Imperial College London

Science and Technology Facilities Council

# Can we really "Re"-interpret data from the LHC?

**Nicholas Wardle**

Software & Computing Round Table (2021)

Analysis II: Reproducibility

**06/07/2021**

# Short answer …

**Yes!** We even have a forum dedicated to doing just that …

TWiki > LHCPhysics Web > LHCPhysics > InterpretingLHCresults (2019-10-26, SabineKraml)

Edit Attach PDF

## Forum on the Interpretation of the LHC Results for BSM studies

The quest for new physics beyond the Standard Model is arguably the driving topic for Run 2 of the LHC. Indeed, the LHC collaborations are pursuing searches for new physics in a vast variety of channels. While the collaborations typically provide themselves interpretations of their results, for instance in terms of simplified models, **the full understanding of the implications of these searches requires the interpretation of the experimental results in the context of all kinds of theoretical models.** This is a very active field, with close theory-experiment interaction and with several public tools being developed.

With this forum, we want to provide a platform for continued discussion of topics related to the BSM (re)interpretation of LHC data, including the development of the necessary **public** RecastingTools and related infrastructure.

If you have questions or want to contribute, contact Sabine Kraml, sabine.kraml@gmail.com, or any of the topical contacts given below.

**Current Members →** ~ 100 participants from pheno & experimental communities

Starting point : https://twiki.cern.ch/twiki/bin/view/LHCPhysics/InterpretingLHCresults
Join the mailing list : info-LHC-interpretation@cern.ch

~ Regular workshops – latest 15th - 19th February 2021 : https://indico.cern.ch/event/982553/

- Dedicated sessions on LLP searches, EFT (re)interpretations & non-LHC experiments (neutrino, dark matter… )
- Tutorial sessions for public re-interpretation tools (all recorded, have a go yourself!)

# Recommendations for re-interpretations

S. Kraml @Reinterp2021

**Recommendations emphasise:**

1. Prompt availability of numerical analysis data in digitised electronic form to enable re-use.
2. More complete publication of full-detail experimental data:
   - correlation information
   - public likelihoods
   - Open Data
   - forensic analysis code preservation
   - ....
3. Community-wide dialogue regarding re-use of unbinned fits and machine-learning algorithms.

***Moreover, theorists should (start) to follow the same reproducibility requirements as we ask them from the experiments.***

*"Re-use means a* ***longer legacy*** *for analyses, as well as compliance with ever stricter requirements of data-publication and reusability for publicly funded research."*

SciPost

SciPostPhys.9.2.022 (2020)

## Reinterpretation of LHC results for new physics: status and recommendations after run 2

The LHC BSM Reinterpretation Forum

### Abstract

We report on the status of efforts to improve the reinterpretation of searches and measurements at the LHC in terms of models for new physics, in the context of the LHC Reinterpretation Forum. We detail current experimental offerings in direct searches for new particles, measurements, technical implementations and Open Data, and provide a set of recommendations for further improving the presentation of LHC results in order to better enable reinterpretation in the future. We also provide a brief description of existing software reinterpretation frameworks and recent global analyses of new physics that make use of the current data.



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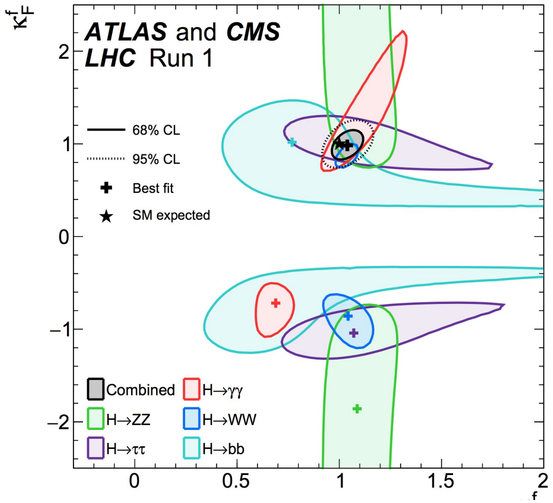
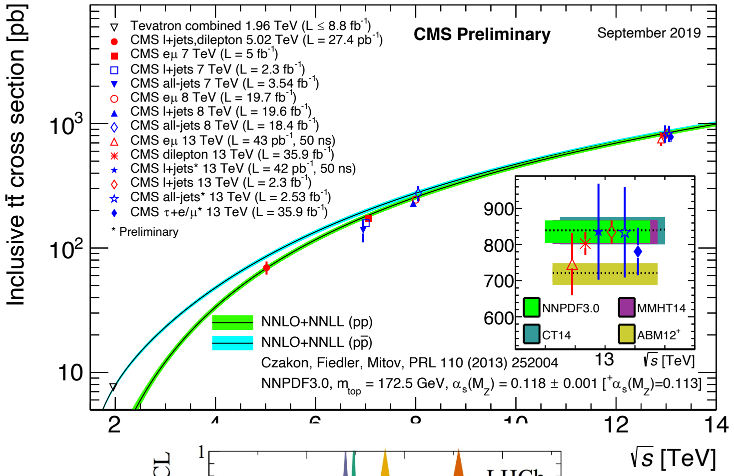
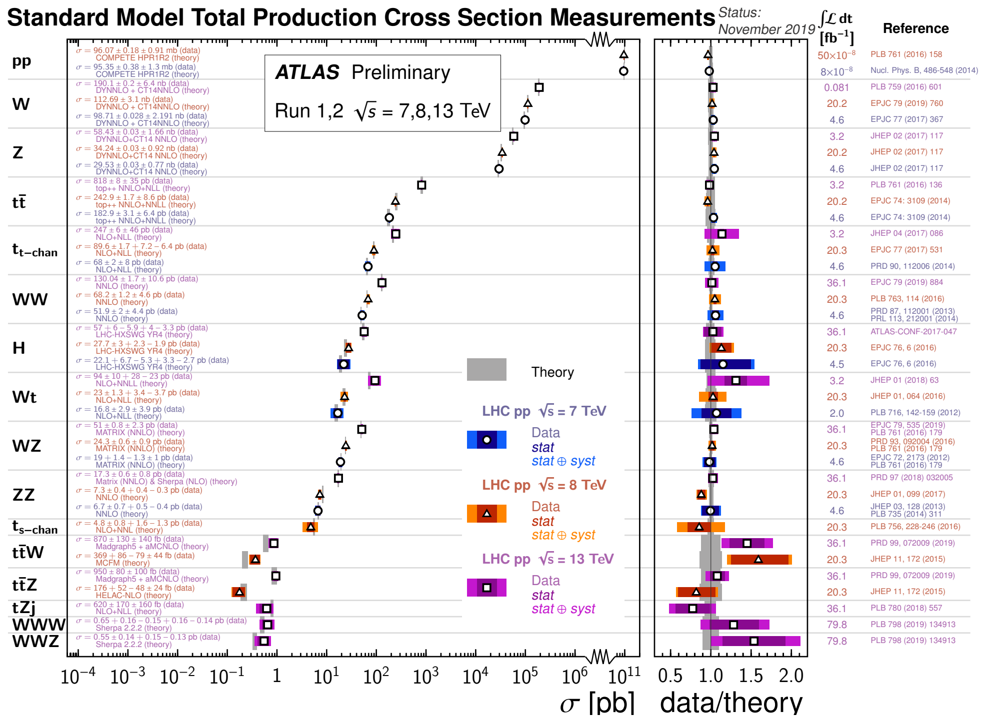
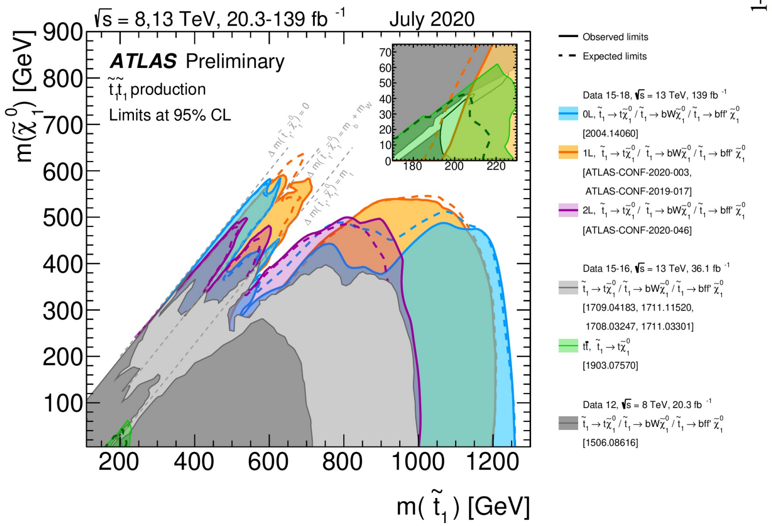
# Can’t spell “re”-interpretation without interpretation

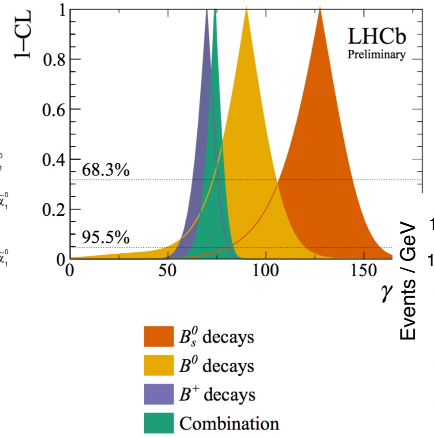
Impossible to summarize the breadth of experimental results (and ways they are presented) in one slide or even one seminar

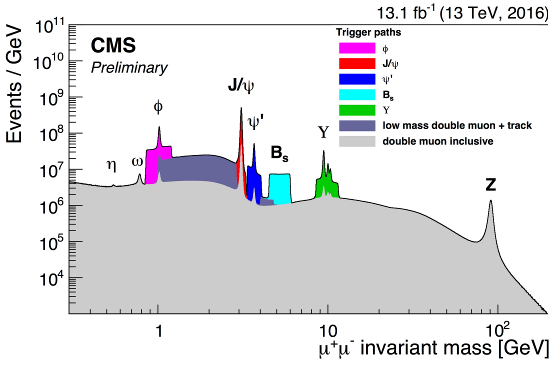


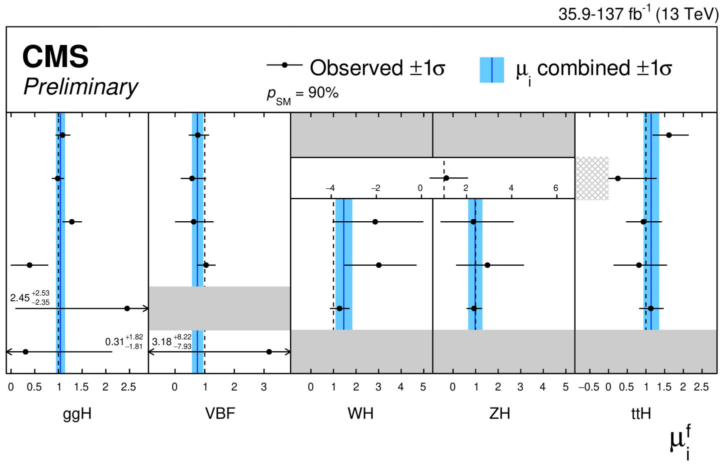



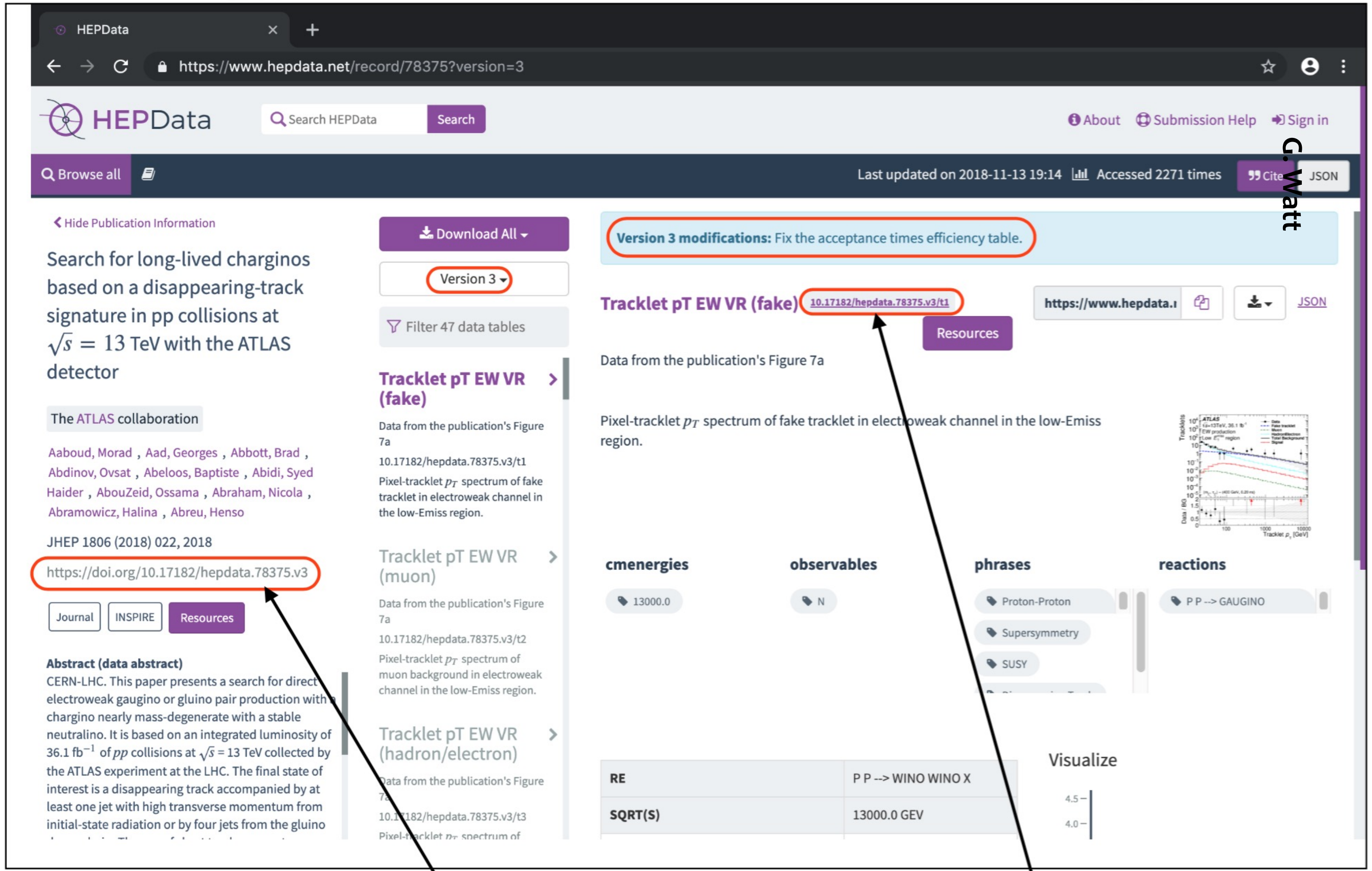



# Where to find them

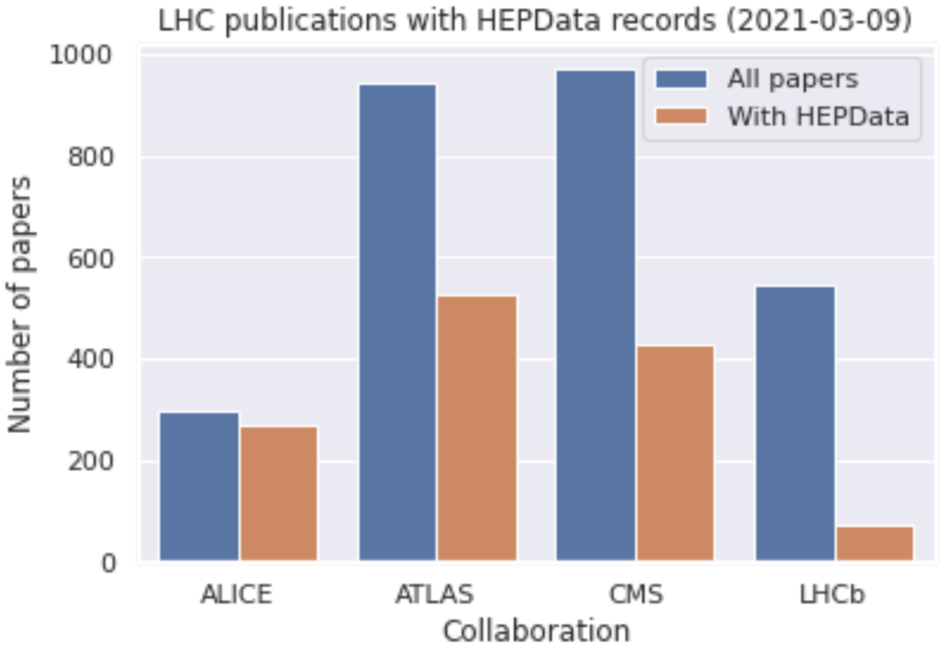


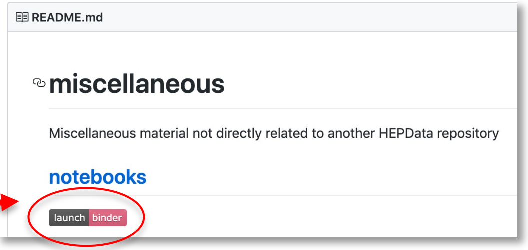

- DOIs minted for whole record and each table via DataCite.

Similar database (HepLike) dedicated for B-physics oriented measurements : https://github.com/mchrzasz/HEPLike

HEPData

Repository for publication-related High-Energy Physics data



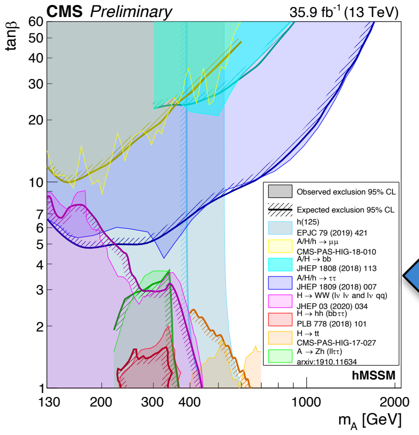




See latest statistics here

https://github.com/HEPData/miscellaneous

# LHC "data" spectrum

Wide spectrum of how experiments do and can present results → spectrum separated in terms of how easy it is to ***re-use*** the results provided



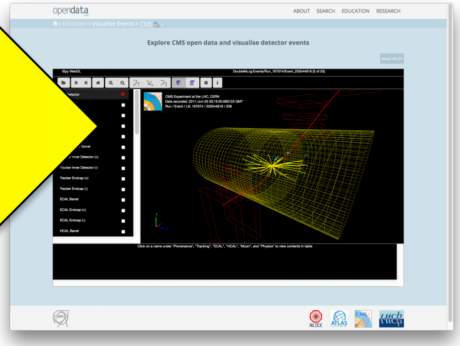

Simplified model limits

Inclusive XS

Simplified Likelihoods

REANA/RECAST workflows

[Inspired by P. Owen @ Reinterp2021]




Exclusion limits/contours In UV-complete models

Signal strengths / Amplitudes

Unfolded/ Fiducial XS

Published (full) likelihoods

Open data

Most assumptions (easy to use)

No assumptions (more expert level)

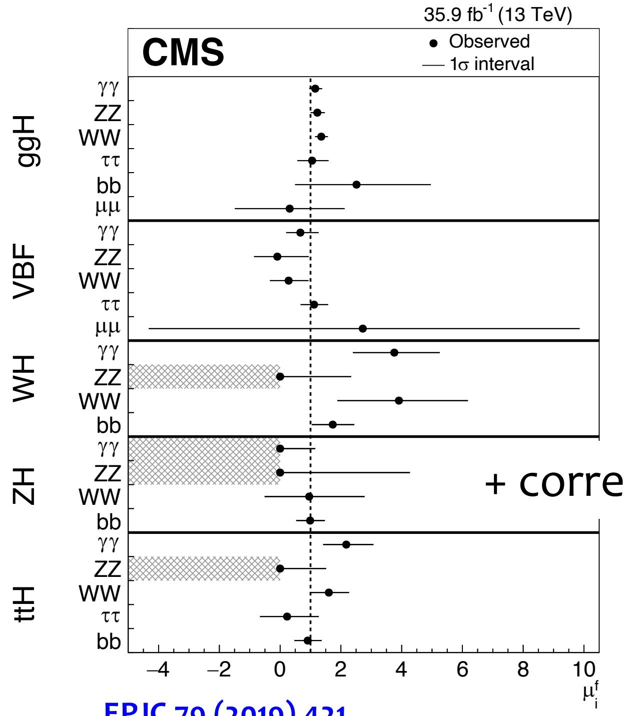
Clearly benefits across the spectrum (we should ***add to*** not ***subtract from*** these!)

