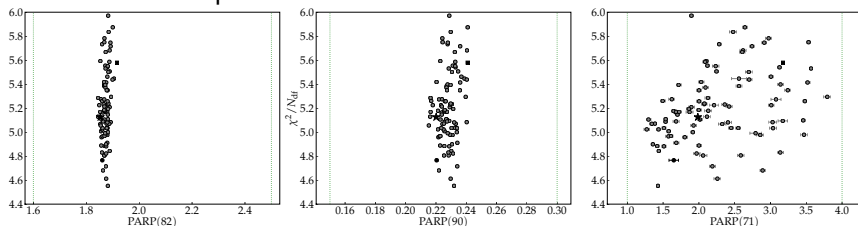
How do we select, which (existing) data to tune to?

- Lots of thinking, reading and consultation of generator authors.
- Checking production (envelopes) \rightarrow helps identify problematic regions.
- Analysing sensitivity of observables to shifts in parameter space: “How much does the bin content change if I vary parameter i ?”



SOME TUNE PARAM SPREADS

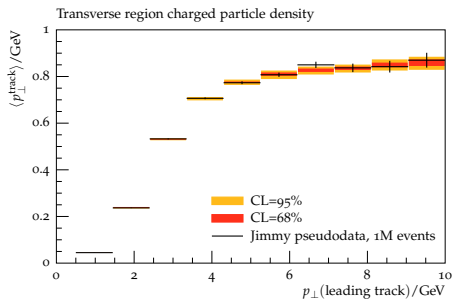
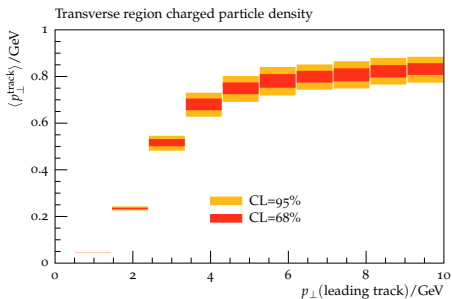
Oversampling required, but if we *really* oversample, then can make many combinations of input MC runs:



- *informal* picture of how well-constrained a parameter is
- We are happy if it looks like a vertical line
- Spread used for tuning-uncertainty estimates

STATISTICALLY-DRIVEN TUNE ERROR BANDS

ERRORS FROM RUN-COMBINATION SAMPLING

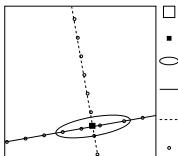
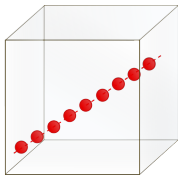


⇒ turned parameter spread into uncertainty belts

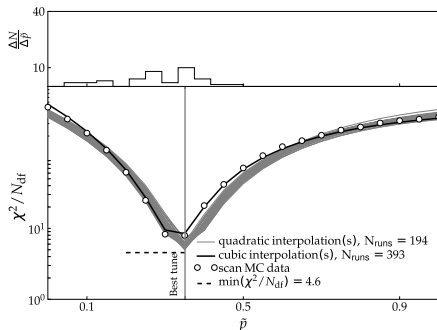
Most complete procedure for full systematics in Les Houches proceedings (arXiv:1003.1643). Full treatment requires asymmetric covariance sampling.

CHECKING PARAMETERISATION: LINE-SCANS

- Sample params from straight hyperline through χ^2 valley

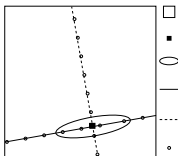
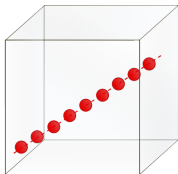


