

Standard communication of analysis data correlations

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⇒ *coherent reinterpretation toolchains with full LHC data coverage*
 - ▶ Primary data faithfully recorded, modulo format details. Issue is with *secondary data*
 - Correlation data
 - For searches: (MC) background estimates
- LHC maturity and large integrated lumi ⇒ a major issue for use of both measurement and search analysis data

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 - For searches: (MC) background estimatesLHC maturity and large integrated lumi ⇒ a major issue for use of both measurement and search analysis data
- ▶ **All data needs to “automatically” flow from experiments → HepData → analysis tools**
⇒ standardise formats and conventions for data & aux data
⇒ *using correlations in MC tuning, EFT fits, BSM scans = “easy”*
(formats like Rivet’s YODA being extended to handle this: correlations via metadata & multiple named error bars)

Correlations in fits/limit setting

Many types of correlation:

- ▶ **SYST:** between bins/SRs, from experiment/theory systematics
- ▶ **STAT:** between bins/analyses, from event-sharing/normalisation
- ▶ **FIT:** between systematic (nuisance) params, via profile fitting

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Possible approaches to providing this information:

- ▶ **full likelihood expression**, e.g. [HistFactory demo](#) ↗
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 - correlated across bins, including between distributions
 - **simplified likelihoods** ↗: drop connection to elementary error sources (opacity = useful?!) \Rightarrow covariance sufficient?
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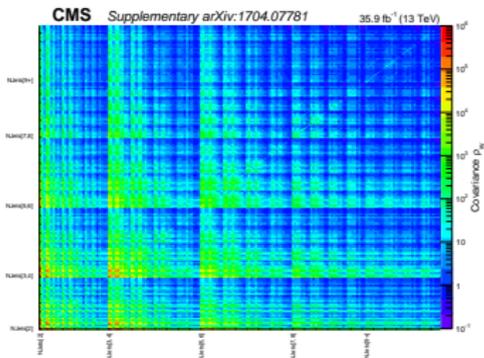
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- ▶ **representation options**: independent error sources on data points; linked primary/secondary datasets; `pyhf`

Correlation formats: error sources vs. bin covariance

CMS $0l$ cov matrix ↗ (log-scale!)



Error breakdown in a HepData record
NB. normal in *Standard Model* analyses

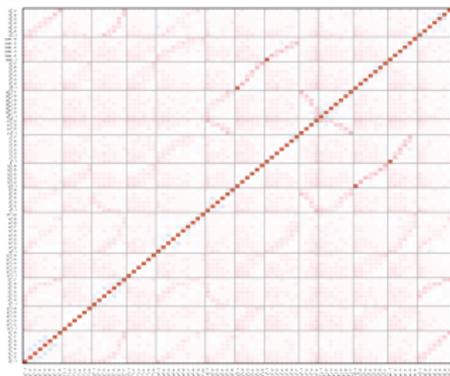
RE	P P → JETS
COS PHI	TEEC
-1 - -0.96	10.5165 ±0.00779481 stat +0.0117651 sys_jestp1 +0.0034300 sys_jestp2 + 71 more errors Show all
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ATLAS $t\bar{t}$ hadronic cov matrix [↗](#)



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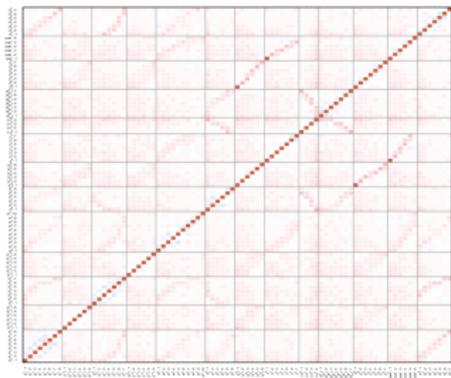
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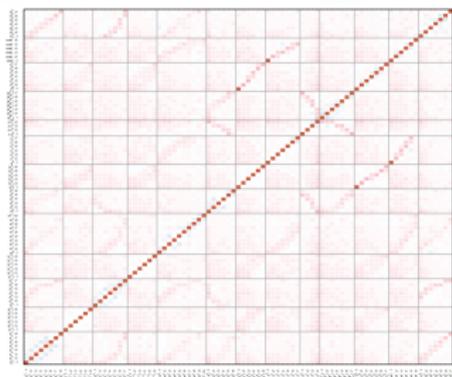
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Error-source representation more flexible: can construct cov matrix