# Meaurements for re-interpretations

In Higgs physics, often find "signal-strength" measurements

→ $\mu_i = \dfrac{\sigma_i}{(\sigma_i)_{\rm SM}}$ and $\mu^f = \dfrac{{\rm BR}^f}{({\rm BR}^f)_{\rm SM}}.$ Standard model defined by $\boldsymbol{\mu}_i = \boldsymbol{\mu}^f = 1$

→ **Assume** only total rate of ii→H→ff is modified by new physics (ok in certain models)




+ correlations

EPJC 79 (2019) 421

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Lilith

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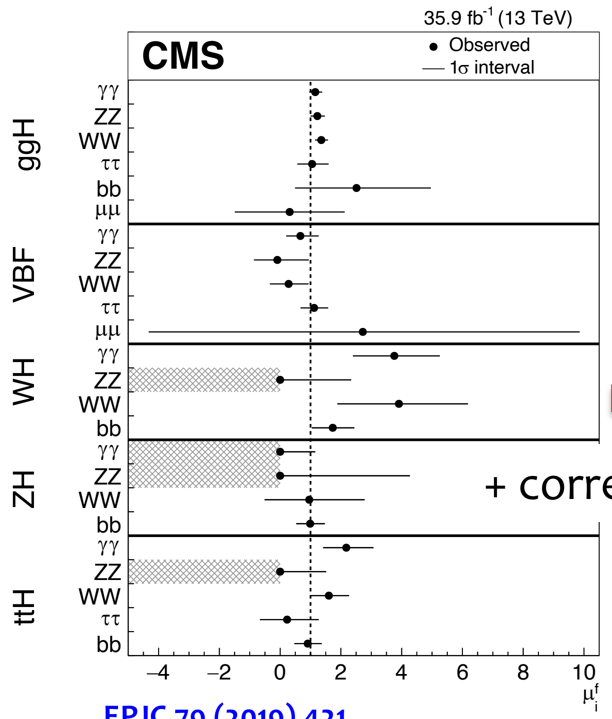



EPJC 79 (2019) 421

+ correlations

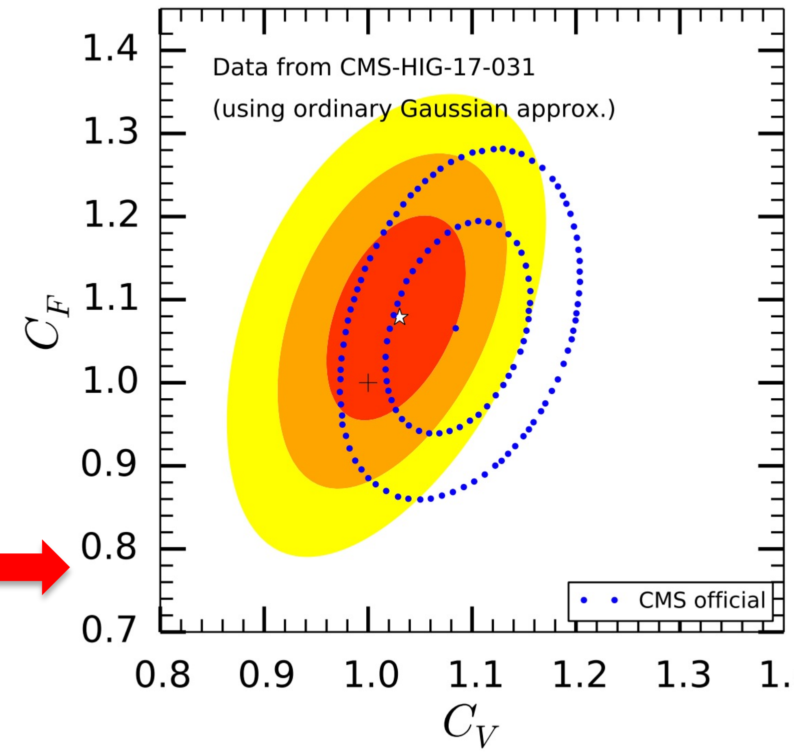
Re-construct *profile* likelihood

$$-2\log L(\boldsymbol{\mu}) = (\boldsymbol{\mu} - \hat{\boldsymbol{\mu}})^T C^{-1} (\boldsymbol{\mu} - \hat{\boldsymbol{\mu}})$$

$$C = \frac{1}{4}[\boldsymbol{\sigma}^+ + \boldsymbol{\sigma}^-].\rho.[\boldsymbol{\sigma}^+ + \boldsymbol{\sigma}^-]$$

Re-parameterize in terms of coupling modifiers

$$\mu_i,\ \mu^f \to \mu_i(C_V, C_F),\ \mu^f(C_V, C_F)$$




S. Kraml, T.Q. Loc, D.T. Nhung, L.D. Ninh

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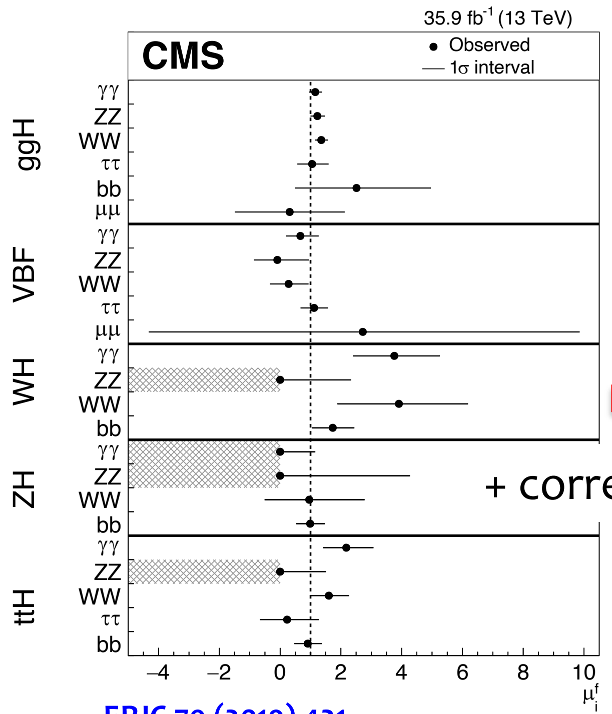


EPJC 79 (2019) 421

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Re-construct *profile* likelihood

$$-2\log L(\boldsymbol{\mu}) = (\boldsymbol{\mu} - \hat{\boldsymbol{\mu}})^T C^{-1} (\boldsymbol{\mu} - \hat{\boldsymbol{\mu}})$$

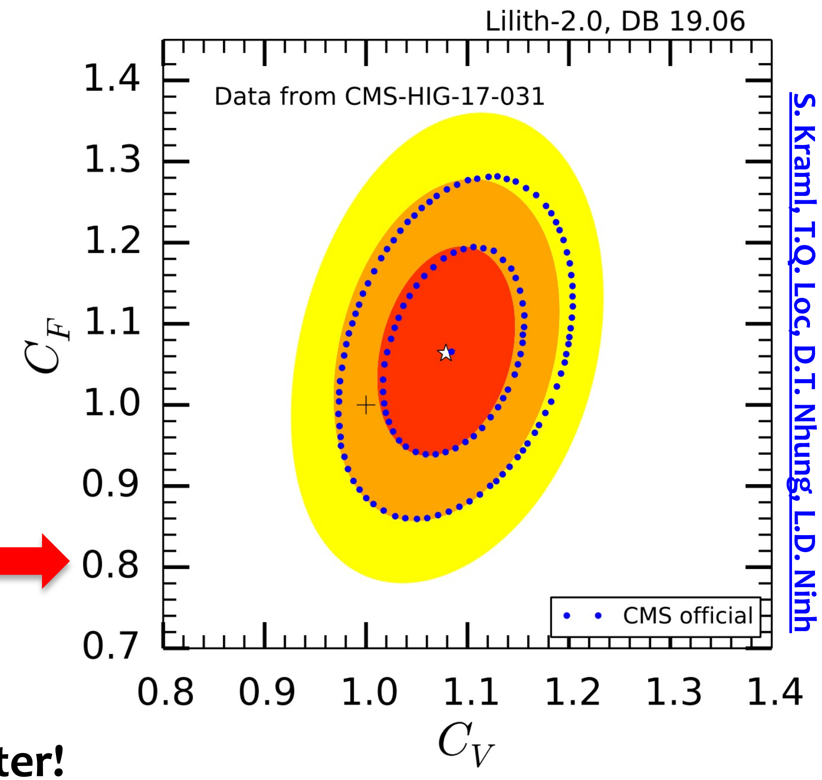
Extend Gaussian approximation with "*variable Gaussian*"

$$C = \boldsymbol{\Sigma}(\boldsymbol{\mu}).\rho.\boldsymbol{\Sigma}(\boldsymbol{\mu})$$

$$\Sigma_i = \sqrt{\sigma_i^+\sigma_i^- + (\sigma_i^+ - \sigma_i^-)(\mu_i - \hat{\mu}_i)},$$

Re-parameterize in terms of coupling modifiers

$$\mu_i,\ \mu^f \to \mu_i(C_V, C_F),\ \mu^f(C_V, C_F)$$




S. Kraml, T.Q. Loc, D.T. Nhung, L.D. Ninh

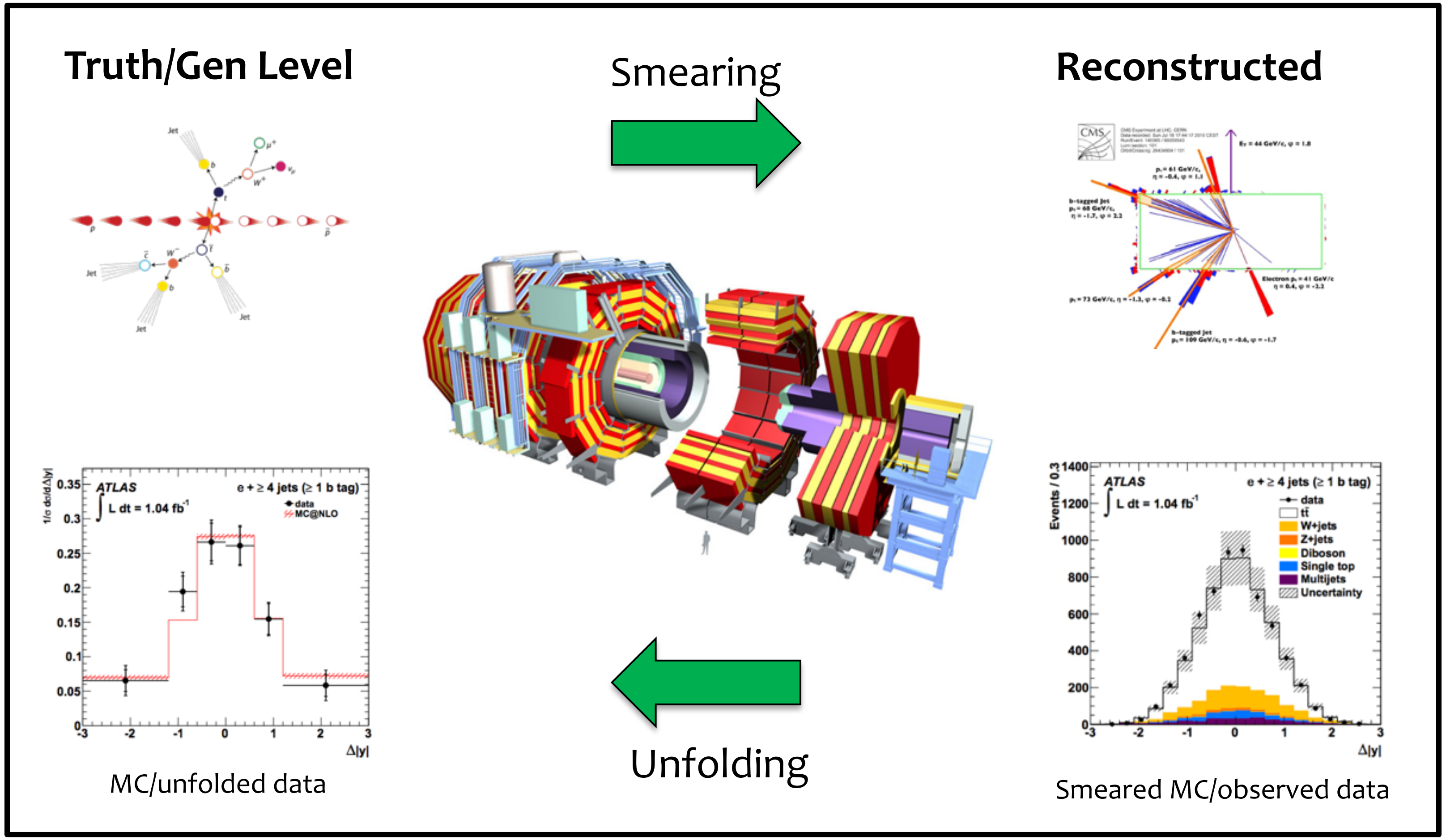
**Non-Gaussian effects matter!**

# Unfolding

Unfolded measurements popular for interpretations

Pros:
- Removes the need to model the detector to compare to theory
- Systematic uncertainties included in the measurements

Unfolded measurements can be used outside of experiments (c.f Contur)




See M. Kuusela's PhyStat Seminar for more unfolding issues

# Unfolding

*"LHC constraints on a B – L gauge model using CONTUR" [1]*

- BSM Model in FeynRules

UFO interface

Final State Particles

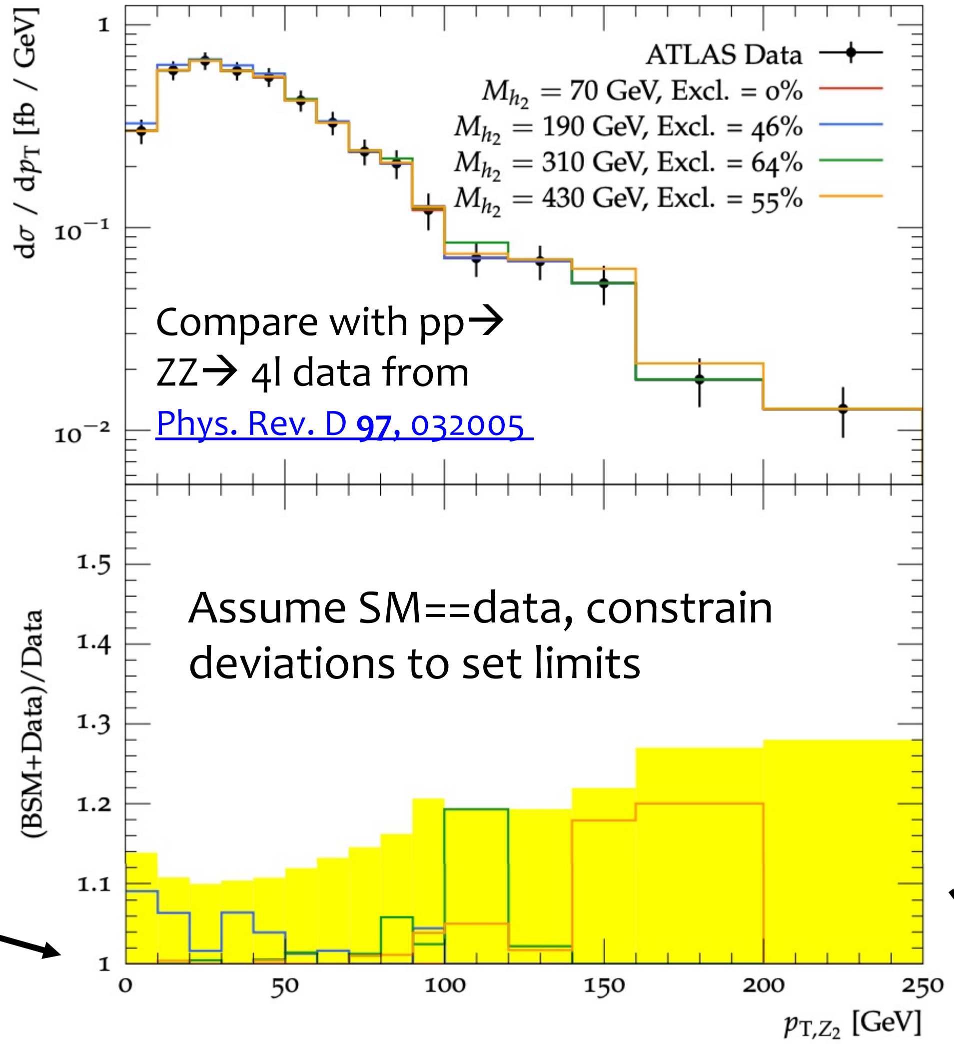
- New processes in Herwig7

[RIVET](#)

+

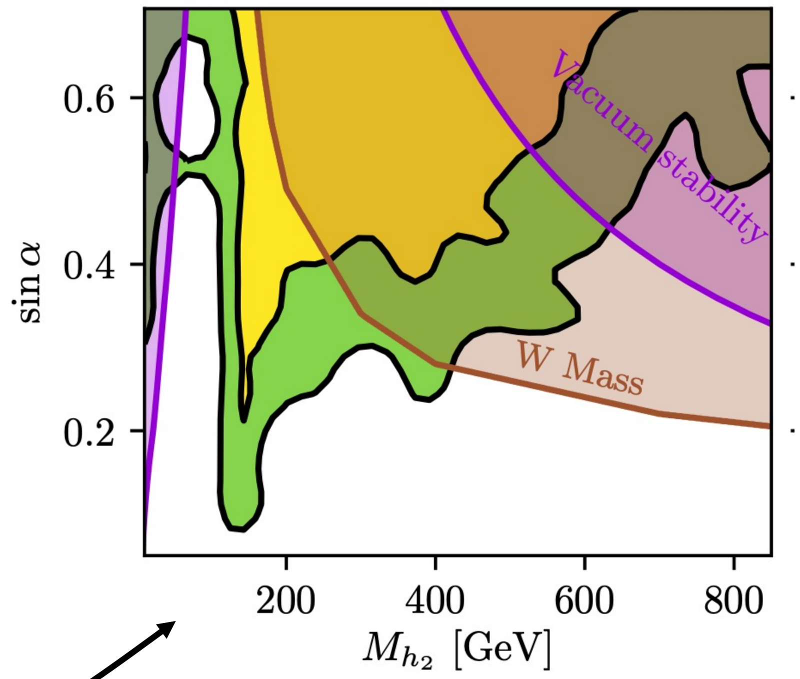
[CONTUR](#)

MCnet




Compare with pp→ ZZ→ 4l data from [Phys. Rev. D **97**, 032005](#)

Assume SM==data, constrain deviations to set limits




[1] S. Amrith, J. M. Butterworth, F. F. Deppisch, W. Liu, A. Varma, D. Yallup [JHEP 1905 (2019) 154](#)

# Unfolding?

[JHEP 01 (2021) 148]

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Pros:

- Removes the need to model the detector to compare to theory
- Systematic uncertainties included in the measurements

Cons:

- Often involves Gaussian approximations
- Regularization required where response matrix very non-diagonal (can lead to biases)

[JHEP 05 (2019) 141]

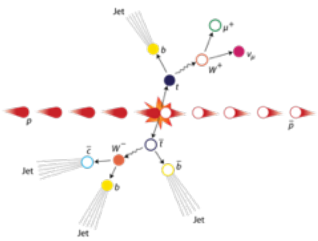
WH(→bb)

