Professor

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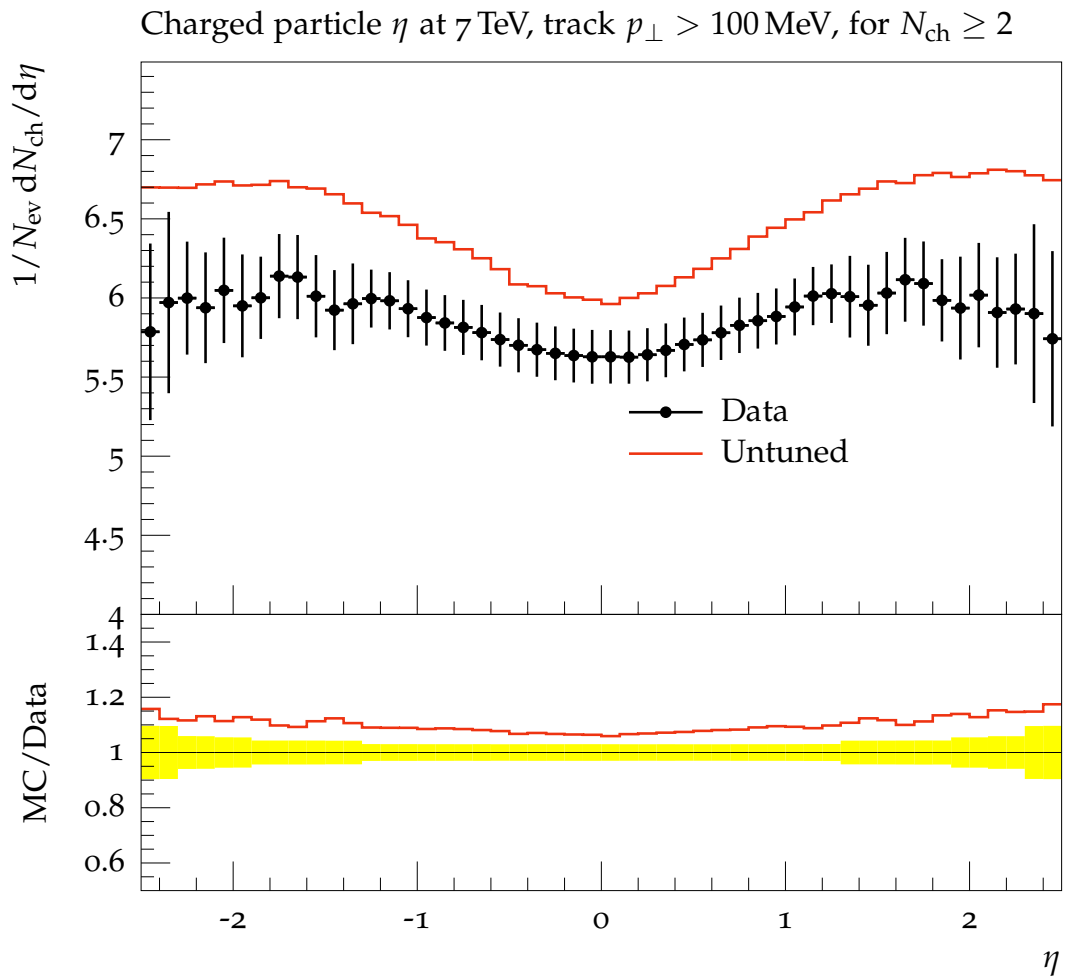
Berlin