- Calculate and compare χ^2 of parameterisation with “true” MC response

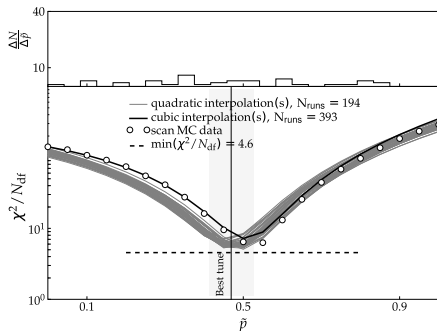


CHECKING PARAMETERISATION: LINE-SCANS

- Sample params from straight hyperline through χ^2 valley



- Calculate and compare χ^2 of parameterisation with “true” MC response



INTERACTIVITY

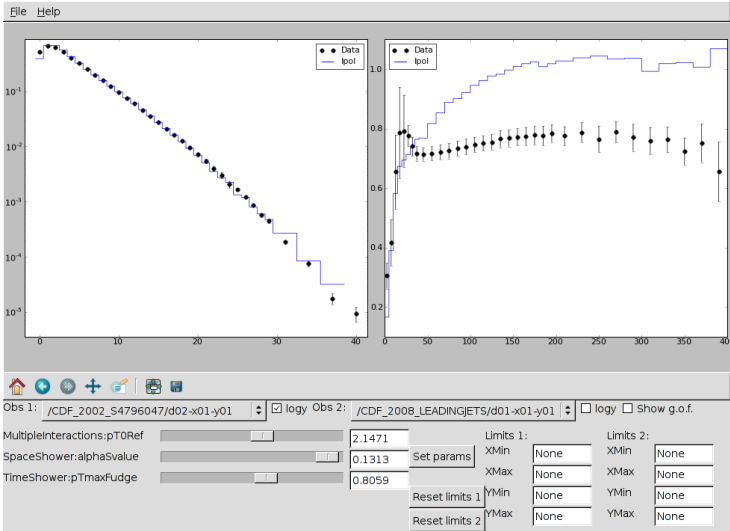
Key feature of Professor:

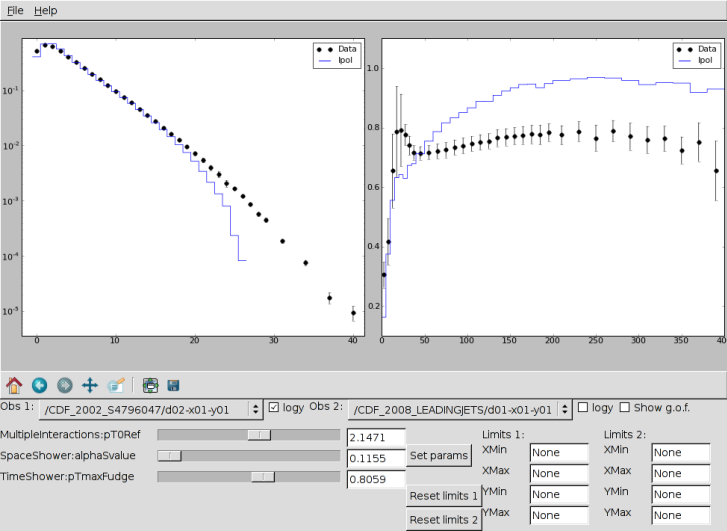
- 1 we are parameterising a very expensive function
- 2 input to that parameterisation can be trivially parallelised
 - Can parallelise parameterisation (for many run combinations)
 - Optimisation, too

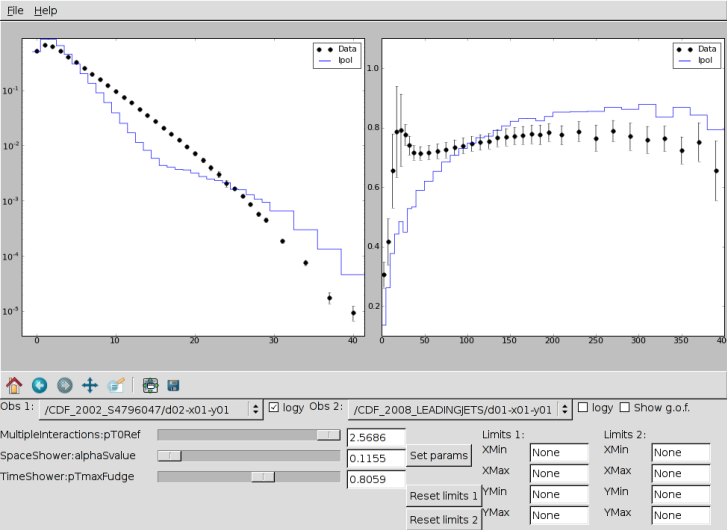
Parameterisation produces a **fast, analytic “pseudo-generator”**

- \Rightarrow Can get a good approximation of what a generator will do when run for many hours/days with particular params, in < 1 second!

Why not make an **interactive MC simulator**?