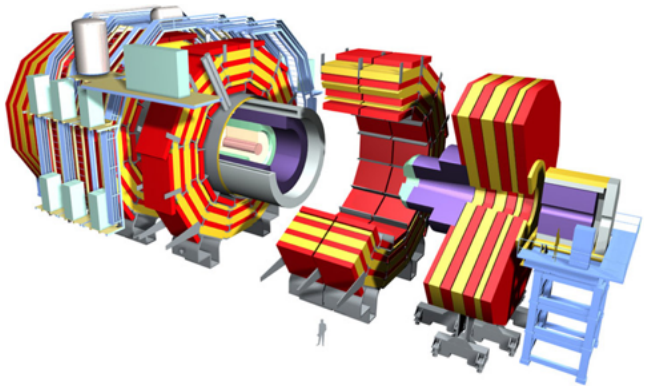
**Truth/Gen Level**

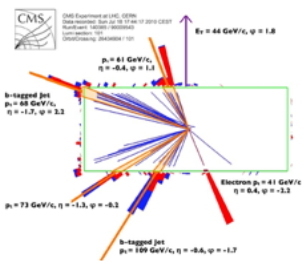
Smearing

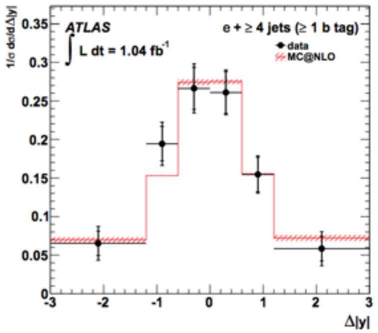
VBF H→μμ

**Reconstructed**



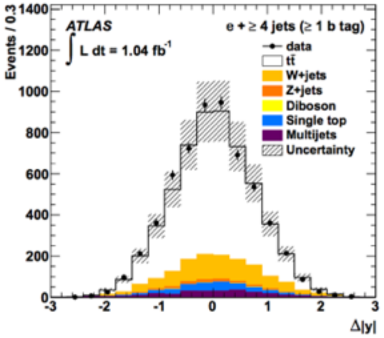








MC/unfolded data

Unfolding




Smeared MC/observed data

# Unfolding?

Unfolded measurements popular for interpretations

Pros:
- Removes the need to model the detector to compare to theory
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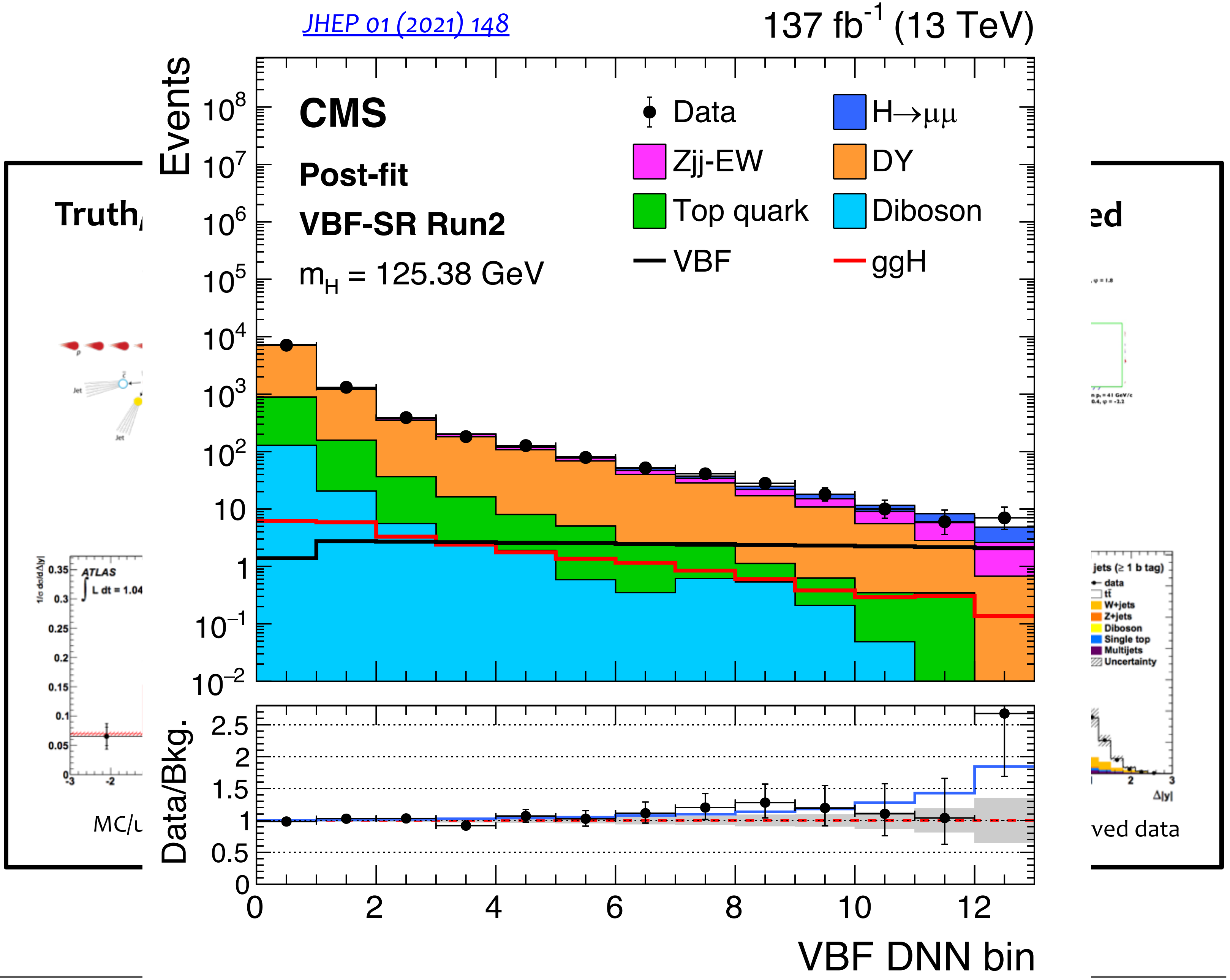
Cons:
- Often involves Gaussian approximations
- Regularization required where response matrix very non-diagonal (can lead to biases)
- Often use ML based quantities to subtract backgrounds/classify signals → how would we unfold these to particle level?

[JHEP 01 (2021) 148]



# ~~Un~~folding

## Instead, we can re-interpret in the folded space
## → ***published likelihoods***

Not really a new idea …

[Workshop on confidence limits (2000)]

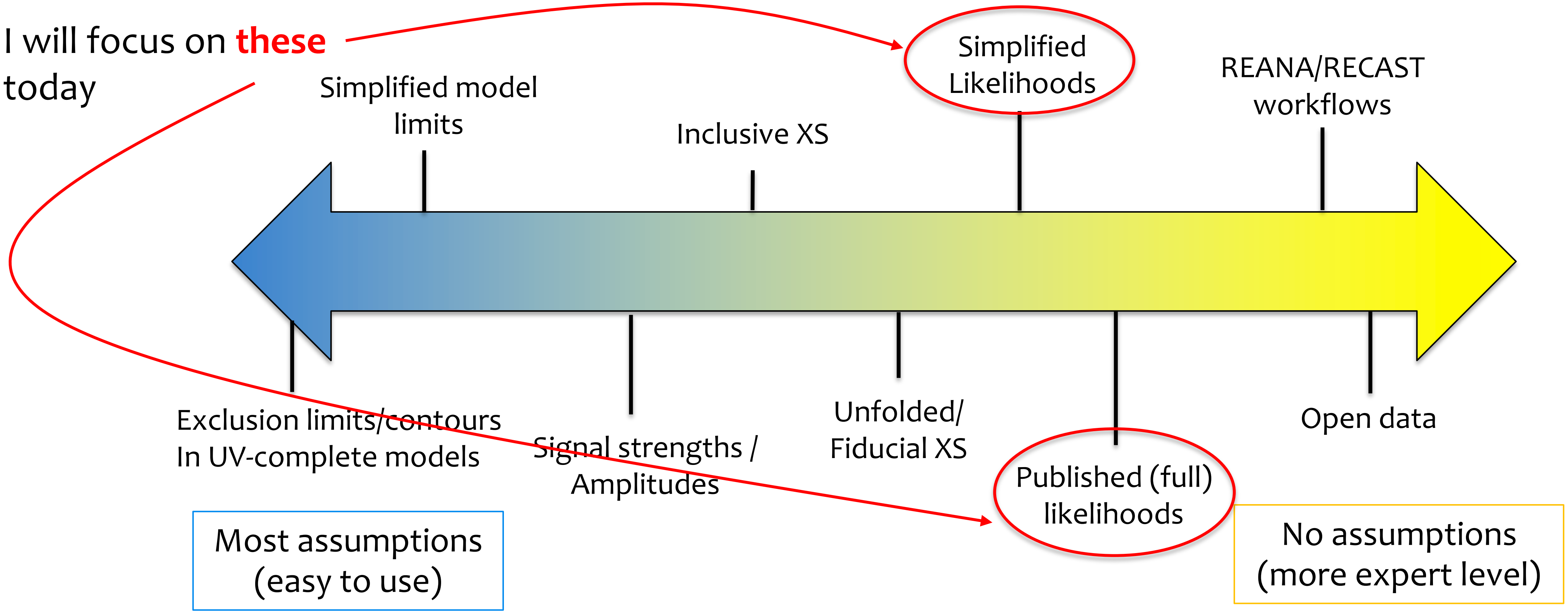
**Massimo Corradi**

It seems to me that there is a general consensus that what is really meaningful for an experiment is *likelihood*, and almost everybody would agree on the prescription that experiments should give their likelihood function for these kinds of results. Does everybody agree on this statement, to publish likelihoods?

**Louis Lyons**

Any disagreement ? Carried unanimously. That's actually quite an achievement for this Workshop.

# LHC "data" spectrum




**Caveat:** I mostly work on high-pT experimental LHC physics so examples mostly inspired from ATLAS/CMS results → most of what I say however applies to LHC analyses in general and even beyond in some cases.

# Common choices for searches at the LHC

General form* for our experimental likelihood (for measurements, searches … ) is

$$L(\boldsymbol{\alpha},\boldsymbol{\delta})\pi(\boldsymbol{\delta}) = \prod_{I=1}^{P} \mathrm{Pr}\Big(n_I^{\mathrm{obs}}\,\Big|\,n_I(\boldsymbol{\alpha},\boldsymbol{\delta})\Big)\pi(\boldsymbol{\delta})$$

Where $\boldsymbol{\alpha}$ are the "parameters of interest" (mass of a new hypothetical particle, cross-section for some new process … ) and $\boldsymbol{\delta}$ are the "nuisance parameters".

[1] G. Cowan, K. Cranmer, E. Gross, O. Vitells Eur.Phys.J.C71:1554,2011

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$$\boldsymbol{\alpha} = \mu$$

At the LHC, the profiled likelihood ratio test statistic is the most common choice [1] → one parameter of interest $\mu$ – common multiplier for total signal yield

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$$n_I(\mu,\boldsymbol{\delta}) \rightarrow \mu \cdot \sum_{\mathrm{sigs}} n_{s_k,I} + \sum_{\mathrm{bkgs}} n_{b_k,I}(\boldsymbol{\delta}) \rightarrow \mu \cdot n_{s,I} + n_{b,I}(\boldsymbol{\delta})$$

Sum over the signals / background contributions

$$Pr(n|\lambda) = \frac{\lambda^n}{n!}e^{-\lambda}$$

Often use *binned* likelihood → Pr(.) are Poisson probabilities

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Sum over the signals / background contributions

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$$\pi(\boldsymbol{\delta})$$

Nuisance parameter priors and/or "in-situ" measurements of **δ**

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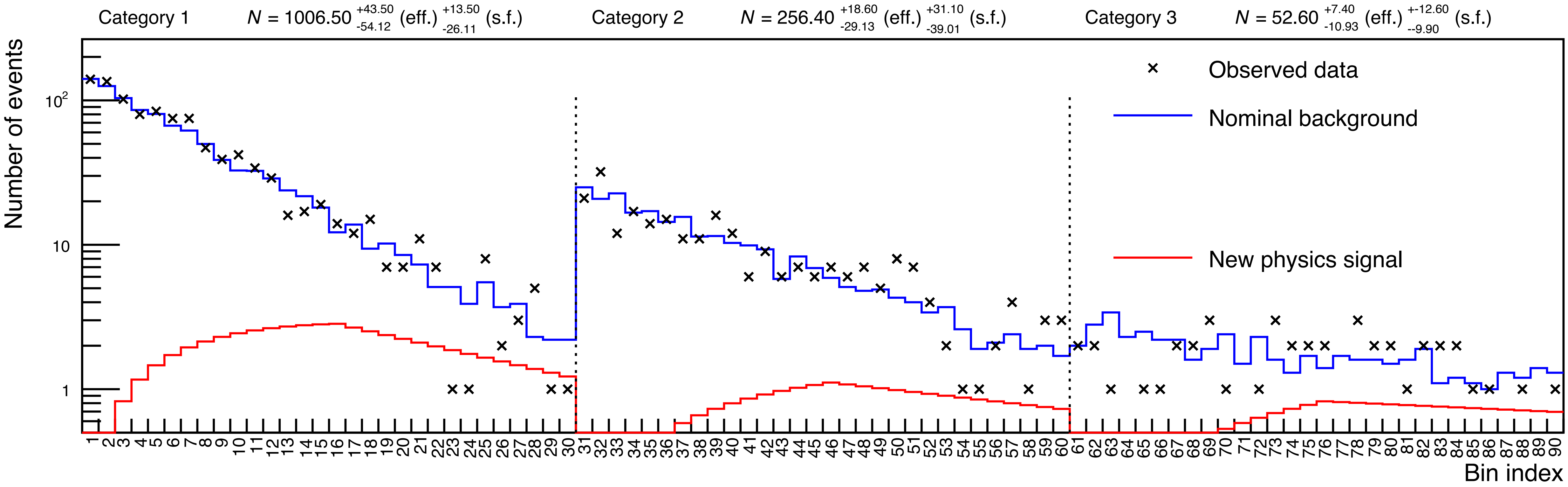
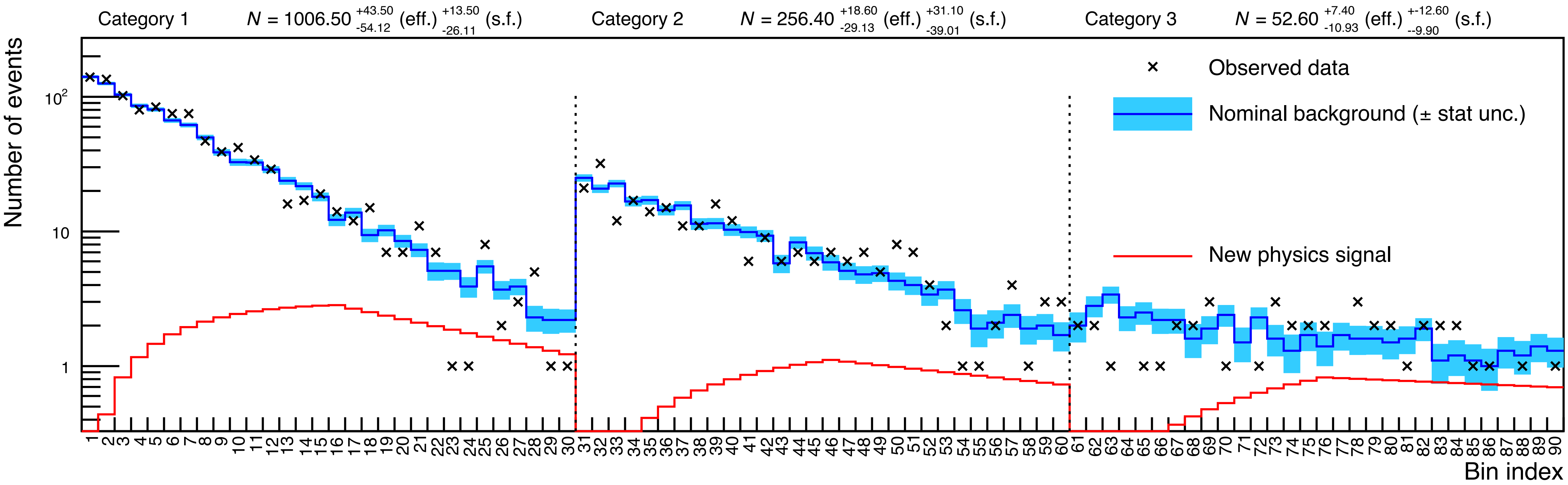
# Toy search for new physics




Imagine a (rather simplified) model inspired by a typical search for some Supersymmetric particle or exotic signature.

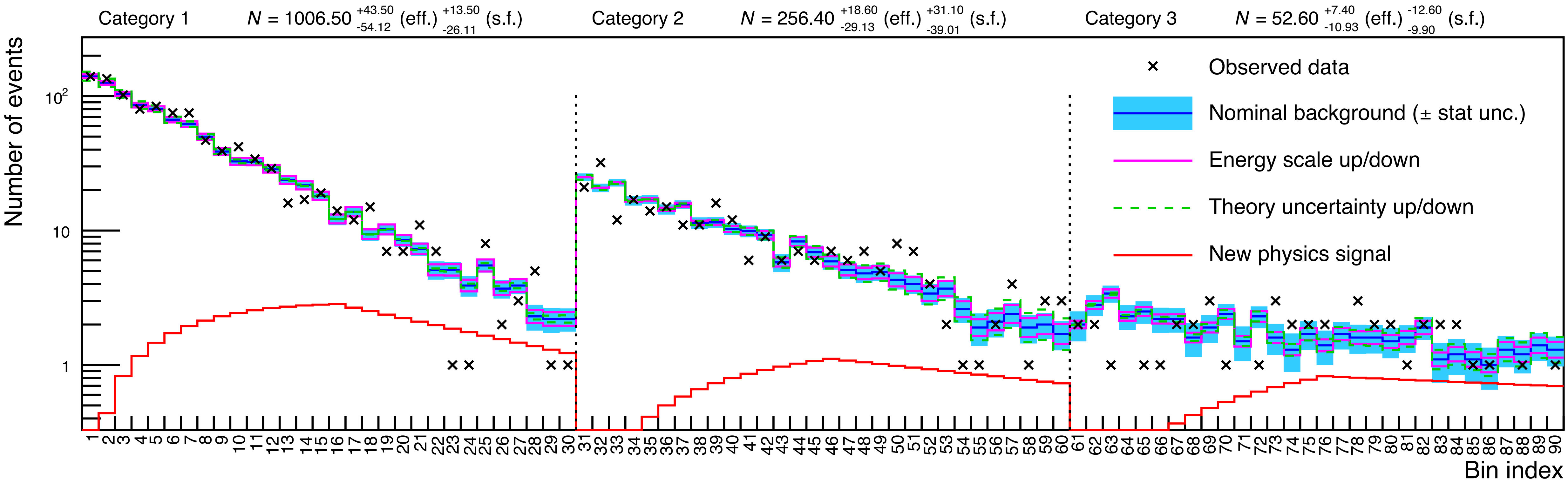
- There is a single source of background (can also think of this as the sum of all backgrounds)
- The data (observations) are divided into regions we have;
    - 3 categories for the data → each category has 30 bins
    - Increasing S/B with bin-number, within each category

# Toy search for new physics




There are ***two*** uncertainties (labelled "efficiency" and "scale-factor") on the background yields ($N$), and ***each bin*** has an uncertainty which is uncorrelated between bins (e.g this could be from limited Monte Carlo statistics used to estimate $n_l$)

# Toy search for new physics

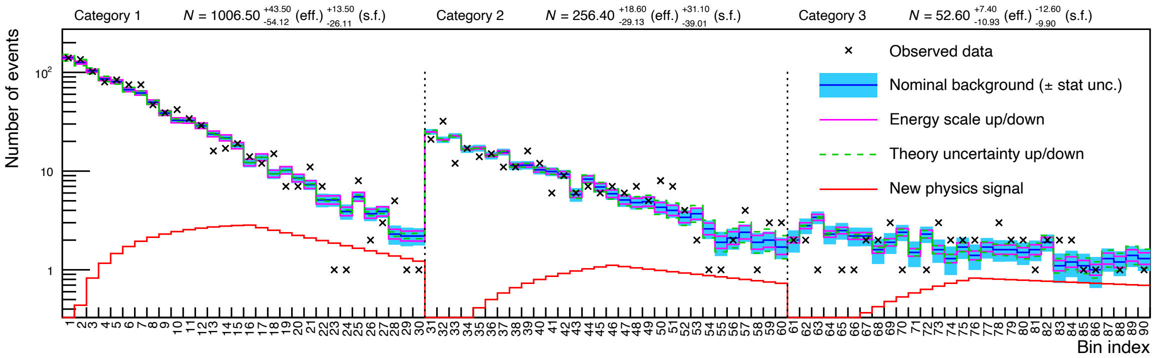



There are ***two*** uncertainties (labelled "efficiency" and "scale-factor") on the background yields ($N$), and ***each bin*** has an uncertainty which is uncorrelated between bins (e.g this could be from limited Monte Carlo statistics used to estimate $n_l$)

Another ***two*** uncertainties correlated between bins ("energy scale" and "theory" uncertainty)

In total this means 94 nuisance parameters

# Toy search for new physics




Think of the expected number of background events in a given bin $I$, as the fraction of events in that bin ($f_I$) multiplied by the total number of events ($N$)

$$\boxed{n_I(\boldsymbol{\delta}) \equiv f_I(\boldsymbol{\delta})N(\boldsymbol{\delta})}$$

**$\boldsymbol{\delta}$** are nuisance parameters representing ***independent*** sources of uncertainty (in our case 94 of them)

$$\boxed{N(\boldsymbol{\delta}) = N^0 \cdot \prod_j (1+K_j)^{\delta_j}}$$

Uncertainties in the normalisation (N) typically follow log-normals

$$\boxed{\frac{n_I(\boldsymbol{\delta})}{n_I^0} = \prod_j (1+\epsilon_{Ij})^{\delta_j}}$$