Tuning

Comparison of SGH predictions might be incompatible with data



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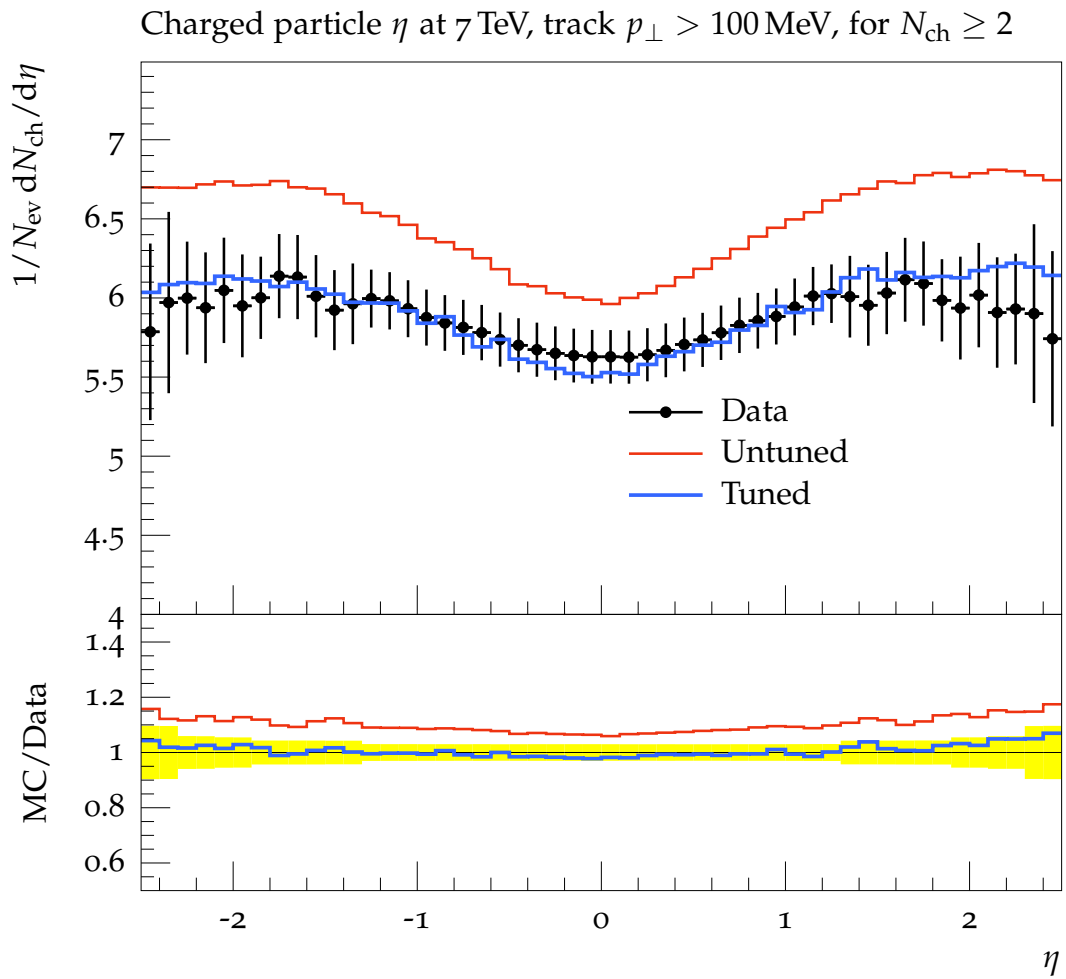