- Analysis system operating on HepMC events
- Emphasis on not messing with the MC implementation details, reconstruct bosons, jets, don't trace back partons
- Lots of standard analyses built in (mostly driven by tuning needs), try to “mimic” experiments:
 - hadron physics: ATLAS, CDF, D0, E735, SFM, STAR, UA1, UA5
 - e^+e^- : ALEPH, BELLE, DELPHI, JADE, OPAL
 - Deep inelastic scattering: H1, ZEUS
 - Pure MC: Jet, W, Z, Photons, SUSY...
- Binning read from data files (check HepData <http://durpdg.dur.ac.uk> for availability)
- Development of new analyses rapid, possible as plug-in (heavily used in ATLAS)
- Most recent version 1.3.0 released a few days ago, patch release 1.3.1 soon
- Recent versions of Sherpa and Herwig++ can be linked against Rivet, Pythia8 will follow soon

TUNING AT THE LHC

Most important requirement for tuning: data, corrected for detector effects \Rightarrow only ATLAS available from LHC in summer

Please correct your data and upload to HepData

CMS

- UE tunes by Rick Field
- Manual tunings of two Pythia 6 parameters to ATLAS data
- Called “Z1”, based on ATLAS AMBT1 tune, available in Pythia6.424

ALICE, LHC_B, LHC_F, TOTEM

?



ATLAS TUNING ACTIVITIES – OVERVIEW

For the moment, concentrated on “work horses” Pythia 6 and Jimmy Herwig 6

- Before we had data, only manual tunes (MC08, MC09)
- Since MinBias data: all tunes done with Professor
- Pythia 6: MC09c, AMBT1 (ATLAS Min Bias Tune 1)
- Jimmy Herwig 6: MC09, AUET1 (ATLAS UE Tune 1)

- Jimmy Herwig 6 tune repeated for different PDFs

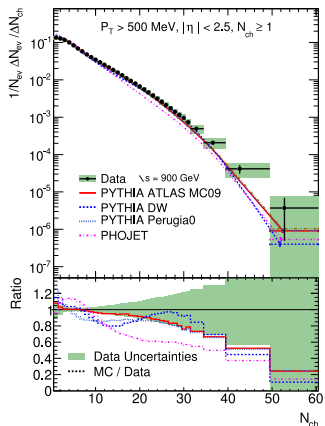
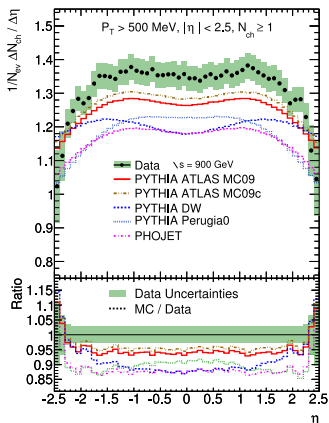
ATLAS now requires that groups provide a Rivet implementation of their analyses. This much more convenient than having to write emails to authors 20 years after publication.



ATLAS TUNING OF PYTHIA 6

There was nice teamwork in ATLAS between tuning and MinBias groups:

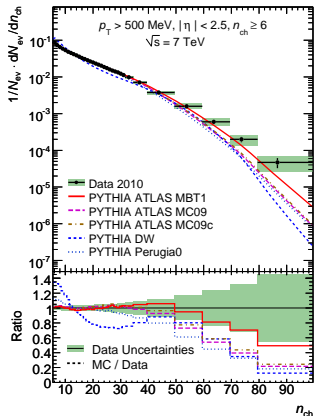
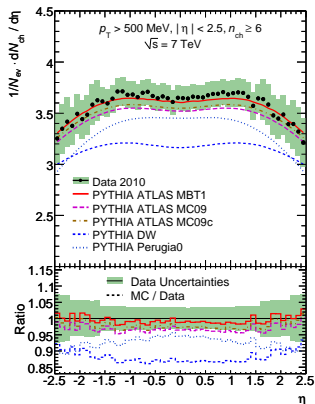
- Used first MinBias data (arXiv:1003.3124 [hep-ex]) to make tuning MC09c
- Not so great because of bad diffraction modelling in Pythia 6 and data being normalised to number of particles



ATLAS TUNING OF PYTHIA 6 (CONTINUED)

Asked MinBias guys to redo analysis with additional cut $N_{\text{ch}} \geq 6$

- Used this data (ATLAS-CONF-2010-031) to make tune AMBT1
- We always had close contact with analysis people, therefore implementation of analyses in Rivet was easy