Similarly for un-correlated bin-by-bin uncertainties

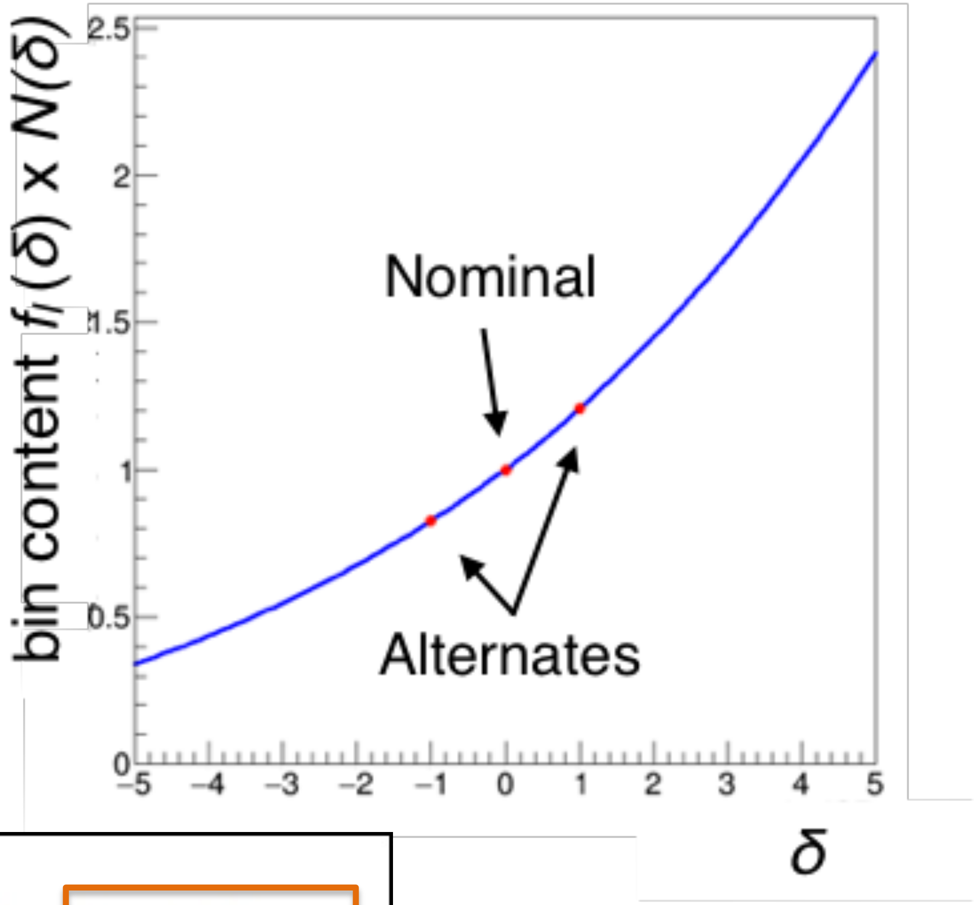
$K_j$ *and* $\varepsilon_{Ij}$ represent the relative size and direction of the uncertainty

# Toy search for new physics

The effects of correlated systematic uncertainties on $n_I$ are modelled using quadratic(linear) interpo(extrapo)lation function

$$f_I(\boldsymbol{\delta}) = f_I^0 \cdot \frac{1}{F(\boldsymbol{\delta})} \prod_j p_{Ij}(\delta_j)$$

$F(\boldsymbol{\delta}) = \sum_I f_I(\boldsymbol{\delta})$




$$p_{Ij}(\delta_j) = \begin{cases} \frac{1}{2}\delta_j(\delta_j - 1)\kappa_{Ij}^{-} - (\delta_j - 1)(\delta_j + 1) + \frac{1}{2}\delta_j(\delta_j + 1)\kappa_{Ij}^{+} & \text{for } |\delta_j| < 1 \\ \left[\frac{1}{2}(3\kappa_{Ij}^{+} + \kappa_{Ij}^{-}) - 2\right]\delta_j - \frac{1}{2}(\kappa_{Ij}^{+} + \kappa_{Ij}^{-}) + 2 & \text{for } \delta_j > 1 \\ \left[2 - \frac{1}{2}(3\kappa_{Ij}^{-} + \kappa_{Ij}^{+})\right]\delta_j - \frac{1}{2}(\kappa_{Ij}^{+} + \kappa_{Ij}^{-}) + 2 & \text{for } \delta_j < -1 \end{cases}$$

# Experimental likelihood

Now we can write the likelihood for this search as follows;

$$L(\mu, \boldsymbol{\delta})\pi(\boldsymbol{\delta}) = \prod_{I=1}^{90} P(n_I^{\text{obs}}|\mu \cdot n_{s,I} + n_{b,I}(\boldsymbol{\delta})) \cdot \prod_{j=1}^{94} e^{-\delta_j^2}$$

$$n_{b,I}(\boldsymbol{\delta}) = N_c^0 \cdot \prod_{k=1}^{2}(1+K_k)^{\delta_k} \cdot f_I^0 \cdot \frac{1}{F(\boldsymbol{\delta})} \prod_{j=3}^{4} p_{I,j}(\delta_j) \cdot (1+\epsilon_I)^{\delta_I}$$

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Specifying these terms with this generic form means the full likelihood can be communicated as plain text!

A lot of physicists' time working on an LHC search is spent on **these**!

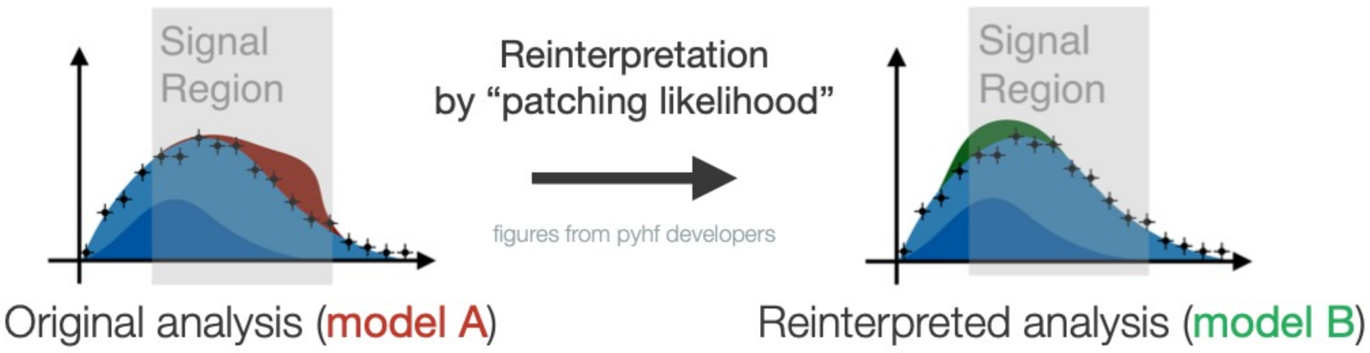
# Published likelihoods in the wild!

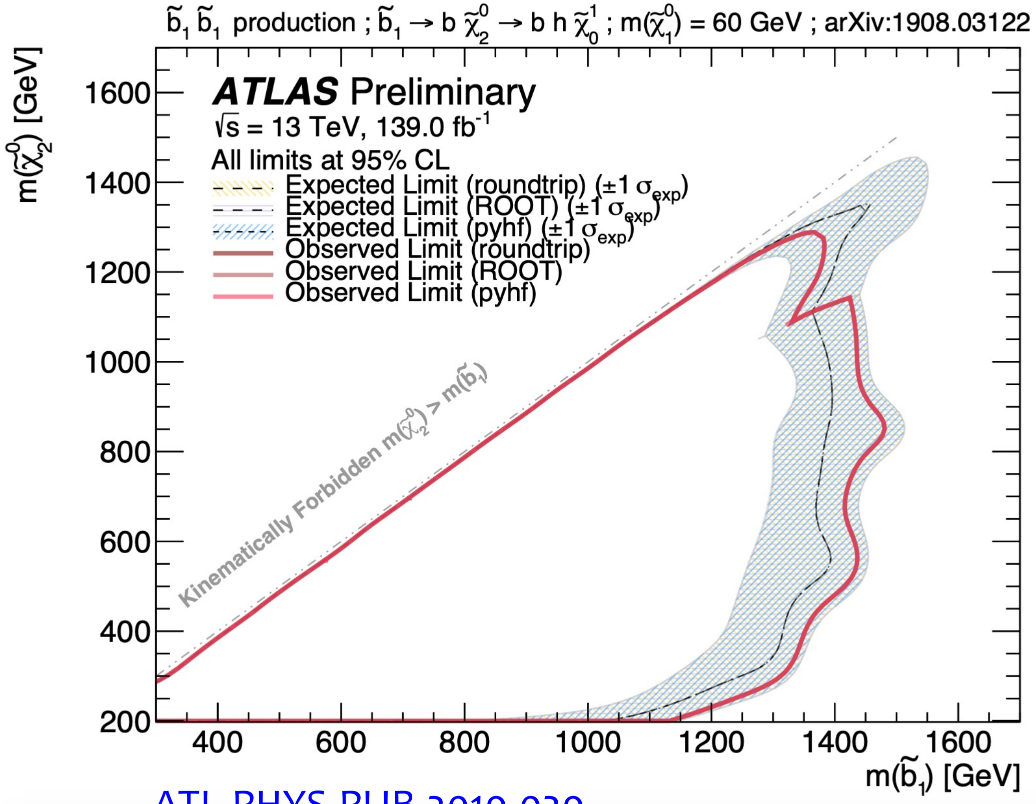
JSON based (ROOT/XML free) encoded workspaces containing ***full*** likelihood model → Build statistical model + perform inference using [pyHF](pyHF) (developed by L. Heinrich, M. Feickert, G. Stark and K. Cranmer. )

DOI 10.5281/zenodo.4484948

Access to ***full binned likelihood***

→ Swap out components of likelihood directly inside JSON for re-interpretations
→ Re-interpret with different signal models via JSON patches



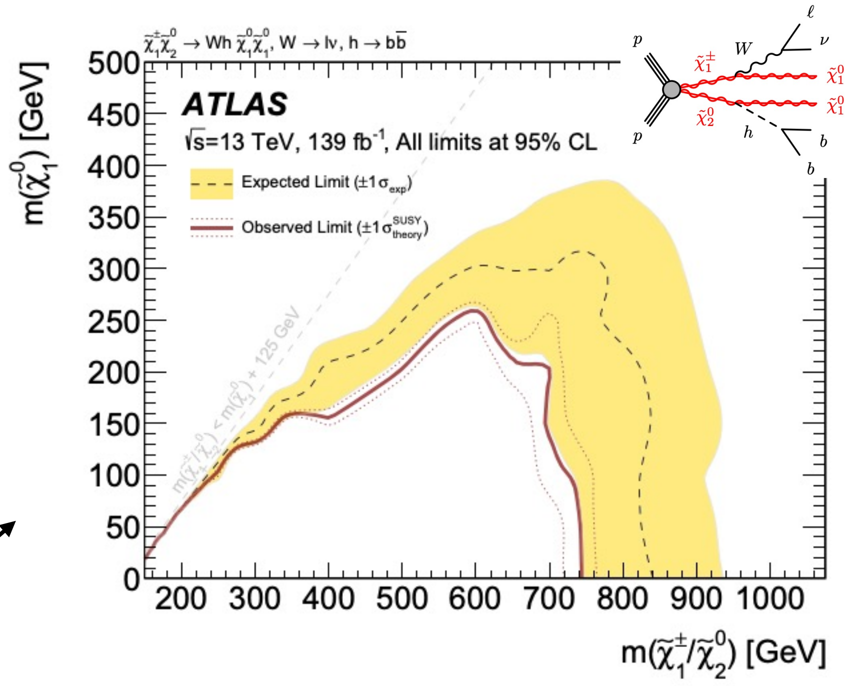

[ATL-PHYS-PUB-2019-029](ATL-PHYS-PUB-2019-029)

[E. Schanet, *Re-interp* 2021](E. Schanet, Re-interp 2021)

# Published likelihoods in the wild!

**Example:** *"Search for direct production of electroweakinos in final states with one lepton, missing transverse momentum and a Higgs boson decaying into two b-jets in pp collisions at √s=13 TeV with the ATLAS detector"* on [HepData]

- Total of 14 bins (split across 8 channels)
- O(100) nuisance parameters
- Signal patches for different chargino/neutralino masses




Eur.Phys.J.C 80 (2020) 691, 2020

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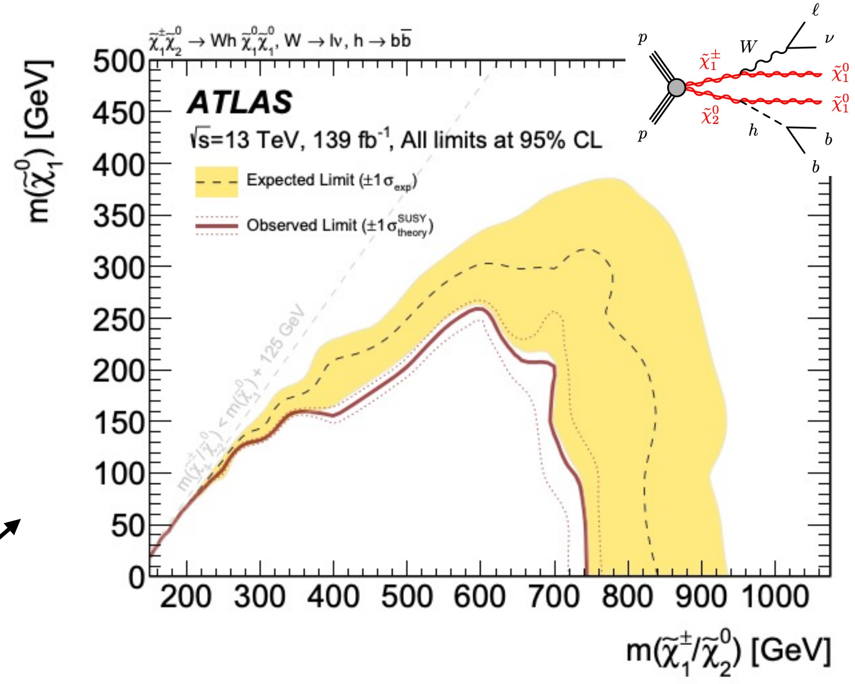



Eur.Phys.J.C 80 (2020) 691, 2020

More likelihoods becoming available using this approach here …

Applied filters:

Keywords: Likelihood available

| Short Title | Group | Journal Reference | Date | √s (TeV) | L | Links |
|---|---|---|---|---|---|---|
| Search for chargino and neutralino pair RPV decays; 3L | SUSY | Submitted to PRD | 20-NOV-20 | 13 | 139 $fb^{-1}$ | Documents \| 2011.10543 \| Inspire HepData \| Briefing \| Internal |
| Search for displaced leptons | SUSY | Submitted to PRL | 13-NOV-20 | 13 | 139 $fb^{-1}$ | Documents \| 2011.07812 \| Inspire HepData \| Briefing \| Internal |
| Chargino-neutralino pair; 3 leptons, weak-scale mass splittings | SUSY | Phys. Rev. D 101 (2020) 072001 | 18-DEC-19 | 13 | 139 $fb^{-1}$ | Documents \| 1912.08479 \| Inspire HepData \| Internal |
| Staus; taus | SUSY | Phys. Rev. D 101 (2020) 032009 | 15-NOV-19 | 13 | 139 $fb^{-1}$ | Documents \| 1911.06660 \| Inspire HepData \| Briefing \| Internal |
| Chargino-neutralino pair; Higgs boson in final state, 2 b-jets and 1 lepton | SUSY | Eur. Phys. J. C 80 (2020) 691 | 19-SEP-19 | 13 | 139 $fb^{-1}$ | Documents \| 1909.09226 \| Inspire HepData \| Internal |
| Stop pair, sbottom pair, gluino pair; two same-sign leptons or three leptons | SUSY | JHEP 06 (2020) 46 | 18-SEP-19 | 13 | 139 $fb^{-1}$ | Documents \| 1909.08457 \| Inspire HepData \| Internal |
| Sbottom; b-jets | SUSY | JHEP 12 (2019) 060 | 08-AUG-19 | 13 | 139 $fb^{-1}$ | Documents \| 1908.03122 \| Inspire HepData \| Briefing \| Internal |

# Counting inputs

Back to our toy search, how many terms are needed to specify the full LH ?

**90** observations (one per bin)

**90** expected signal yields

$$L(\mu,\boldsymbol{\delta})\pi(\boldsymbol{\delta}) = \prod_{I=1}^{90} P(\boxed{n_I^{\mathrm{obs}}}|\mu\cdot\boxed{n_{s,I}} + n_{b,I}(\boldsymbol{\delta}))\cdot\prod_{j=1}^{94} e^{-\delta_j^2}$$

Gaussian prior for each nuisance parameter

One term per category → 3*2+3 = **9**

1 term for each bin → **90**

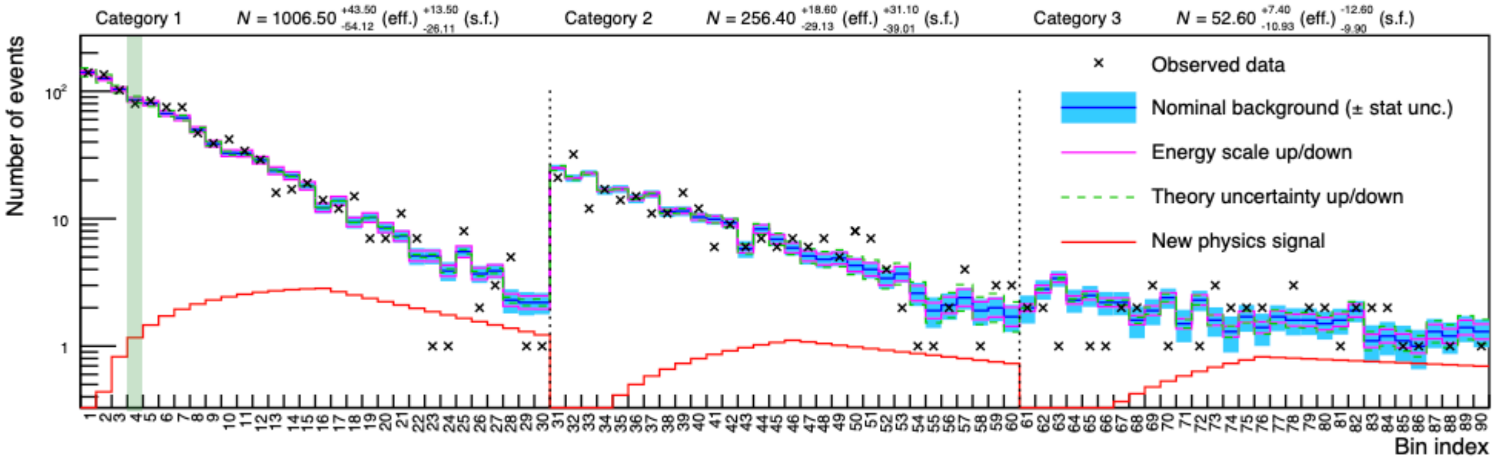
$$n_{b,I}(\boldsymbol{\delta}) = \boxed{N_c^0\cdot\prod_{k=1}^{2}(1+K_k)^{\delta_k}}\cdot\boxed{f_I^0\cdot\frac{1}{F(\boldsymbol{\delta})}\prod_{j=3}^{4} p_{I,j}(\delta_j)}\cdot\boxed{(1+\epsilon_I)^{\delta_I}}$$

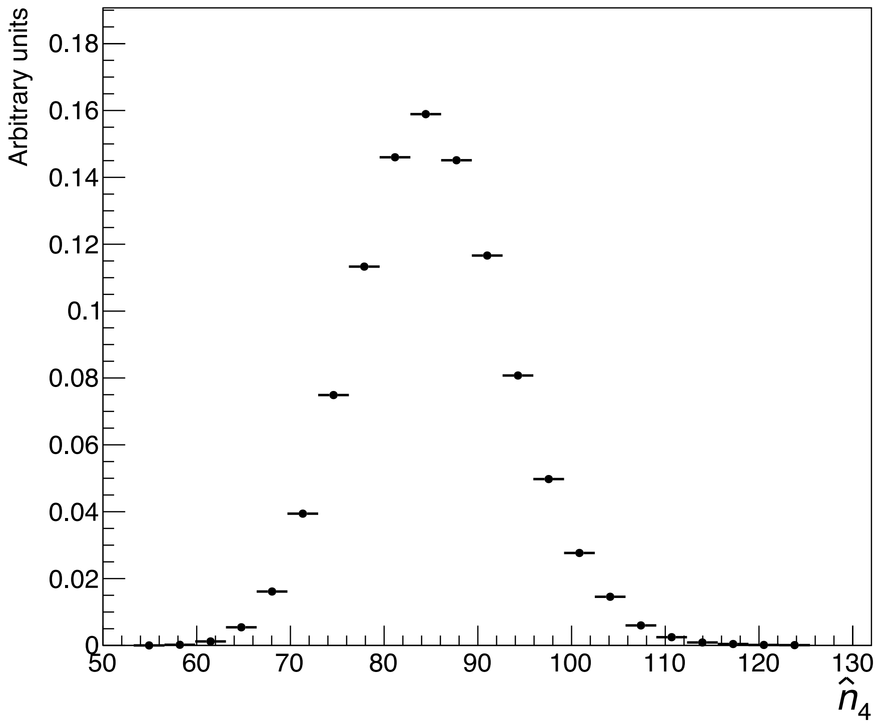
90 functions; each requires 1+4 quantities to specify → **450**