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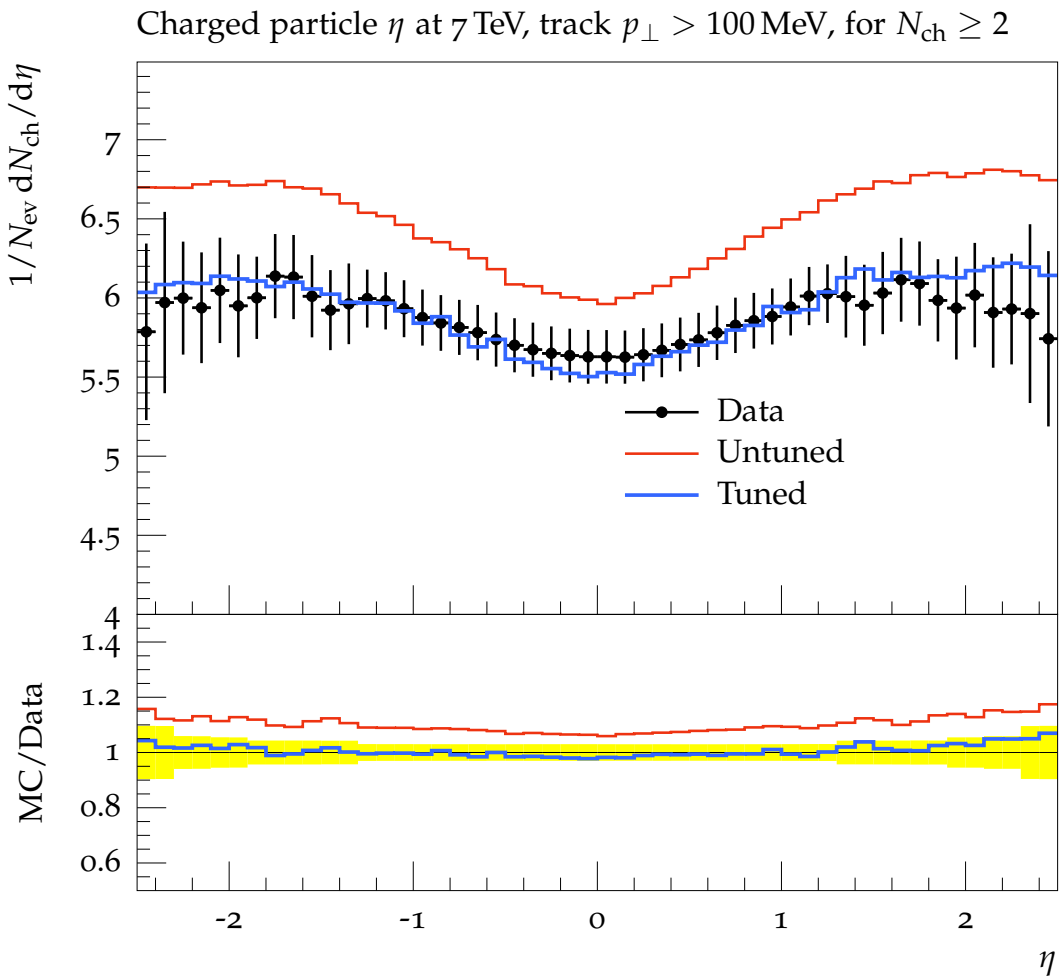
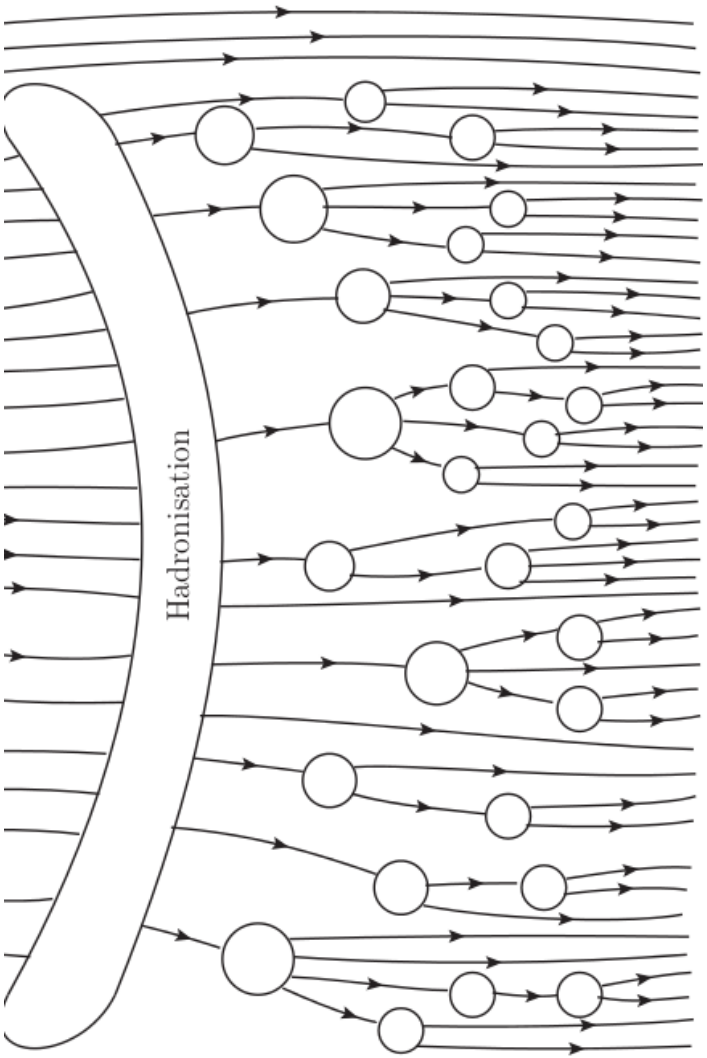