ATLAS TUNING AND SYSTEMATIC STUDIES

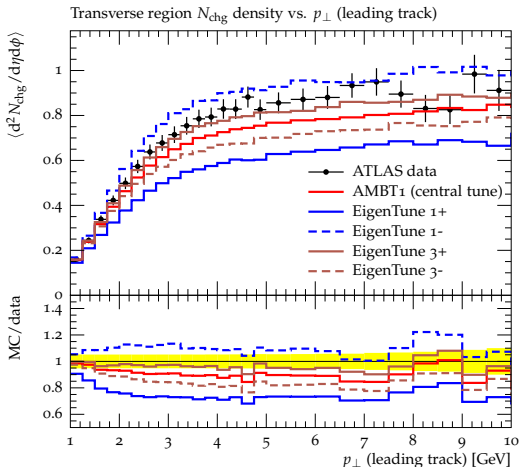
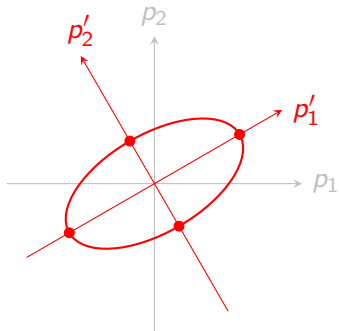
- For efficiency studies, people need tunings “that have 20% more UE activity”
- How do you do that without breaking model agreement with data too much?
- Pheno. parameters may be highly correlated \Rightarrow varying a single parameter can be a bad idea
- Invented “Eigentunes” in Professor



EIGENTUNES

Pick the extremal points of the χ^2 contour hyper-ellipsoid as representative tunes, cf. Hessian PDF errors.

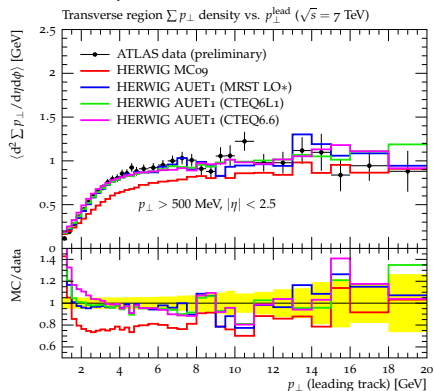
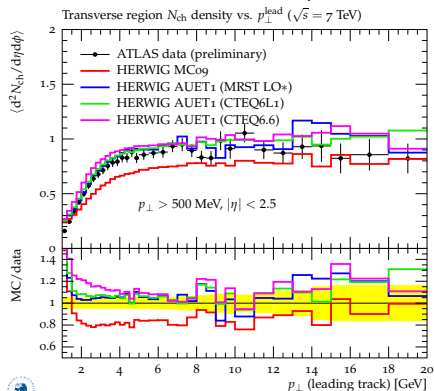
\Rightarrow obtained Eigentunes stay consistent, respect correlations



RETUNING FOR DIFFERENT PDFs

- In ATLAS, different physics groups prefer different PDFs
- Changing the PDF requires retuning of e.g. MPI parameters
- Once tuning successful for one PDF, repetition for others trivial
- Run generator once more with new PDF, tune to **same** weights
- So far: good observable descriptions achievable independent on PDF choice

Examples for Jimmy Herwig (ATL-PHYS-PUB-2010-014)



SUMMARY

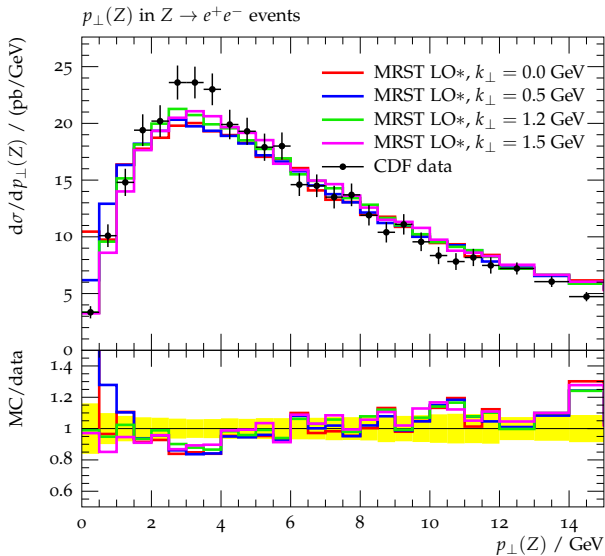
- Tuning important for best possible modelling of soft (QCD) physics
- Rivet and Professor have become standard tools to do this systematically
- We need data corrected for detector effects
- Quick turn-around from data-taking at LHC to tuning possible ($\mathcal{O}(\text{few days})$)
- Can quantify tuning uncertainties
- Can produce tunings for different purposes (Eigentunes, many PDFs)
- Interactive Explorer (model developers like it)
- More ideas? What about cosmic rays?

Thank you!