For our toy search, we need **729 inputs**

# Re-parameterize the backgrounds

We can generate pseudo-experiments for $n_{b,I}$ since we know $p(\boldsymbol{\delta}) := \pi(\delta) \sim e^{-\frac{1}{2}\boldsymbol{\delta}\cdot\boldsymbol{\delta}}$
Use randomly sampled $\boldsymbol{\delta}'$ and $\hat{n}_I = n_{b,I}(\boldsymbol{\delta}')$ to determine the distribution of the backgrounds…




In some bins, distributions looks symmetric and Gaussian
→ can be described by 2 moments (mean and variance)

# Re-parameterize the backgrounds

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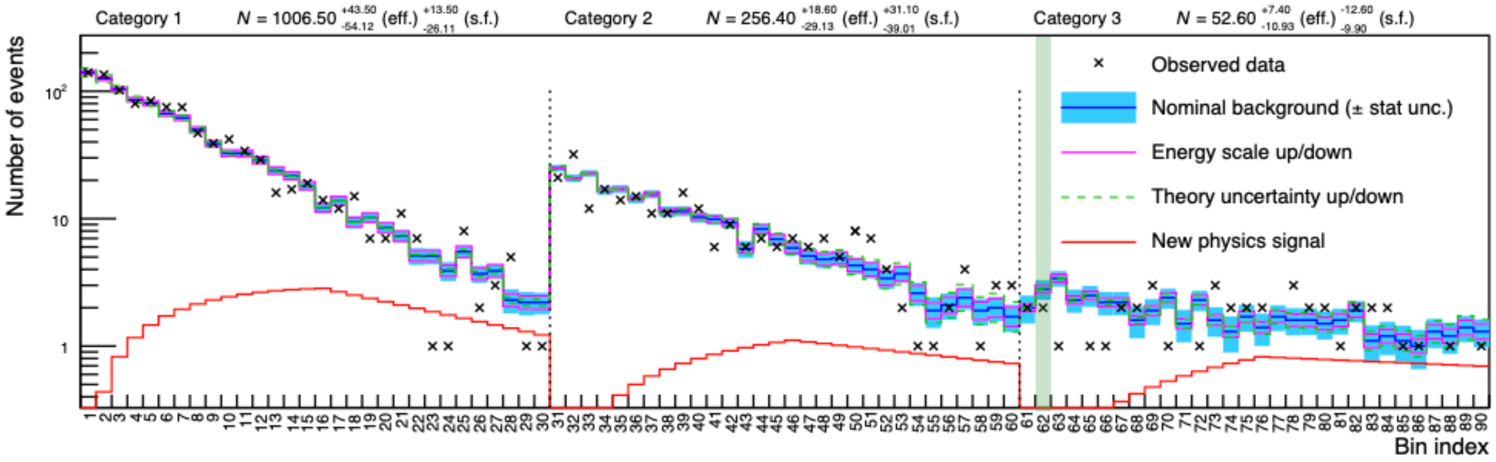


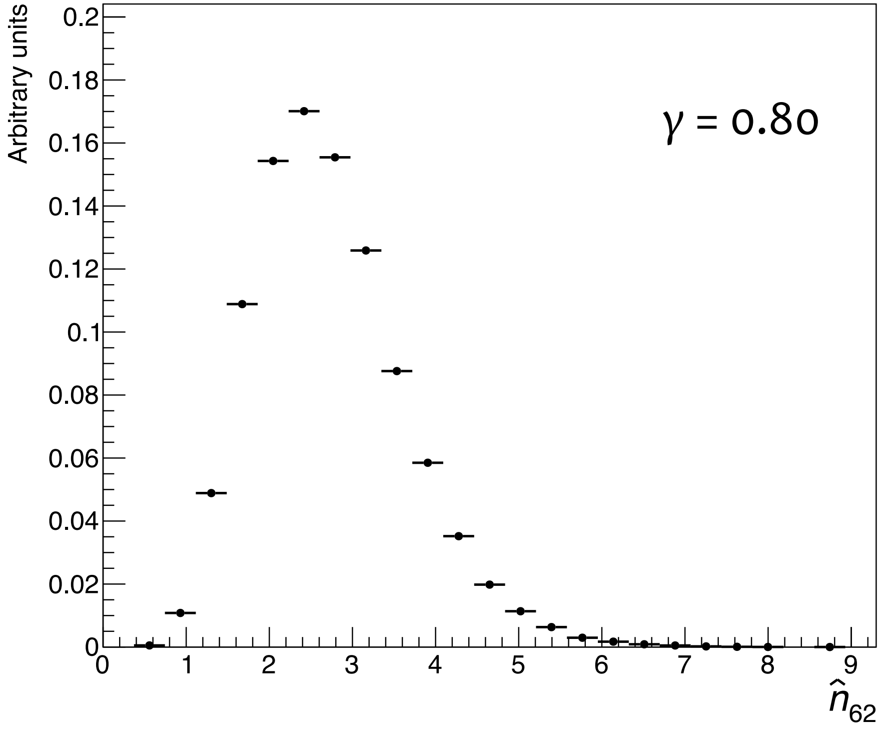


In other cases however, distributions are very asymmetric
→ Skewness (γ) provides a measure of asymmetry
→ 3rd moment relevant for describing backgrounds

$$\gamma = \frac{m_3}{(m_2)^{\frac{3}{2}}}$$

# Simplifying the likelihood?

For statistical (re-) interpretation purposes we eliminate nuisance parameters (**δ**)

→ We are mainly interested in profiled / marginalized likelihoods $L(\mu, \boldsymbol{\delta}) \rightarrow L(\mu)$

Since the "backgrounds" are only dependent on the nuisance parameters, we can approximate in such a way that the profiled (or marginal) likelihood is preserved as follows [1];

1. Express $n_{b,I}$ as a simple expansion (quadratic) in terms of **combined nuisance parameters** $\vartheta_I$

$$n_{b,I} \simeq a_I + b_I\theta_I + c_I\theta_I^2$$

$I = 1 \ldots 90$

[1] A. Buckley, M. Citron, S. Fichet, S. Kraml, W. Waltenberger, **NW** *J. High Energ. Phys.* **2019,** 64 (2019)

* We can restore $\mu \cdot n_{s,I} \rightarrow n_{s,I}(\boldsymbol{\alpha})$ if needed, but for this toy we keep $\mu$

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2. Re-parameterize likelihood in terms of $\mu^*$ and $\vartheta_I$ → Need to derive $\pi(\boldsymbol{\vartheta})$!

$$L(\mu, \boldsymbol{\delta})\pi(\boldsymbol{\delta}) \rightarrow L(\mu, \boldsymbol{\theta})\pi(\boldsymbol{\theta}) = \prod_{I=1}^{P=90} P(n_I^{\text{obs}}|\mu \cdot n_{s,I} + a_I + b_I\theta_I + c_I\theta_I^2) \cdot \frac{1}{\sqrt{(2\pi)^P}} e^{-\frac{1}{2}\boldsymbol{\theta}^T\boldsymbol{\rho}^{-1}\boldsymbol{\theta}}$$

*P(x|y)* = Poisson probability as before

These are the same as the *full* likelihood

$\rho_{I,J} = \rho_{J,I}$

[1] A. Buckley, M. Citron, S. Fichet, S. Kraml, W. Waltenberger, **NW** *J. High Energ. Phys.* **2019,** 64 (2019)

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# Nearly done with the formulae…

Coefficients obtained by matching moments and appealing to CLT at NLO.

Coefficients *a*, *b* and *c* are determined from the first 3 central moments of the joint distributions of $n_{b,I}$ - Mean, covariance ***and skew***

Solutions valid for $$\frac{8(m_{2,II})^3}{(m_{3,I})^2} \geq 1$$

$$c_I = -\mathrm{sign}(m_{3,I})\sqrt{2m_{2,II}}\cos\left(\frac{4\pi}{3} + \frac{1}{3}\arctan\left(\sqrt{8\frac{m_{2,II}^3}{m_{3,I}^2} - 1}\right)\right)$$

$$b_I = \sqrt{m_{2,II} - 2c_I^2}\,,$$

$$a_I = m_{1,I} - c_I\,,$$

$$\rho_{IJ} = \frac{1}{4c_I c_J}\left(\sqrt{(b_I b_J)^2 + 8c_I c_J\, m_{2,IJ}} - b_I b_J\right).$$

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Solutions valid for $\dfrac{8(m_{2,II})^3}{(m_{3,I})^2} \geq 1$

Moments can be calculated analytically or (my preference) using pseudo experiments

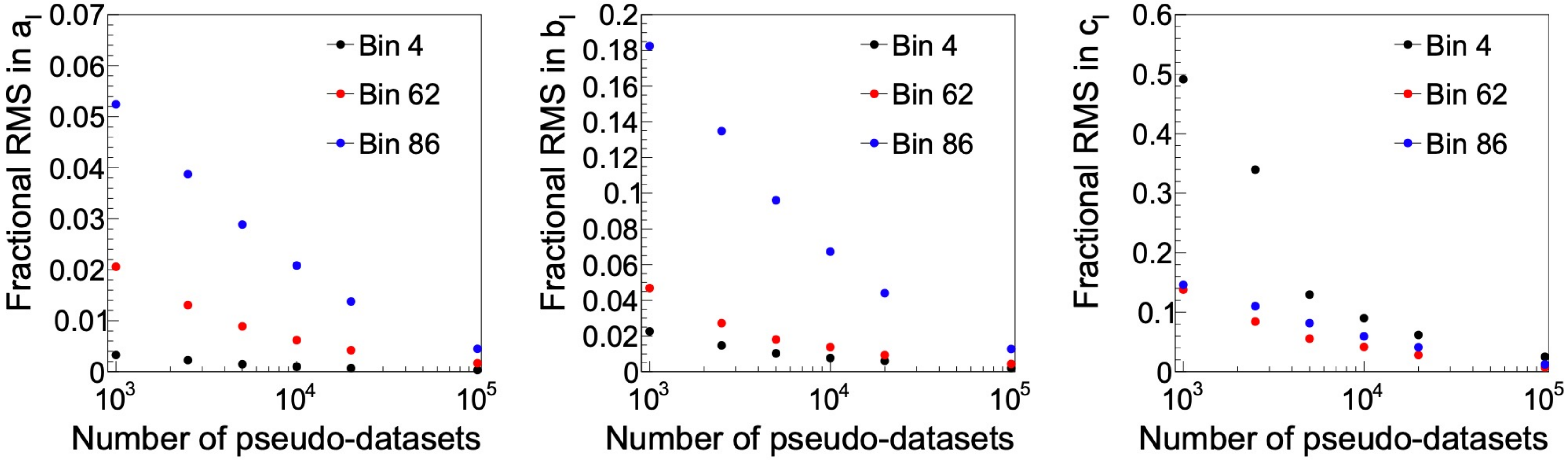
$$\boxed{m_{1,I}} = \mathbf{E}[\hat{n}_I]$$

$$\boxed{m_{2,IJ}} = \mathbf{E}[(\hat{n}_I - \mathbf{E}[\hat{n}_I])(\hat{n}_J - \mathbf{E}[\hat{n}_J])]$$

$$\boxed{m_{3,I}} = \mathbf{E}[(\hat{n}_I - \mathbf{E}[\hat{n}_I])^3]$$

**These quantities** are the inputs needed to determine the ***simplified likelihood***

# Convergence of moment calculation with pseudo-data



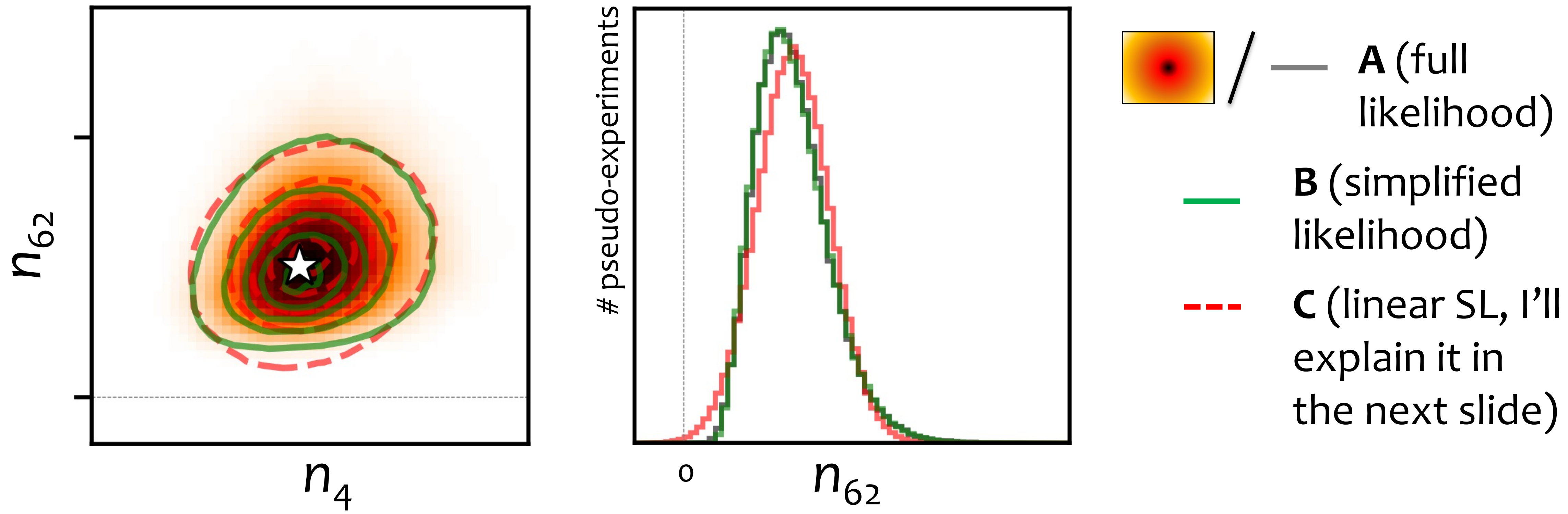

3[rd] Moment typically requires most toys to get accurate value, however this is mostly true when $m_3$ is small and therefore not so relevant!

# How well does this approximate the distribution of $n_I$?

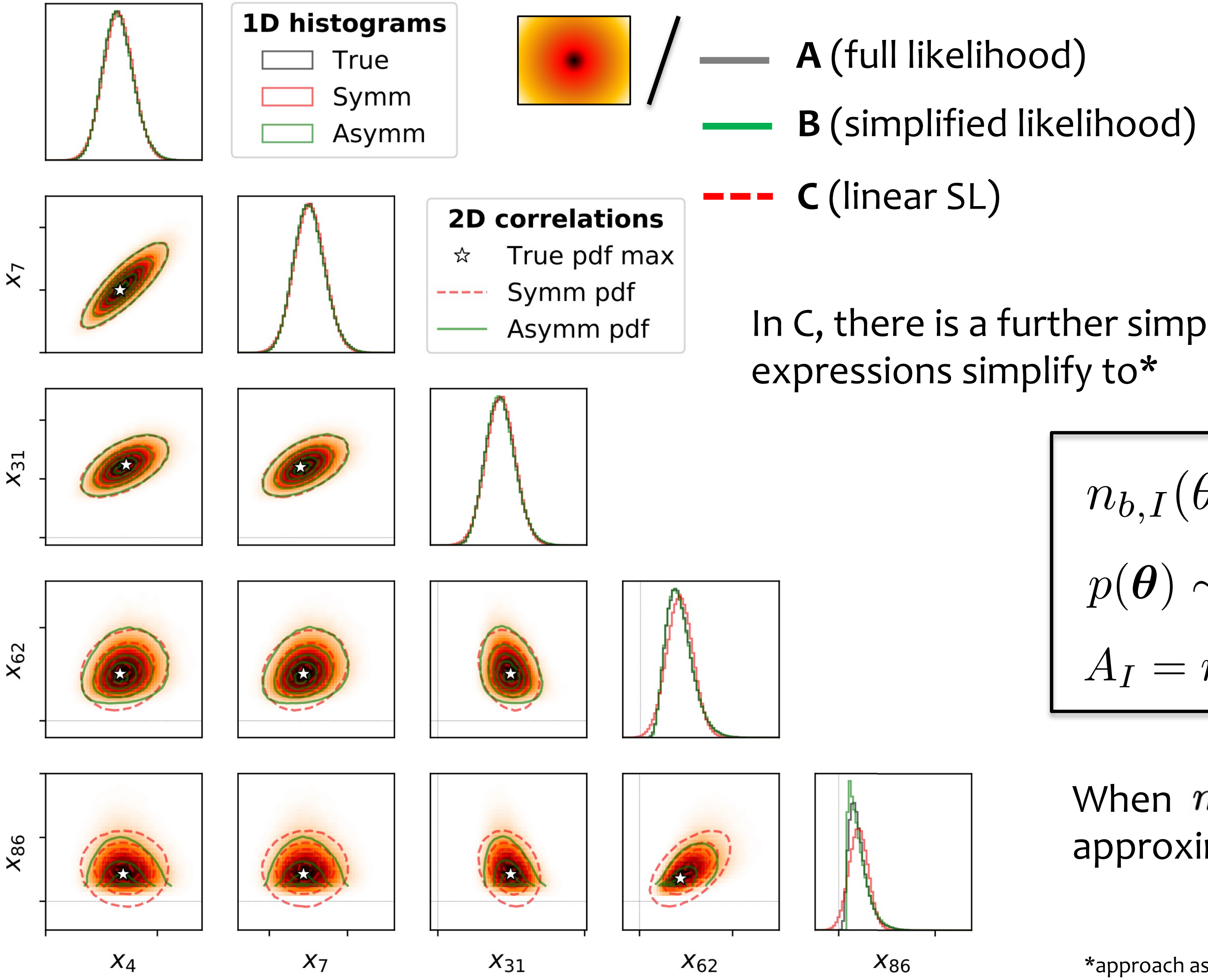
We can compare the distribution of $\hat{n}_I$ obtained in the pseudo-data from

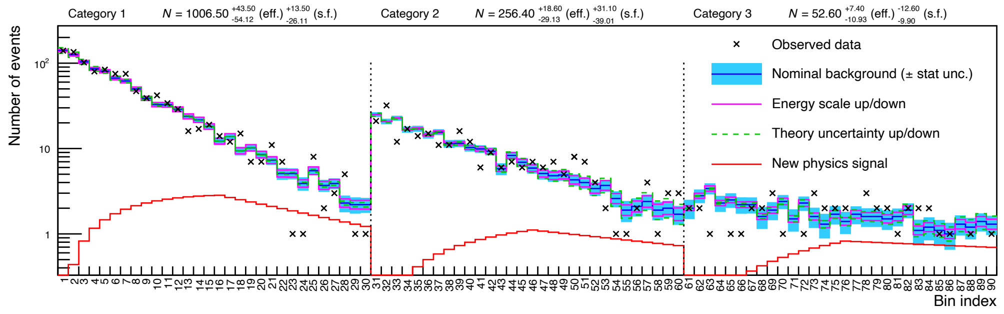
A. $\hat{n}_I = n_{b,I}(\boldsymbol{\delta}')$ generating from $p(\boldsymbol{\delta}) := \pi(\delta) \sim e^{-\frac{1}{2}\boldsymbol{\delta}\cdot\boldsymbol{\delta}}$

B. $\hat{n}_I = n_{b,I}(\theta_I')$ generating from $p(\boldsymbol{\theta}) \sim e^{-\frac{1}{2}\boldsymbol{\theta}^T\rho^{-1}\boldsymbol{\theta}}$



# How well does this approximate the distribution of $n_I$?




In C, there is a further simplification that $m_{3,I}$ is 0. In this case, the expressions simplify to*

$$n_{b,I}(\theta_I) = A_I + B_I\theta_I$$

$$p(\boldsymbol{\theta}) \sim e^{-\frac{1}{2}\boldsymbol{\theta}^T\boldsymbol{v}^{-1}\boldsymbol{\theta}}$$

$$A_I = m_{1,I},\ B_I = m_{2,II},\ v_{IJ} = m_{2,IJ}$$

When $m_{3,I}/(m_{2,II})^{\frac{3}{2}}$ (the skew) is small, the linear approximation is fairly good, as expected.