In the following: how to compare MC with data, how to get from red to blue

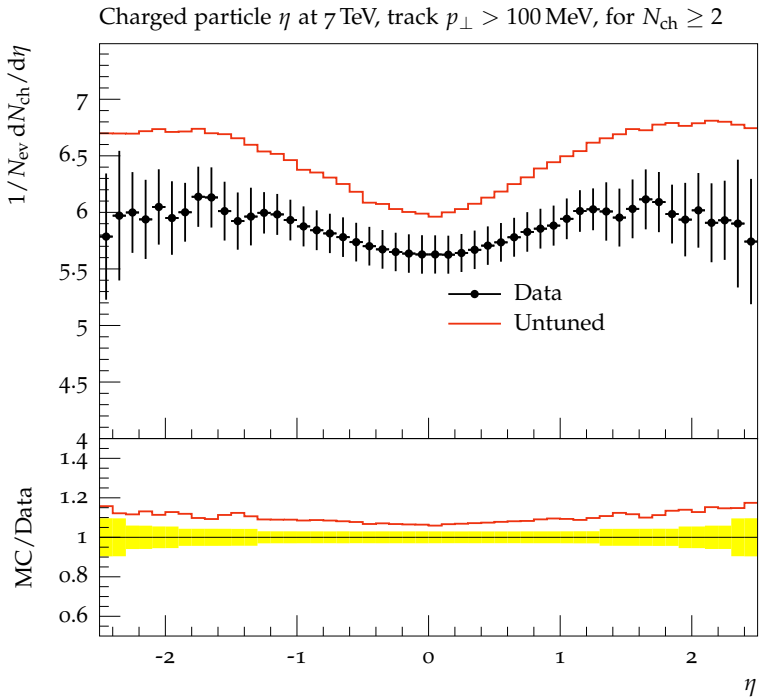
Rivet

- Analysis tool for MC events, generator agnostic via HepMC
- Provides most relevant methods for multi particle final states:
  - Cuts
  - Jets
  - Boson finders
  - Event shapes
  - ...
- Writes out histogram (YODA format)
- Strong ties to HepData
- Implementation and validation of new (data) analyses provided by experiment
- Easy to write new analyses for signal and background estimates from MC



Tuning

- Set of tuneable parameters $\vec{p}$
- For bins b have data D_b and $MC_b(\vec{p})$
- Looks like a χ^2 minimisation problem:
  $\chi^2(\vec{p}) = \sum_b (D_b - MC_b(\vec{p}))^2$
- However, $MC_b(\vec{p})$ is an expensive function
- Professor: replace $MC_b(\vec{p})$ with fast approximation $I_b(\vec{p})$



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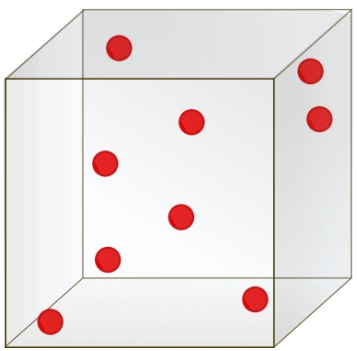
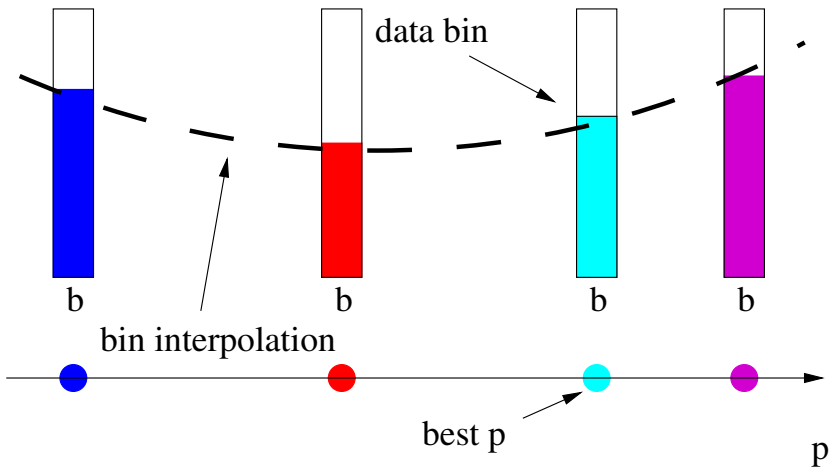
Tuning with Professor

