

Statistical models for recasting of unfolded measurements and combination with searches

Andy Buckley
University of Glasgow

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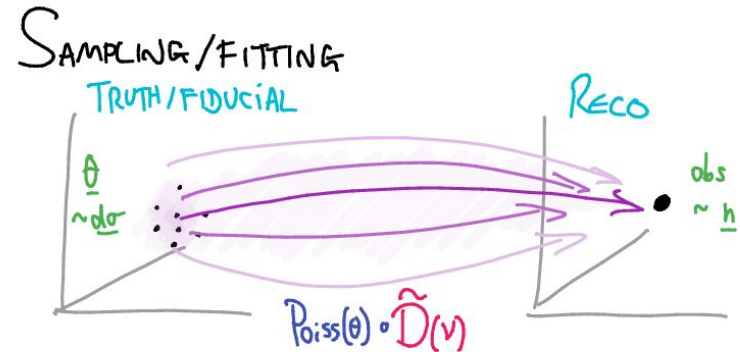
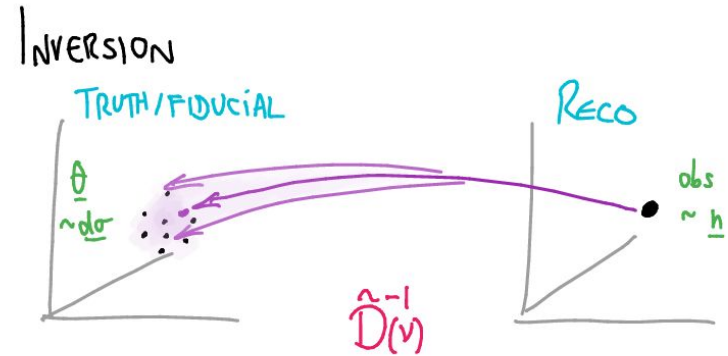


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Executive briefing: unfolding

- ❖ **Unfolding has been around for decades**
 - General principle is to correct reco data for effects distorting our view of the physics of interest
 - LHC in particular has refined this to mean unfolding to a *fiducial volume*: correct \sim only for detector effects, to a well-defined final-state, cuts similar to reco
 - Non-fiducial extrapolations, too — *in addition to fid xs*
 - **Necessarily propagate uncertainties from both detector understanding, and the unfolding mechanism**

- ❖ **Main methods/tools**
 - **Regularised inversion:**
 - Iterative Bayes IBU (RooUnfold, pyunfold)
 - SVD/Tikhonov reg (RooUnfold, TUnfold)
 - **“Forward-propagation” with sampling/fitting:**
 - TReXfitter, pyhf?
 - PyFBU, (hunfold)



Unfolding vs search profiling

❖ MC-driven unfoldings need the same things

- Binned data observable
- Binned MC truth and reco observables
 - Generally, truth/reco binnings (and even the observable!) don't need to match: *bin reco tighter*
- A response matrix of $p(\text{reco}_j | \text{truth}_i)$ for truth, reco bins i, j
 - A good unfolding requires a “tight” response matrix, not a “diagonal” one
- Lots of standard methods to assess unfolding non-closure and MC-model dependence

❖ Aim of unfolding is to extract fiducial, particle-level bin values & errors

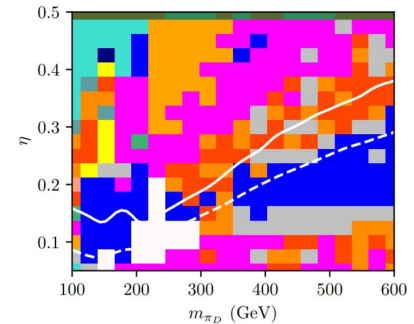
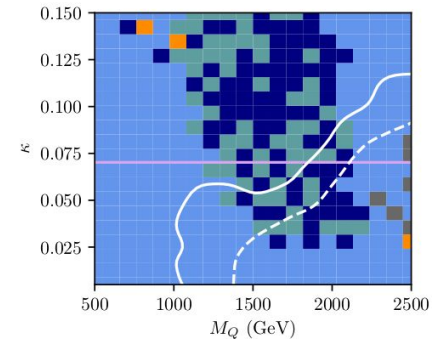
- Note, not the true, integer bin-populations, but physics params e.g. $d\sigma_i$ (differential xs in bin i)
 - ⇒ $L_{\text{search}}(\text{obs} | \text{BSM params})$ vs $L_{\text{meas}}(\text{obs} | d\sigma\text{'s})$
- Different methods use different Poisson/multinomial internal models, plus inversion heuristics
- Fit methods not so different from a BSM-search fit/scan: POIs are bin-values, not model params
- We don't often think of measurements as limit contours in a N_{bin} -dim space, but they are!

❖ Systematic uncertainties

- Need some mechanism to propagate systematic uncertainties
- Intrinsic/natural in fit/scan methods, just extend the param space to bin vals \oplus nuisances
- More *ad hoc* in (most?) inversion tools — updates coming in RooUnfold?

Stat models from unfolding, and combination

- ❖ **Search-likelihood publication quite advanced now**
 - Particularly via pyhf, path to common format for Poisson model in searches
 - Don't want measurements to get left out, cf. e.g. Contur (and others') uses of LHC measurements for complementary BSM constraints
- ❖ **Statistical models from unfolding tools**
 - Obvious for sampling tools: Poisson likelihood/posterior are explicit
 - Maybe less clear for inversion tools, but means and (correlated) uncertainties calculated \Rightarrow implicit b2b Gaussian pdf — maybe templated wrt nuisances
 - **Obstacles to encoding unfolded likelihoods in pyhf?**
 - **Alternatively, publish sampled point sets?**
- ❖ **Issues shared with searches**
 - elementary nuisances needed for fully coherent combination
 - some standardisation and versioning of nuisance names needed — and gauging degree of correlation between versions (nice problem to have...)
 - Freq vs Bayes: combining likelihoods & posteriors?



Summary/discussion

Input from toolkit authors

- Inversion and sampling methods — developments, current and planned output data and formats.
- Possible to achieve technical compatibility with pyhf/etc. direct searches?
- In pyhf and similar tools: how best to encode Gaussian uncertainty models? Extend pyhf, build on pyhf, include one more stat distribution in common format?

Experience of unfolding with model publication

- 2x public ATLAS top analyses, [1 total](#), [1 differential](#)
- More?

Experience of combination (e.g. Convino)

- Need for standards / understanding of common & related systematics
- Combining limits from different stat paradigms

More?