*approach as in CMS-NOTE-2017-001, and K. Cranmer, S. Kreiss, D. López-Val, T. Plehn, PhysRevD 91 054032

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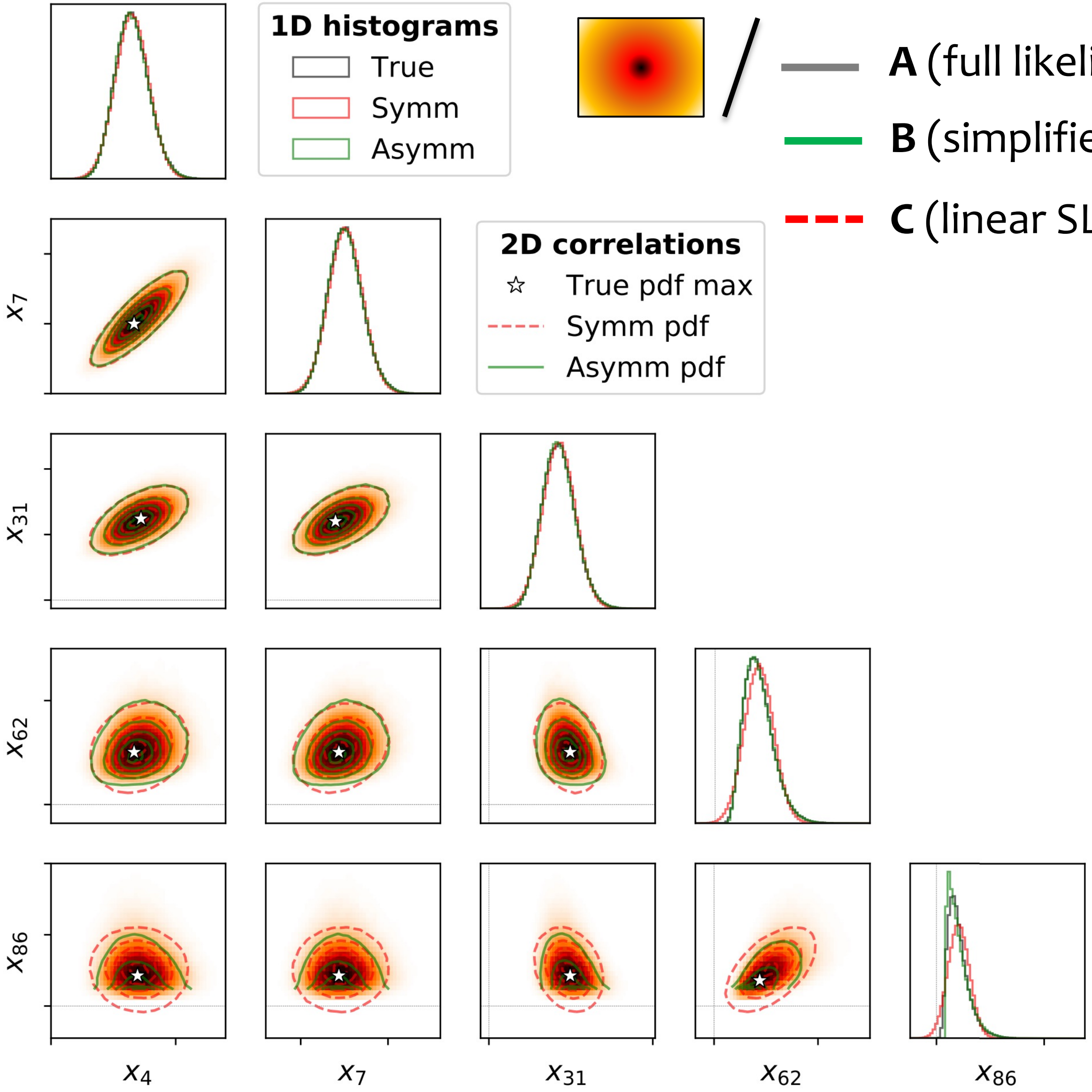
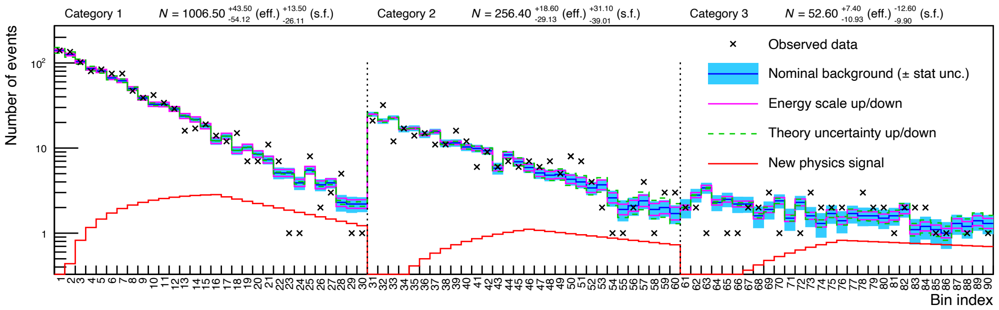



**A** (full likelihood)

**B** (simplified likelihood)

**C** (linear SL)

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# Get to the punchline already Nick …

Eliminating nuisance parameters (δ or θ) indicates how *accurately* we can reproduce statistical interpretations.

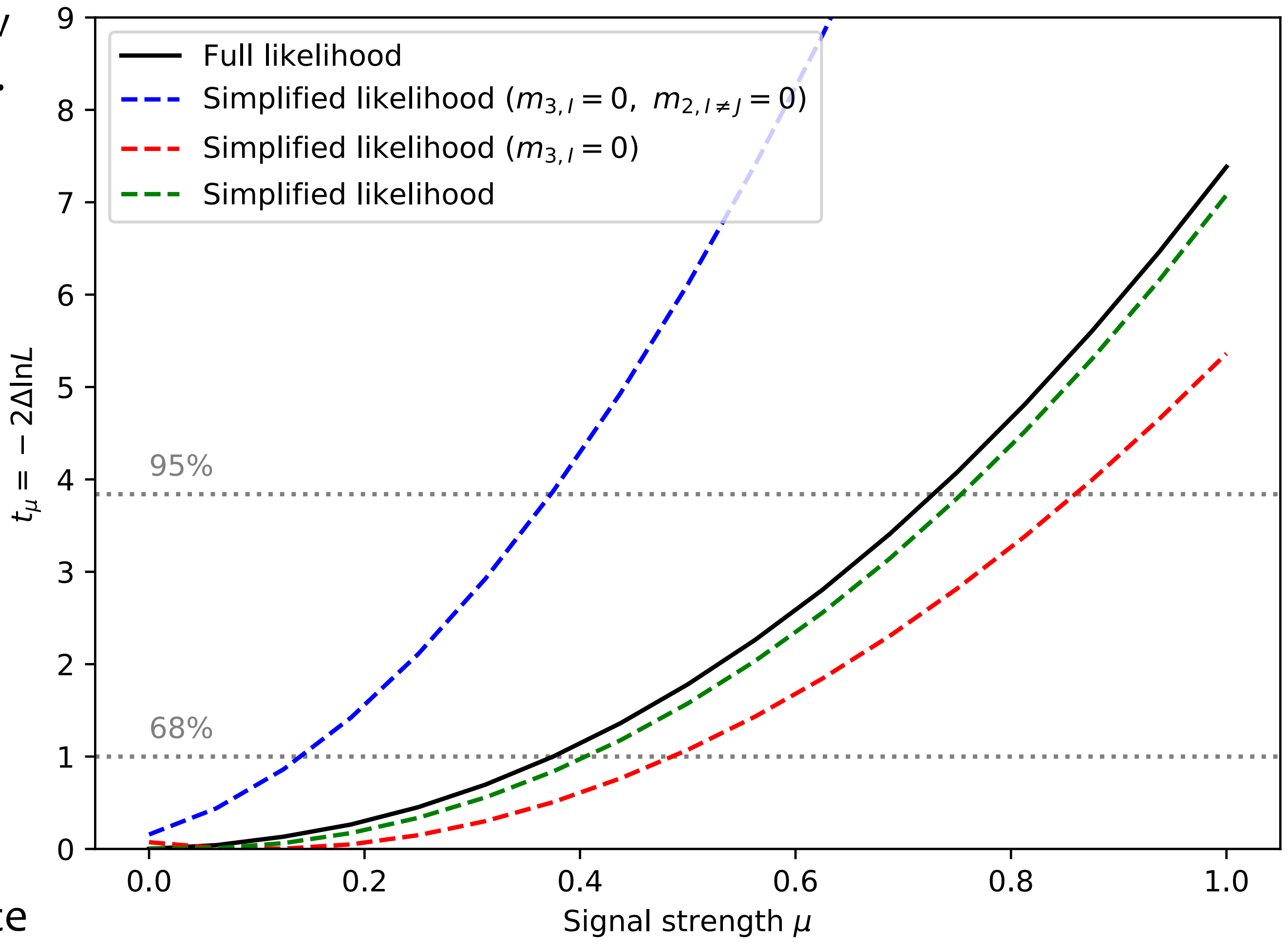
e.g. the profiled likelihood ratio test-statistic* is used to set limits on new physics processes at the LHC

$$t_{\mu} = -2\ln\frac{L_{\mathrm{S}}^{\max}(\mu)}{L_{\mathrm{S}}^{\max}}$$

$$L_{\mathrm{S}}^{\max}(\mu) = \max_{\theta_{\mathrm{I}}}\{\mathrm{L_S}(\mu,\boldsymbol{\theta})\}$$

Inputs for toy search uploaded to [HepData]

Public scipy-based code to calculate SL coefficients and run statistical tests on [GitLab]




*No reason why we couldn't have marginalised the likelihood to compare Bayesian posterior distributions instead of profiling.

# How simple is that ?

Counting all the inputs needed

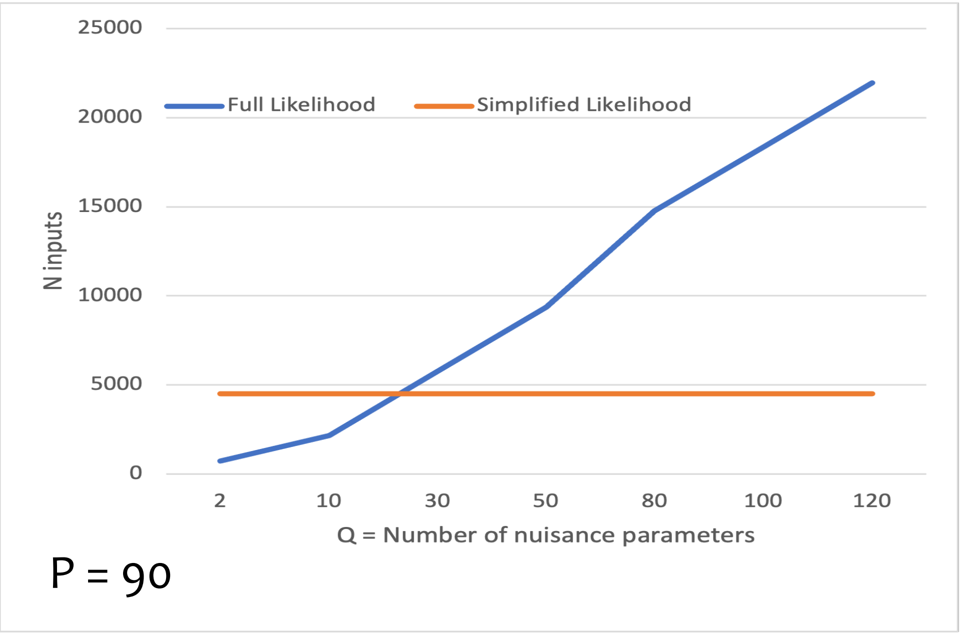
In our toy search, we need 90+90+90+(90*90)/2 = **4320** terms to specify the background yields

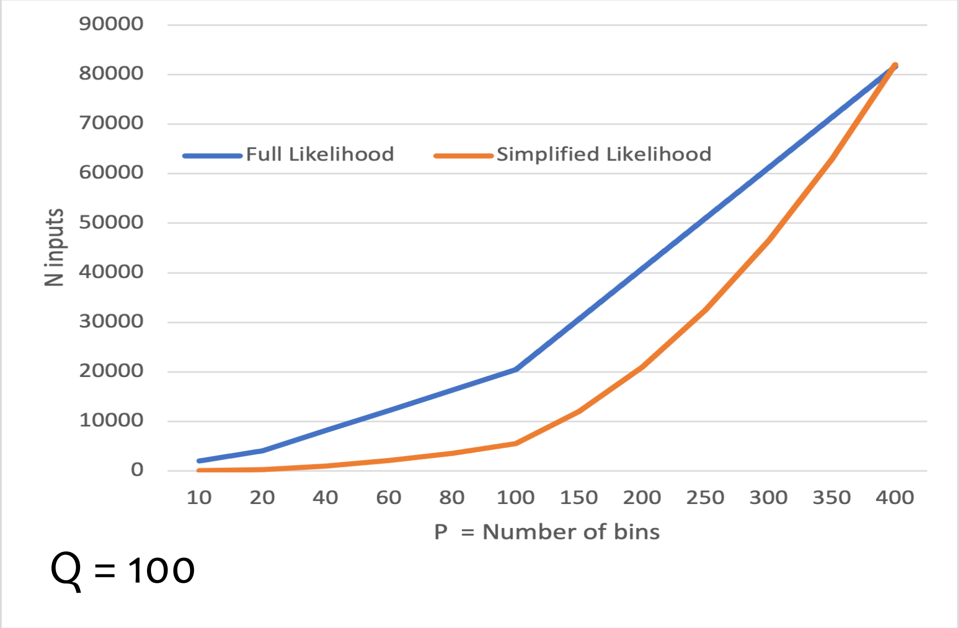
→ Total of **4500** to specify the *simplified* likelihood (with signal and data)

→ Only needed **729** inputs to specify the *full* likelihood

If P = number of bins, Q = number of nuisance parameters

- Number of inputs needed for full likelihood ~ 2Q (at large Q)
  → constant for simplified likelihood
- Number of inputs needed for simplified likelihood
  ~ $(P^2)/2 + P$ (at large P)



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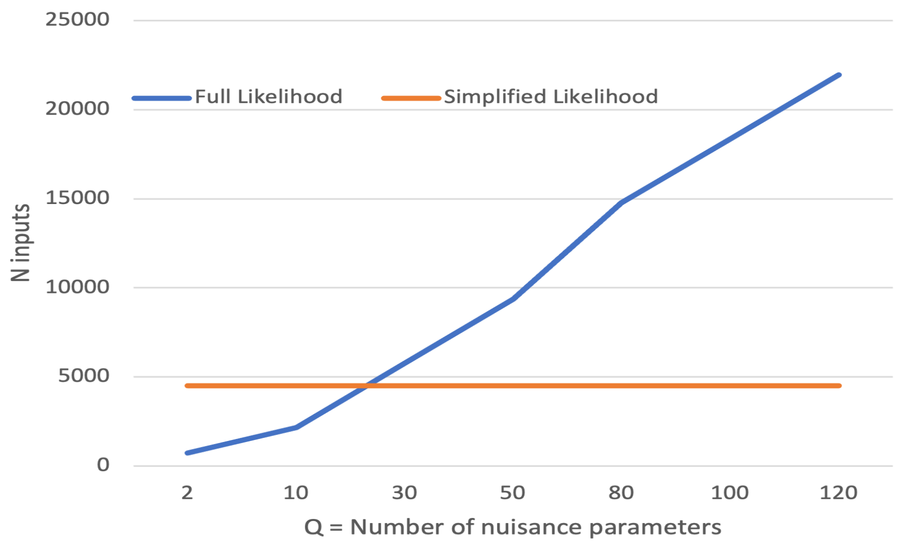
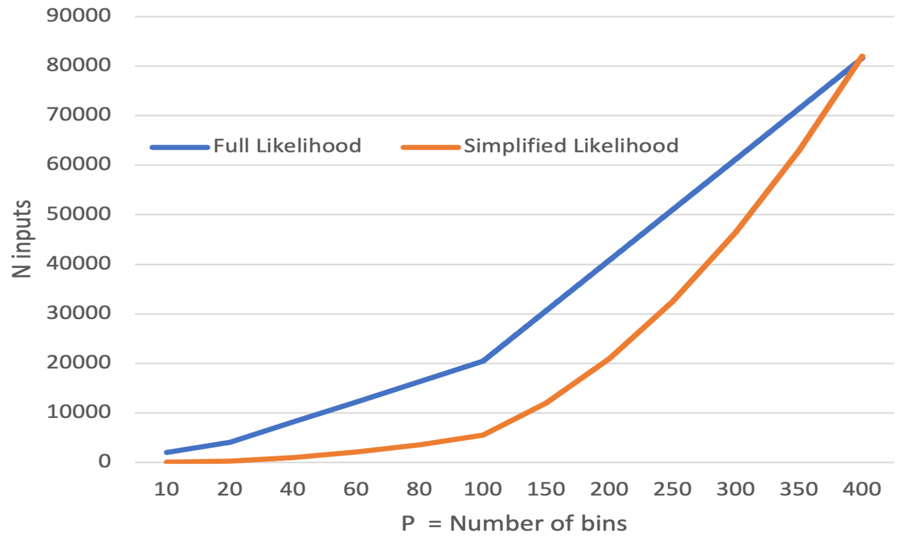
  ~ $(P^2)/2$ + P (at large P)

Simplified likelihood greatly reduces complexity for P << Q !




P = 90



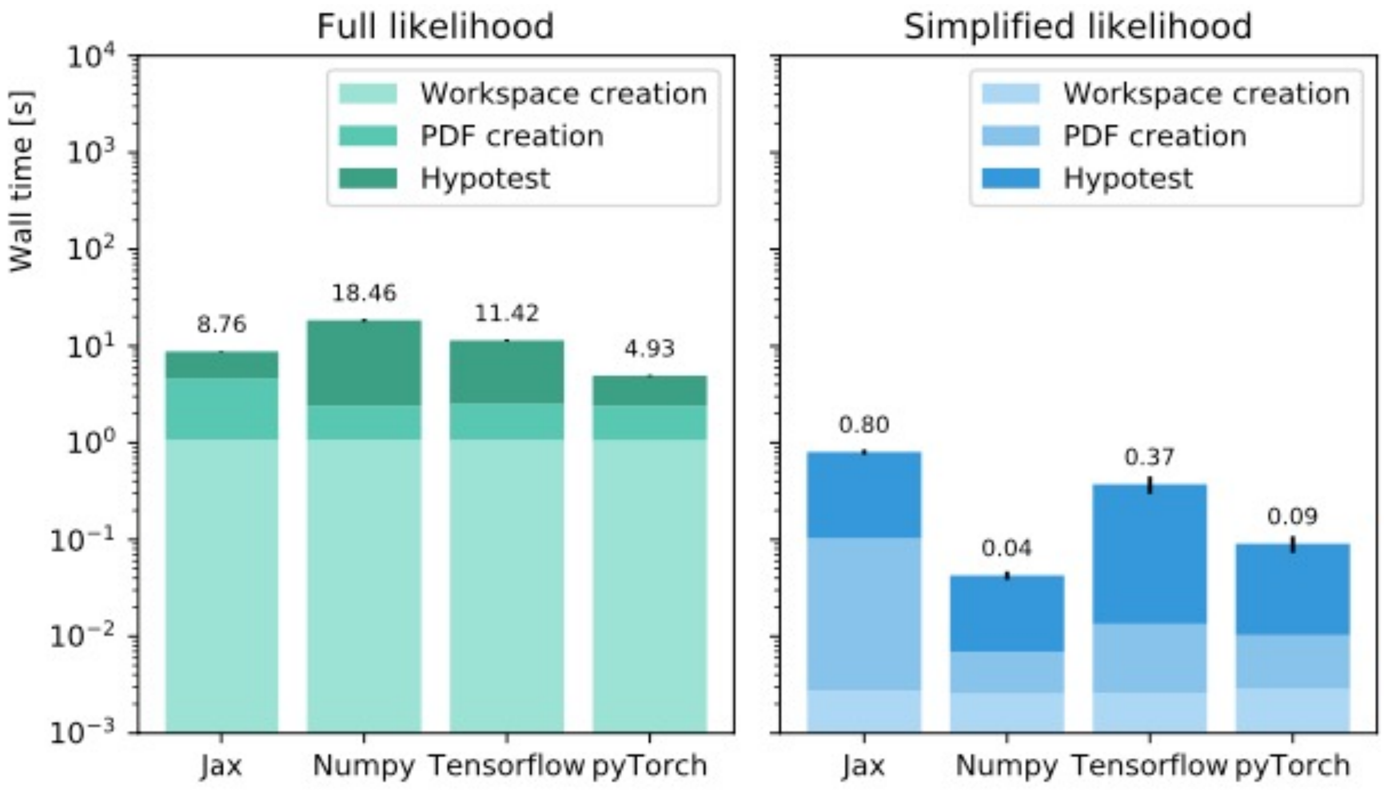

Q = 100

# What about fitting time?

ATLAS Search

O(100) nuisance parameters simplified using python-simplify

Creating PDF/LH and calculating upper limit:




E. Schanet, Re-interp 2021

Toy Search

94 nuisance parameters

Evaluate 16 points in a profiled likelihood scan:

RooFit/MINUIT based full likelihood:
~ 31 s on CPU

SLtools based simplified likelihood:
~ 1.6 s on CPU

Easily find speed-up of 10-100x in terms of fitting / statistical inference time when using simplified likelihoods!