- Random sampling: N parameter points in n-dimensional space
- Run generator and fill histograms (e.g. Rivet)
- For each bin:
  - Don't care about actual dependence on parameters
  - Polynomial approximation
- Construct overall (now trivial) $\chi^2(\vec{p}) \approx \sum_{bins} \frac{(D_b - I_b(\vec{p}))^2}{error^2}$
- and numerically *minimise* with `iminuit`





Professor 2

- `http://professor.hepforge.org`, release 2.1.3
- Complete rewrite
- Parametrisation now in C++ (Eigen)
  - Usage in other codes (`arXiv:1511.05170[hep-ph]`, `arXiv:1506.08845[hep-ph]`)
- Python bindings (through cython) for flexibility:

```
import professor2 as prof
# X ... parameter points, e.g. 3-dimensional
# Y ... corrsponding values
I=prof2.Ipol(X,Y, order=5)
print I.val([0, -.5, 13])
```

- HepMC to Rivet to YODA to Professor tool chain of course still supported with set of scripts
- Much improved command line
- Parametrisations stored in text files
- Added derivatives

Professor approach

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- Thus replace CPU time for evaluation from hours . . . days to milliseconds

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Basic work cycle

1. Define and sample M-times from d-dimensional parameter space $\mathcal{P}$
2. For each of the M points $\vec{p}_i$: evaluate exact $f(\vec{p}_i)$

   N.b. this step is trivially parallelisable
3. Fit **polynomial** $I(\vec{p})$ through
   $[(\vec{p}_1, f(\vec{p}_1)), (\vec{p}_2, f(\vec{p}_2)), \cdots, (\vec{p}_M, f(\vec{p}_M))\ ]$

   e.g. $$I(p_1, p_2) = \alpha_0 + \beta_1 p_1 + \beta_2 p_2 + \gamma_{11} p_1^2 + \gamma_{12} p_1 \cdot p_2 + \gamma_{22} p_2^2$$

   Store coefficients in text file

Parametrisation validation

- E.g. histogram H with N bins:
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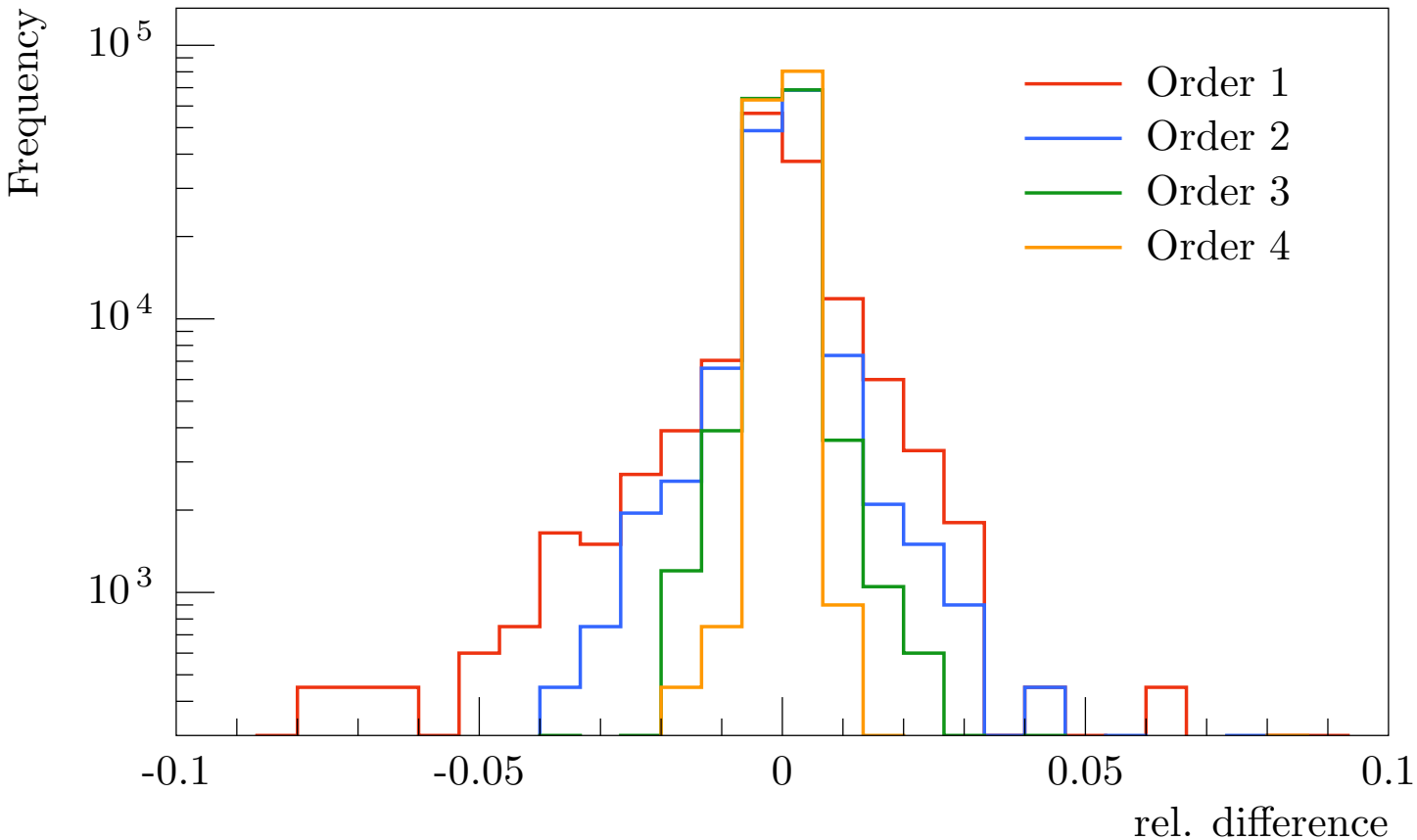