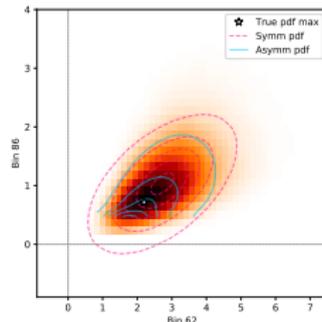
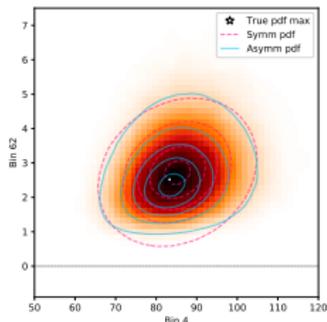
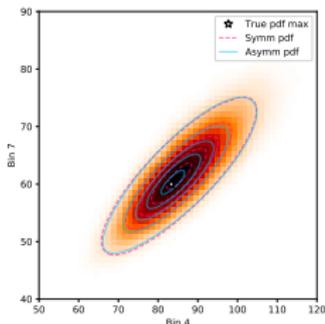
$$C_{ij} = \sum_e \sigma_i \sigma_j, \text{ or asymm by toy-sampling}$$

Logistical issues & extensions

- ▶ Need standard names, esp. to distinguish uncorr stat errors
- ▶ Also need groupings, e.g. to separate theory/MC errors from experimental/detector resolutions
⇒ future reinterpretations with theory improvements

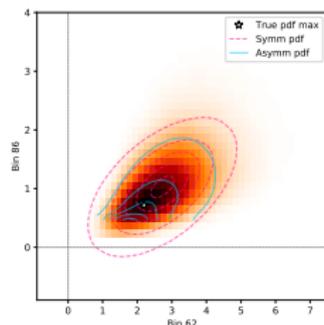
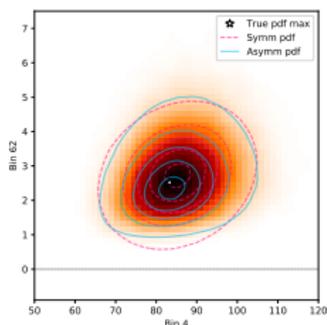
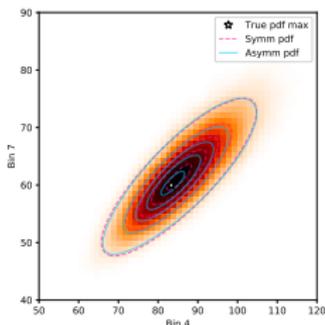
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Extend HD for *semantic correlation awareness?* *pyhf* again...

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YODA data format used by Rivet. Gradually extending data types to better match SM & BSM requirements. [Input welcome...](#)

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```
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Corr: {0: {alphas: {dn: -0.02646259, up: 0.0003289776},
           norm: {dn: -0.1191564, up: 0.1191564},
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Further work to support multiple errors on bins / data-points approaching release

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What's the best way to propagate this info in a ROOT workflow?

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- ▶ **Standardised reporting via HepData is key. Not all representations are equally good.**
 - “Matrix datasets” are least flexible
 - Error-source (+ skew?) or full likelihood are best. Some standard naming required
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 - Integration of `pyhf` into HepData would allow for full semantic awareness of links between an analysis' primary & secondary datasets
- ▶ **If we can access correlation data in a standard form, downstream tools will definitely use it**

Backup

MC and background data

- ▶ Correlations are the most technically complex demand, since the data objects are semantically different from “normal” datasets
- ▶ Not the only requirement for scalable recasting, though: background estimates are also crucial
- ▶ Typical BSM reinterpretations only have the capacity to generate (maybe LO) signal events
- ▶ Backgrounds computed by experiments using vast MC datasets with very complex and CPU-intensive high-sophistication modelling: not reproducible, so needs to be published
- ▶ This has started, but – again – **how to make HD (and its API) *semantically* aware of what is data and what’s the corresponding MC?**

And background process breakdown? And pre-/post-fit? ...