# Can we do even better?

Essentially what we are doing is to approximate the distribution of the mean for the Poisson probabilities, i.e we want;

$$p(\mathbf{n}(\delta)|\boldsymbol{\delta})$$

So that we can plug ***n*** into the Poisson terms and constrain them. But why stop there? At the end, we care about *****

$$L(\boldsymbol{\alpha},\boldsymbol{\delta}) \propto p(\mathbf{x}|\boldsymbol{\alpha},\boldsymbol{\delta})\pi(\boldsymbol{\alpha},\boldsymbol{\delta})$$

Which, once we specify **x** is just a function;

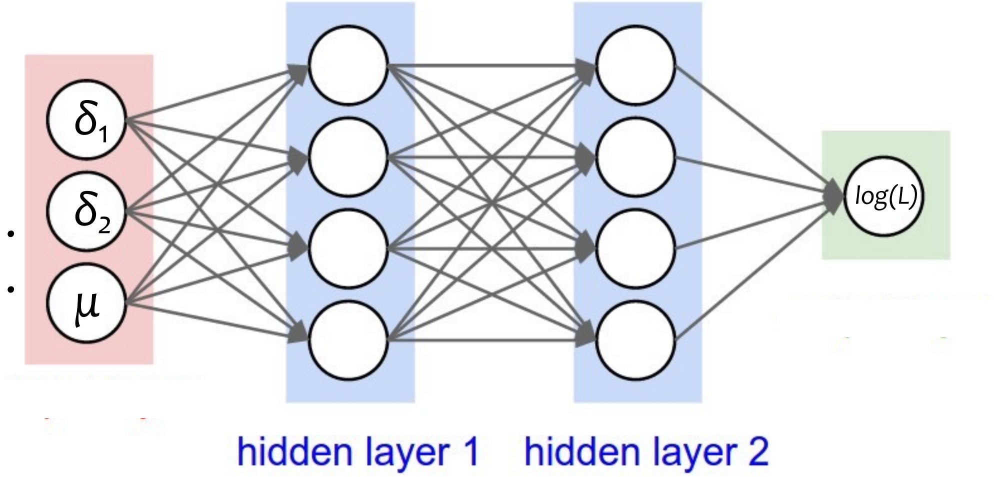
$$(\boldsymbol{\alpha},\boldsymbol{\delta}) \rightarrow L(\boldsymbol{\alpha},\boldsymbol{\delta})$$

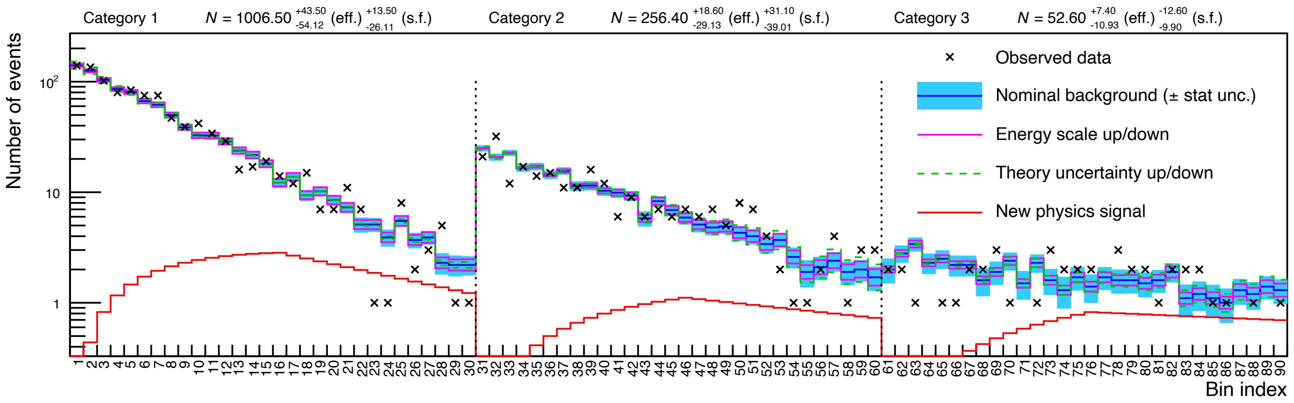
We know of statistical models that can be trained to "learn" this function → Use ***machine learning*** to approximate and communicate the likelihood!

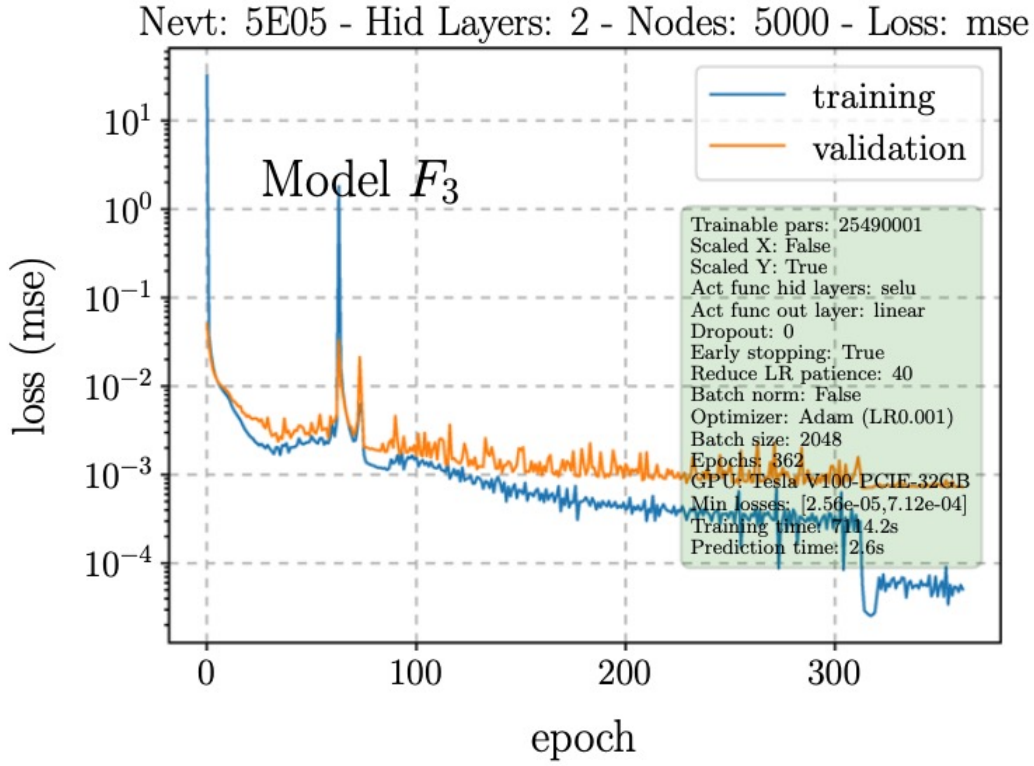
***** I know, I know, here I use *L* for a product of the likelihood and the priors!

# DNN based likelihoods

Random samples from the toy search experimental likelihood serve as training data for a Deep Neural Network [1]




- 2 hidden layer NN, with SELU activation functions between layers – tested different #nodes in hidden layers.
- Adam optimizer with MSE as loss function to train the NN parameters.
- Sampling based on p(**x**) – in this case known from the expt. LH

[1] A. Coccaro, M. Pierini, L. Silvestrini, R. Torre: *Eur. Phys. J. C* **80,** 664 (2020).

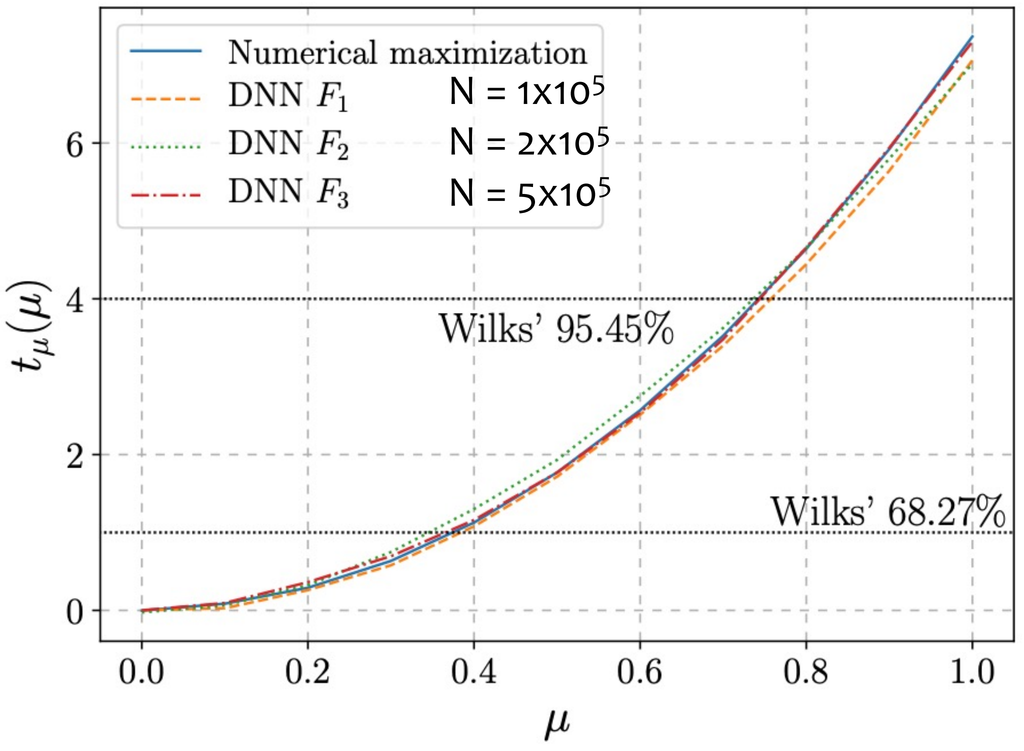
# DNN based likelihoods

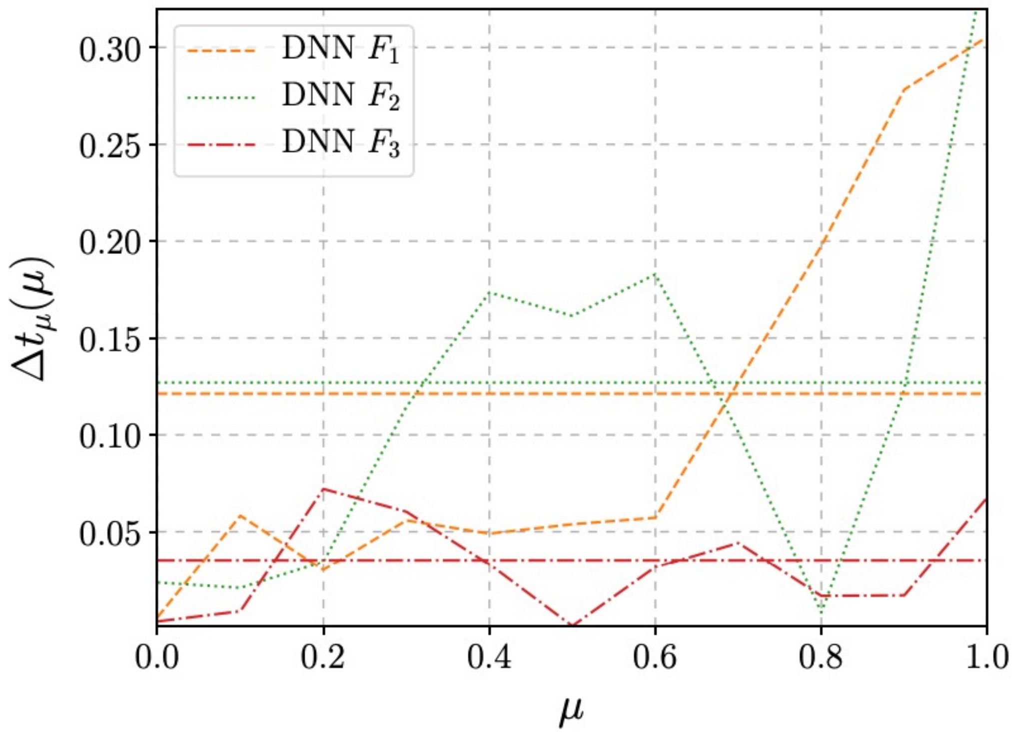
Profiled log-likelihood ratio demonstrates accuracy of DNN likelihood in terms of statistical inference

- Accuracy depends on number of sample points (N)used to train (more than required to determine covariances+skew but not prohibitively large)

Python based code for training and evaluating DNN LH

ONXX format for publishing LH



# ML-based likehood(ratios)

In some cases, it may be more challenging than necessary to learn the likelihood directly

→ if $p(\mathbf{x}|\alpha)$ must be obtained from some complex simulation, but can still generate from $p$

If you can find a function $s(\mathbf{x})$ that is monotonic with $r(\mathbf{x};\, \alpha_0,\alpha_1)$ [1], then;

$$r(\mathbf{x}|\alpha_0,\alpha_1) = \frac{p(\mathbf{x}|\alpha_0)}{p(\mathbf{x}|\alpha_1)} = \frac{p(s(\mathbf{x})|\alpha_0)}{p(s(\mathbf{x})|\alpha_1)}$$

e.g $s(\mathbf{x})$ can be a classifier trained to separate $\alpha_0$ vs $\alpha_1$

[1] arXiv:1506.02169

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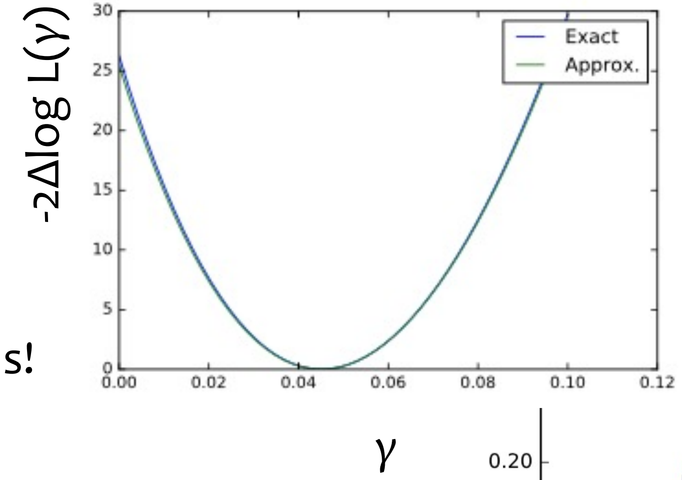
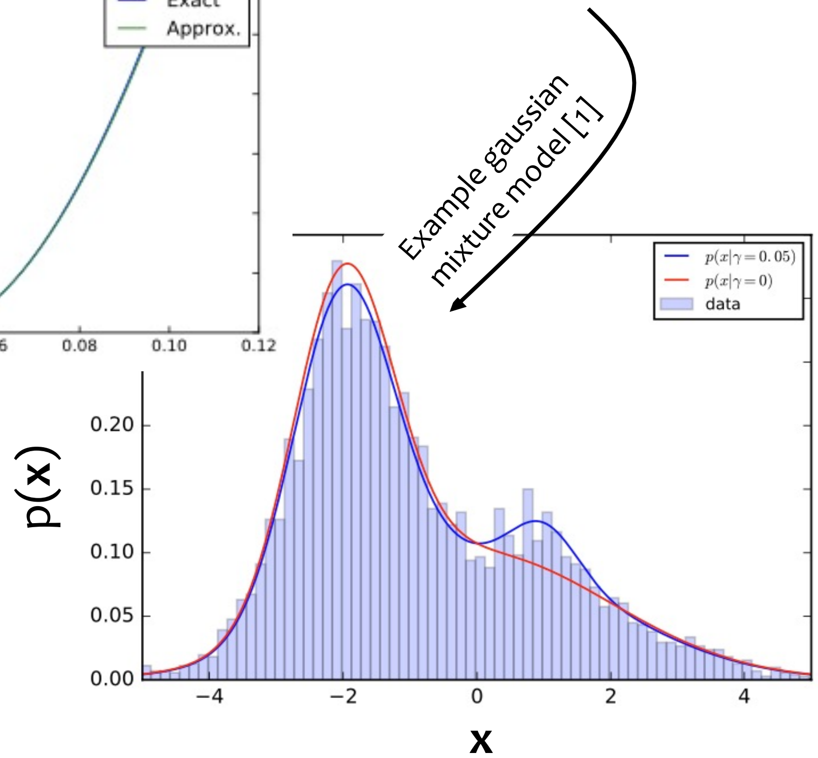
e.g $s(\mathbf{x})$ can be a classifier trained to separate $\alpha_0$ vs $\alpha_1$

Here **x** can be anything → not restricted to binned likelihoods!

$$p(\mathbf{x}|\gamma) = (1-\gamma)\frac{p_{c_0}(\mathbf{x}) + p_{c_1}(\mathbf{x})}{2} + \gamma\, p_{c_2}(\mathbf{x})$$




[1] arXiv:1506.02169

CARL GitHub

# ML-based likehood(ratios)

In some cases, it may be more challenging than necessary to learn the likelihood directly
→ if $p(\mathbf{x}|\alpha)$ must be obtained from some complex simulation, but can still generate from $p$

If you can find a function $s(\mathbf{x})$ that is monotonic with $r(\mathbf{x};\alpha_0,\alpha_1)$ [1], then;

$$r(\mathbf{x}|\alpha_0,\alpha_1) = \frac{p(\mathbf{x}|\alpha_0)}{p(\mathbf{x}|\alpha_1)} = \frac{p(s(\mathbf{x})|\alpha_0)}{p(s(\mathbf{x})|\alpha_1)}$$

e.g $s(\mathbf{x})$ can be a classifier trained to separate $\alpha_0$ vs $\alpha_1$

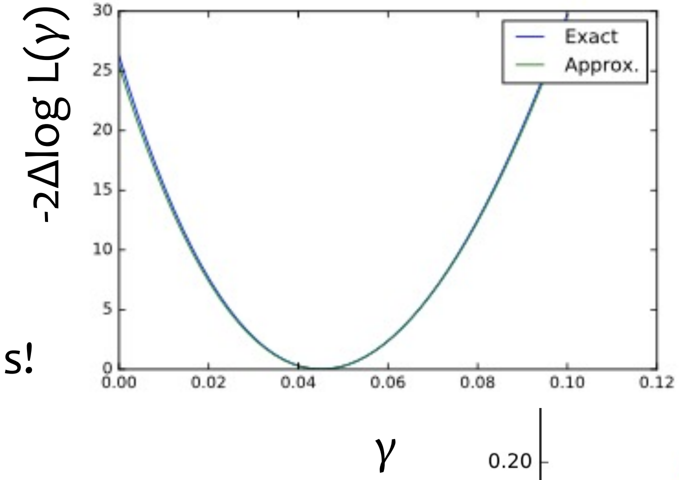
Here **x** can be anything → not restricted to binned likelihoods!

*likelihood-free* based inference or Approximate Bayesian Computation (ABC) more common outside HEP - See [2] for a very nice review of applications in HEP!

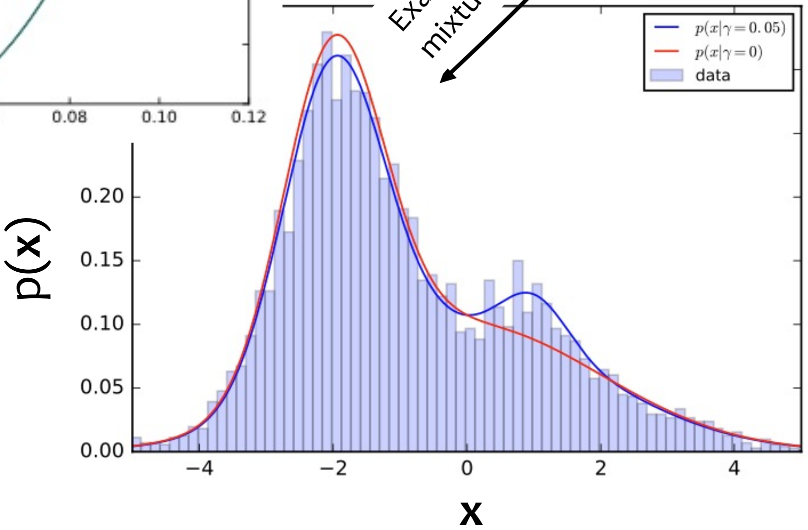
[1] arXiv:1506.02169
[2] arXiv:2010.06439

See the PhyStat seminar from Kyle Cranmer for more ML based approaches

$$p(\mathbf{x}|\gamma) = (1-\gamma)\frac{p_{c_0}(\mathbf{x}) + p_{c_1}(\mathbf{x})}{2} + \gamma\, p_{c_2}(\mathbf{x})$$




Example gaussian mixture model [1]




CARL GitHub

## Re-interpret != Re-produce

I was supposed to be talking about Re-***interpretation***.