Backup

Advantages

- $I(\vec{p})$ fast, analytical $\rightarrow$ suitable for numerical applications

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- $I(\vec{p})$ fast, analytical $\rightarrow$ suitable for numerical applications
- Fitting against data cheap, can bias minimisation e.g. if $f(\vec{p})$ known to be imperfect (AMBT2 and AUET2)

$$\chi^2(\vec{p}) = \sum_{b}^{\text{Nbins}} w_b \cdot \left(\frac{I_b(\vec{p}) - D_b}{\Delta(\vec{p})} \right)^2$$

Advantages

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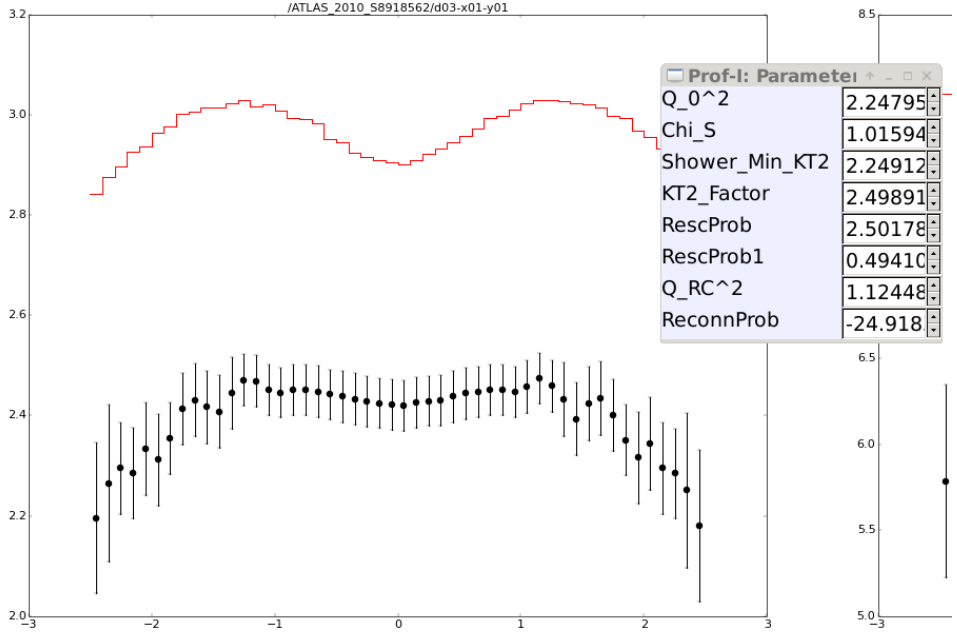
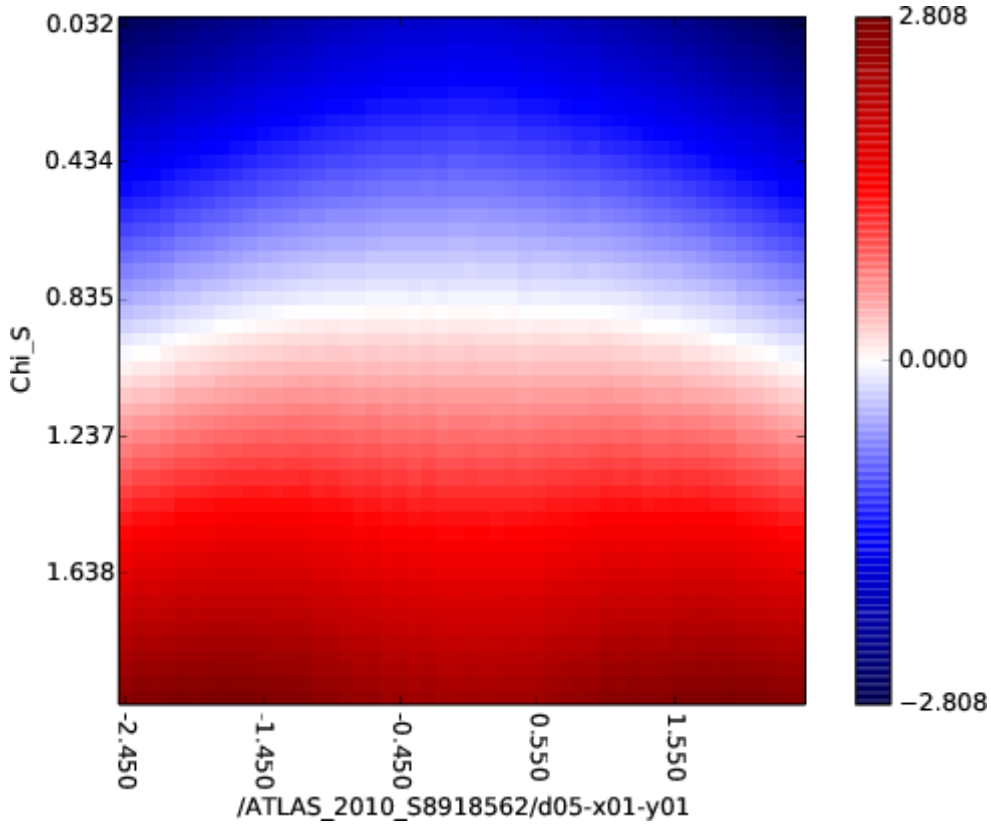
- Interactive parametrisation explorer



Advantages

- $I(\vec{p})$ fast, analytical $\rightarrow$ suitable for numerical applications

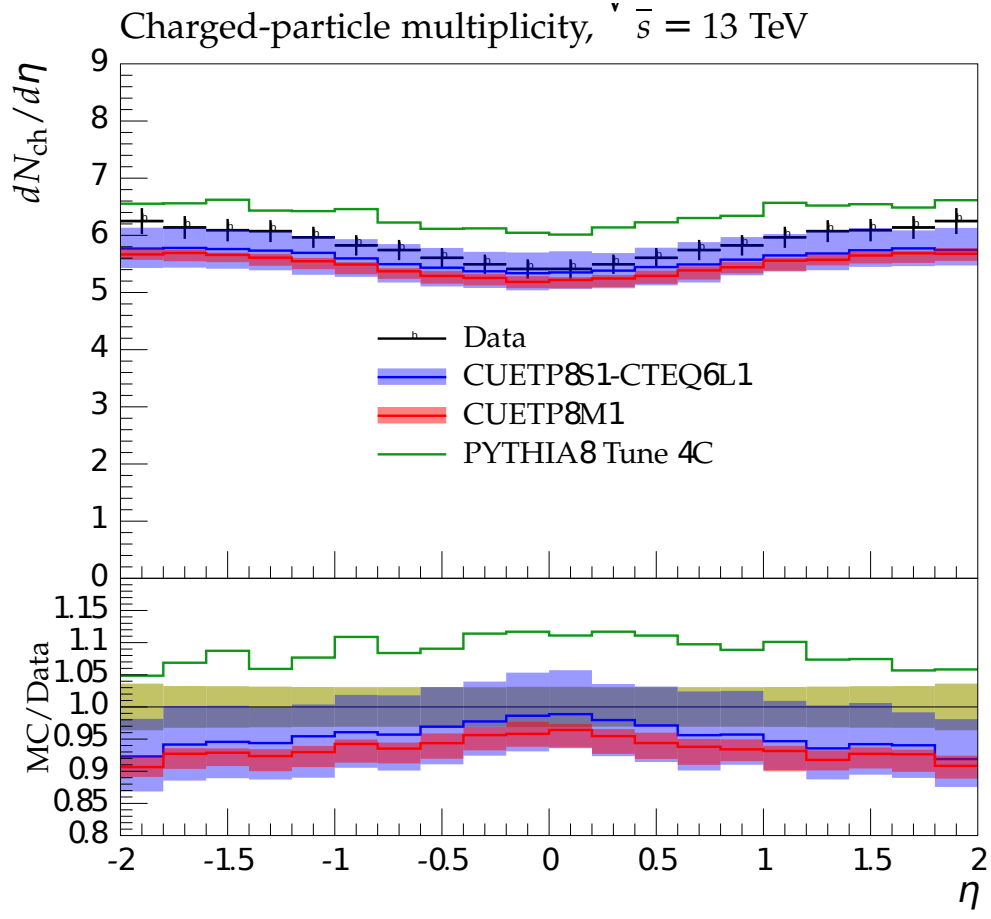
- Sensitivity and correlation analysis cheap $\rightarrow$ find parameters that do nothing $\rightarrow$ reduce dimensionality