Backup

INTRINSIC k_{\perp}



AUET1 PARAMETERS

Parameter i	MC09 LO*	i_{\min}	i_{\max}	LO*	AUET1 CTEQ6L1	CTEQ6.6
Parameters fixed before numerical tuning						
ISPAC	ISR-shower scheme	0	2	2		
PTRMS	Primordial k_{\perp}	0	0.5	2.0	1.2	1.2
Tuned cutoff meta-parameters						
PTJIM0	MPI cut-off scale	3.6	1.5	5.5	2.86	2.32
EXP	MPI cut-off evolution	0.274	0.2	0.35	0.273	0.220
Tuned Jimmy parameters						
PRRAD	(Anti)proton radius	2.2	1.5	2.5	1.69	1.90

TUNED PARAMETERS

- MPI cut-off:

naive PTJIM \rightarrow PTJIM(\sqrt{s}) = PTJIM0 \cdot $\left(\frac{\sqrt{s}}{1800 \text{ GeV}}\right)^{\text{EXP}}$ (yes, same as in Pythia)

- (Anti-) protonradius **PRRAD**
- Primordial k_{\perp} -width **PTRMS**: ATLAS oversight number two, was left at unreasonable default 0, we tuned it manually
- ISR-cut-off scale **QSPAC**: we tried tuning but observables not sensitive, kept it at MC09 value of 2.5 GeV

2nd order polynomial includes lowest-order correlations between parameters

$$MC_b(\vec{p}) \approx f^{(b)}(\vec{p}) = \alpha_0^{(b)} + \sum_i \beta_i^{(b)} p_i' + \sum_{i \leq j} \gamma_{ij}^{(b)} p_i' p_j'$$

Now use N generator runs, i.e. N different parameter sets x,y:

$$\underbrace{\begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_N \end{pmatrix}}_{\vec{v} \text{ (N values, i.e. N bin contents)}} = \underbrace{\begin{pmatrix} 1 & x_1 & y_1 & x_1^2 & x_1 y_1 & y_1^2 \\ 1 & x_2 & y_2 & x_2^2 & x_2 y_2 & y_2^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_N & y_N & x_N^2 & x_N y_N & y_N^2 \end{pmatrix}}_{\tilde{\mathbf{P}} \text{ (N sampled parameter sets)}} \underbrace{\begin{pmatrix} \alpha_0 \\ \beta_x \\ \beta_y \\ \gamma_{xx} \\ \gamma_{xy} \\ \gamma_{yy} \end{pmatrix}}_{\vec{c} \text{ (coeffs)}}$$

Therefore: $\vec{c}_b = \tilde{\mathcal{I}}[\tilde{\mathbf{P}}]\vec{v}$ where $\tilde{\mathcal{I}}$ is the pseudoinverse operator.

$$\vec{c}_b = \tilde{\mathcal{I}}[\tilde{\mathbf{P}}]\vec{v}$$

- Use Singular Value Decomposition (SVD), a general diagonalisation for all normal matrices $M: M = U\Sigma V^*$
- Method available in SciPy.linalg
- Minimal number of runs = number of coefficients in \vec{c}_b :

$$N_{\min}^{(n)} = 1 + n + n(n+1)/2 + \underbrace{(n+1)(n+2)/6}_{\text{cubic only}}$$

$$\vec{c}_b = \tilde{\mathcal{I}}[\tilde{\mathbf{P}}]\vec{v}$$

- Use Singular Value Decomposition (SVD), a general diagonalisation for all normal matrices $M: M = U\Sigma V^*$
- Method available in SciPy.linalg
- Minimal number of runs = number of coefficients in \vec{c}_b :

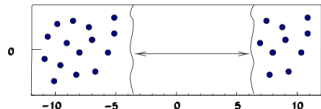
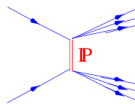
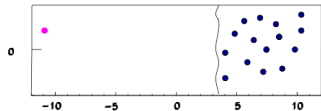
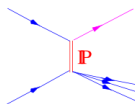
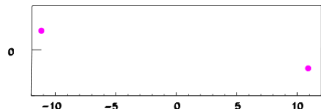
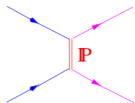
$$N_{\min}^{(n)} = 1 + n + n(n+1)/2 + \underbrace{(n+1)(n+2)/6}_{\text{cubic only}}$$

- Oversampling by a factor of three has proven to be much better

Num params, P	$N_2^{(P)}$ (2nd order)	$N_3^{(P)}$ (3rd order)
1	3	4
2	6	10
4	15	35
6	28	84
8	45	165
9	55	220
10	66	286

DIFFRACTIVE PROCESSES

- Diffractive means exchange of *colourless* object (Pomeron, glueball, no gluon!)
- Leads to “rapidity gap” in detector (e.g. no hits in $|\eta| < 3$)
- Single diffractive (SD) = only one proton dissociates
- Double diffractive (DD) = both protons dissociate
- Contributions to lowest multiplicity bins
- \rightarrow wrong estimate affects dN/dN_{ch} !



Mario Deile et al. (arXiv:hep-ex/0602021)