Advantages

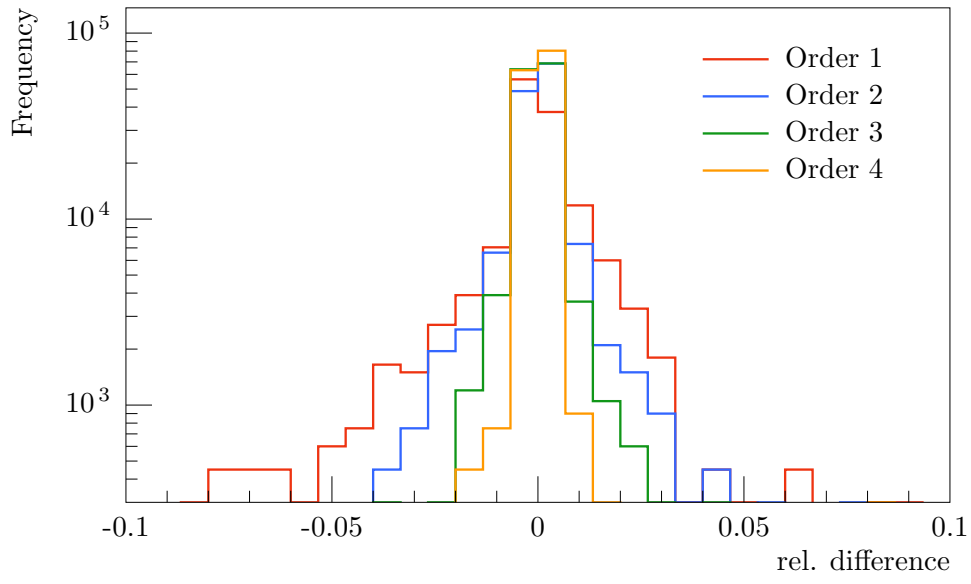
- $I(\vec{p})$ fast, analytical $\rightarrow$ suitable for numerical applications

- Can exploit χ^2 valley to get error-tunes `http://inspirehep.net/record/1407839`



Advantages

- $I(\vec{p})$ fast, analytical $\rightarrow$ suitable for numerical applications
- Validation of parametrisation allows to catch errors early on
- Improve quality by
  - Throwing and exact evaluation for more points
  - Using higher order polynomials



Technicalities

- Core functionality (parametrisation) written in `C++`
- Allows for usage in programs such as `GFitter`
- Arbitrary polynomial order and first derivative automatically
- Dependency: Eigen3 ($\geq v2.6$)
- Platform independent storage of parametrisation (ASCII)
- Tuning system: set of factorised python scripts (via cython)
- Minimisation done using `iminuit` `https://github.com/iminuit/`
- ROOT support via YODA

`PROFESSOR.HEPFORGE.ORG`

- Current version: Professor 2.1.3
- Bootstrap script
- Exhaustive documentation with videos