All I've done is show you how we can re-***produce*** an experimental searches (or measurement)

# Re-interpret != Re-produce

Experimental likelihood

$$L(\mu,\boldsymbol{\delta})\pi(\boldsymbol{\delta}) = \prod_{I=1}^{90} P(n_I^{\mathrm{obs}}|\boxed{\mu\cdot n_{s,I}} + n_{b,I}(\boldsymbol{\delta}))\cdot\prod_{j=1}^{94} e^{-\delta_j^2}$$

This part is the same for both LHs
→ Changing $n_{s,I}$ allows for re-use of the likelihood for ***other signal hypotheses***

Simplified likelihood

$$L(\mu,\boldsymbol{\theta})\pi(\boldsymbol{\theta}) = \prod_{I=1}^{P=90} P(n_I^{\mathrm{obs}}|\boxed{\mu\cdot n_{s,I}} + a_I + b_I\theta_I + c_I\theta_I^2)\cdot\frac{1}{\sqrt{(2\pi)^P}}e^{-\frac{1}{2}\boldsymbol{\theta}^T\boldsymbol{\rho}^{-1}\boldsymbol{\theta}}$$

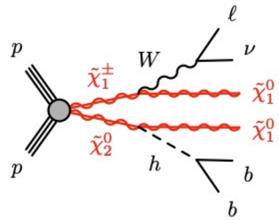
The same can be true for machine-learned based models for $n_{b,I}$ or $p(x|n_{s,I},\boldsymbol{\vartheta})$

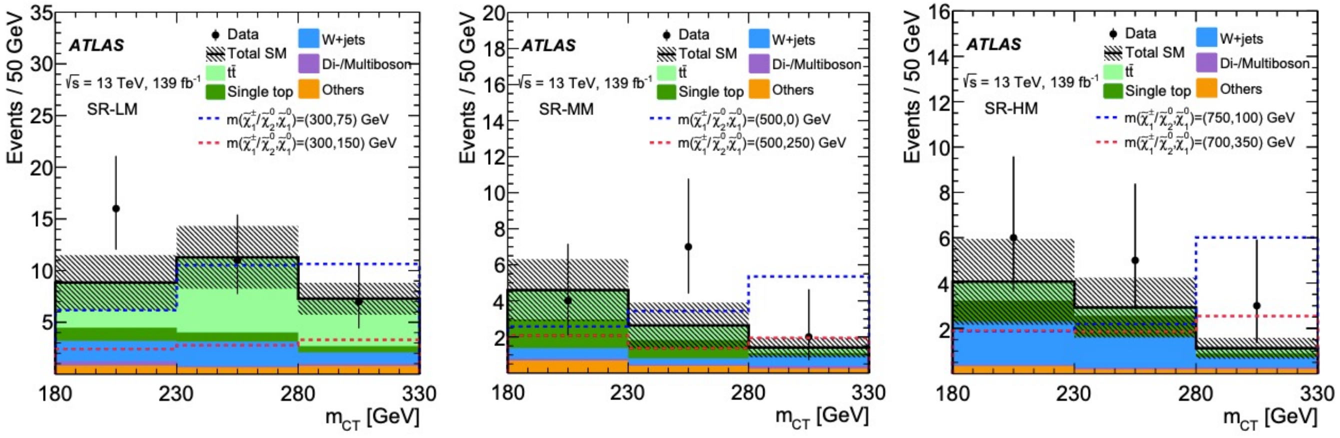
# Simplified likelihoods in the wild!

Real experimental likelihoods converted into simplified likelihoods…

*"Search for direct production of electroweakinos in final states with one lepton, missing transverse momentum and a Higgs boson decaying into two b-jets in pp collisions at sqrt{s}=13 TeV with the ATLAS detector"* [E. Phys. J. C 80, 691 (2020)]

Categorize data based on sensitivity to mass difference of $\tilde{\chi}_1^{\pm}$ and $\tilde{\chi}_1^{0}$, bin in $m_{\mathrm{CT}} = \sqrt{2 p_{\mathrm{T}}^{b_1} p_{\mathrm{T}}^{b_2} (1 + \cos \Delta\phi_{bb})}$,




* In this case, assume $m_{2,I\neq J} = 0, m_{3,I} = 0$

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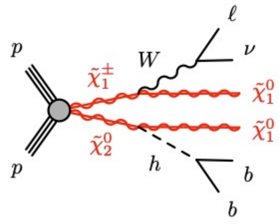


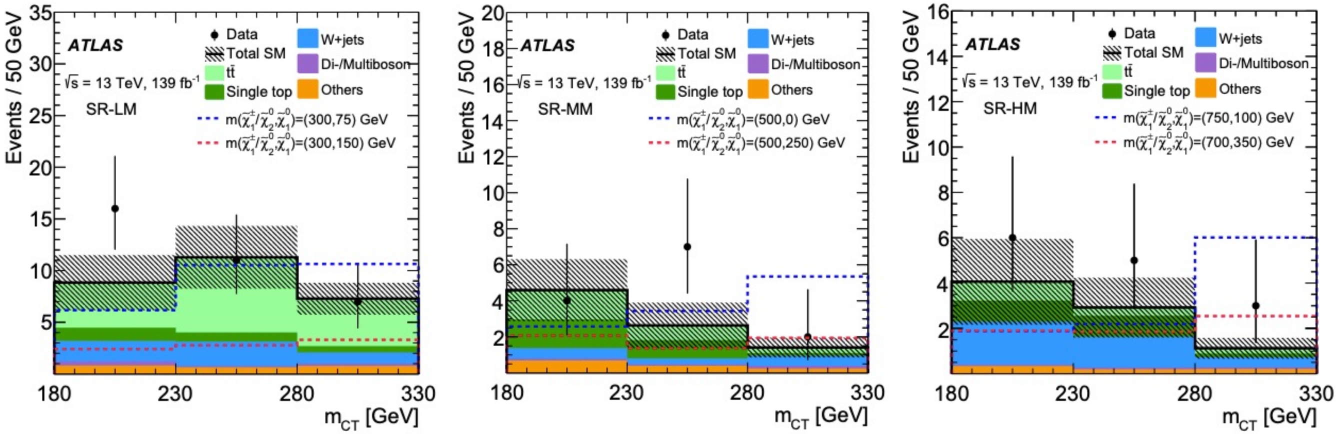


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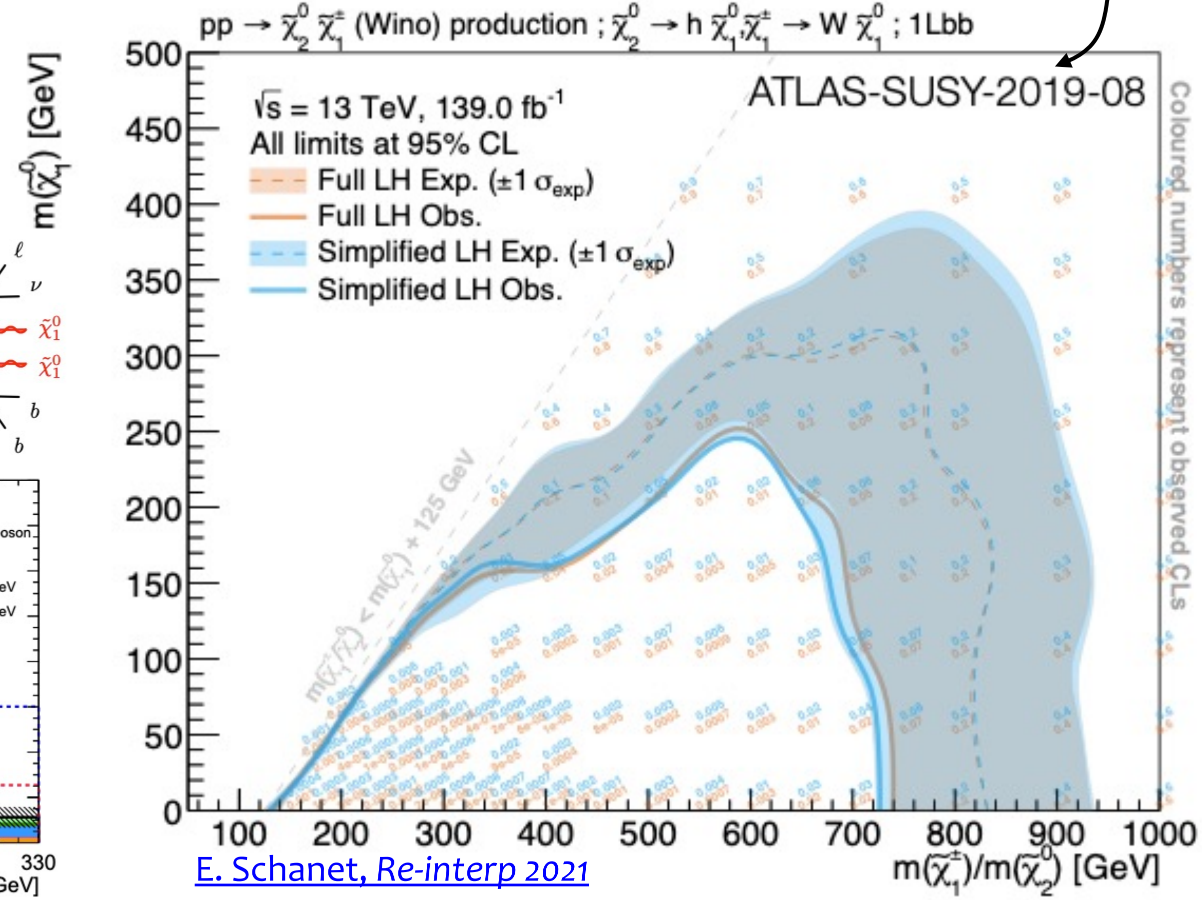
Comparison of **full** and **simplified likelihood*** based exclusion contours

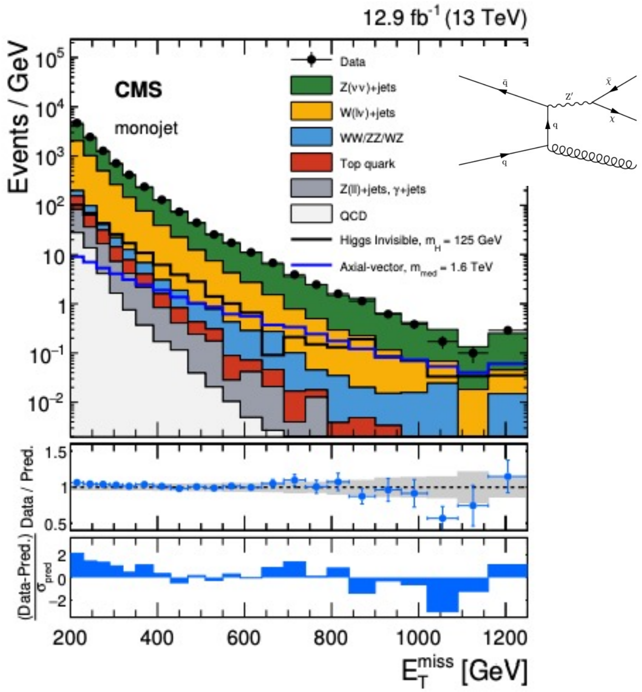


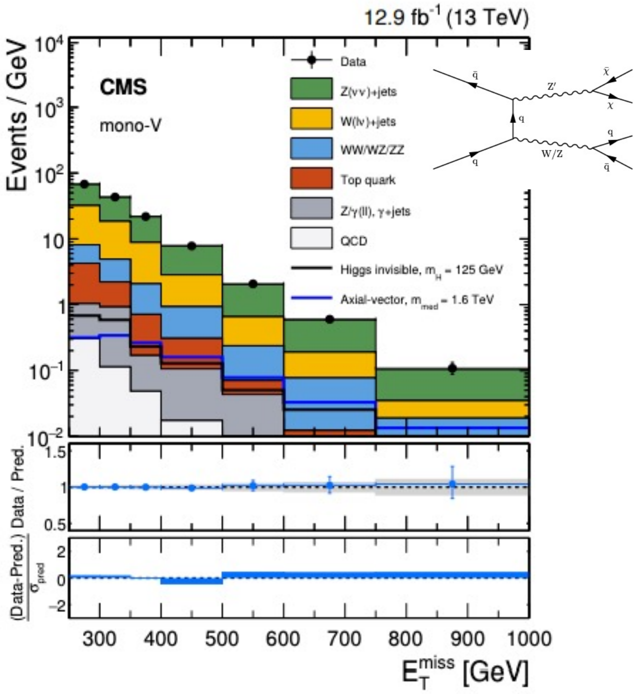

[E. Schanet, *Re-interp 2021*]

# Simplified likelihoods in the wild!

*"Search for dark matter produced with an energetic jet or a hadronically decaying W or Z boson at √s= 13 TeV"* [JHEP 07 (2017) 014]

- Data separated into 1 or 2 jet topologies
- Binned missing transverse momentum distribution used to separate signal from background
  → 29 bins



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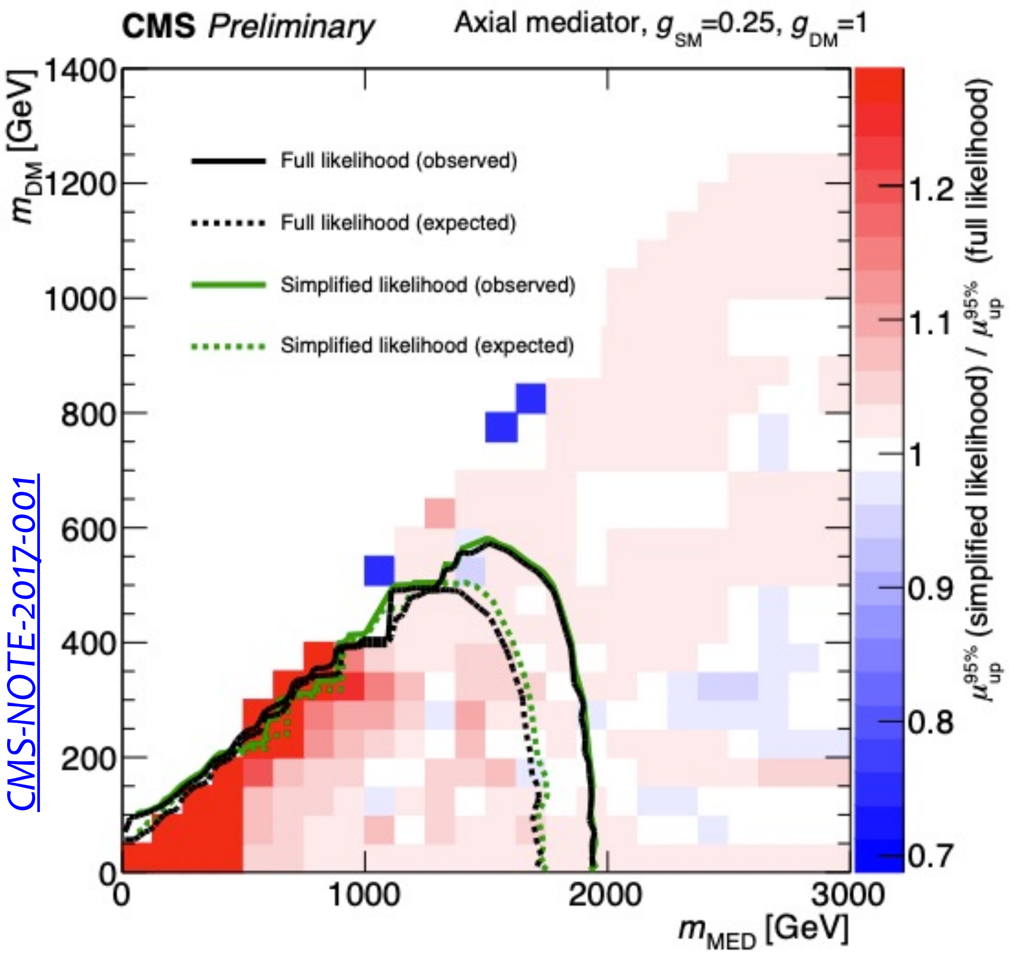


CMS-NOTE-2017-001

* In this case, assume $m_{3,I} = 0$

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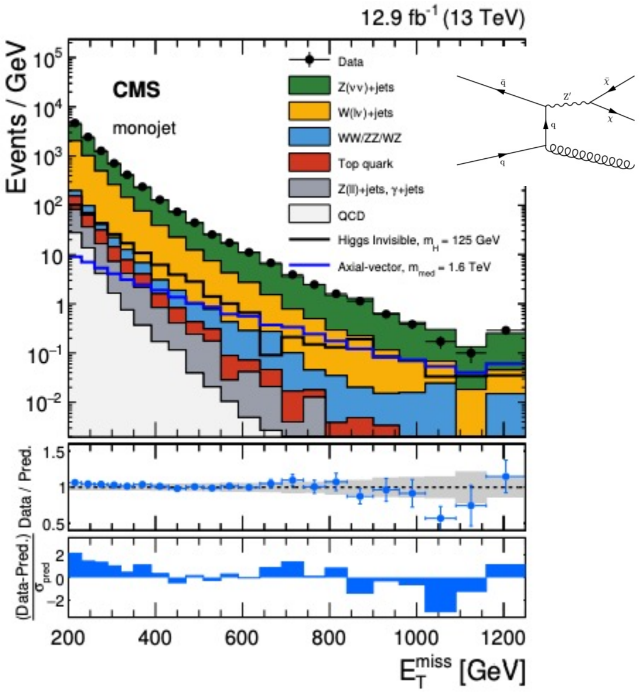
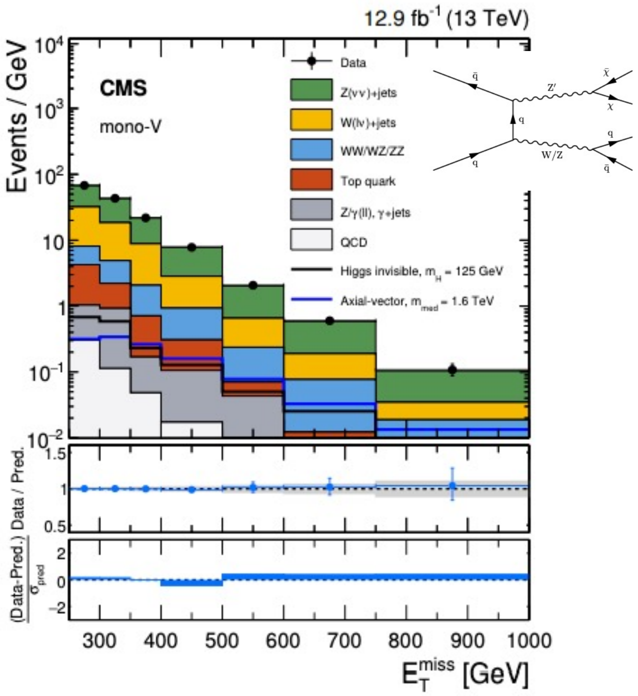


# We != experimentalists

I was supposed to be answering whether ***we*** can re-interpret data from the LHC.

Just because ***I*** have the info necessary, doesn't mean ***you*** do (or someone 10 years from now does)!

# Workflows

Reproducible research data analysis platform

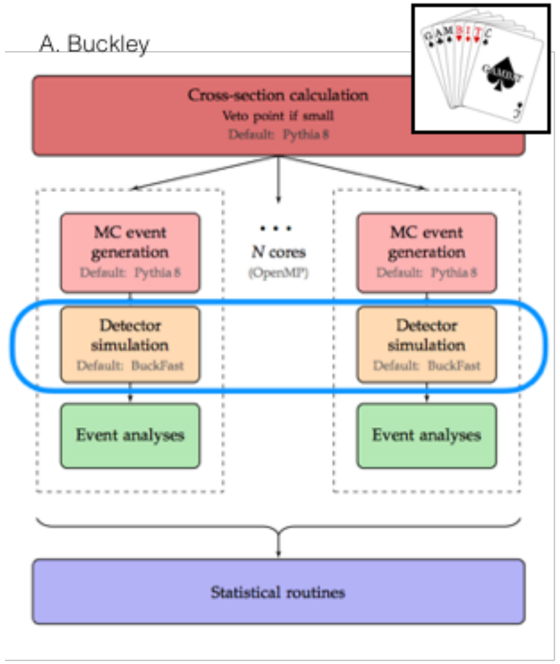
## Standard workflow for predictions

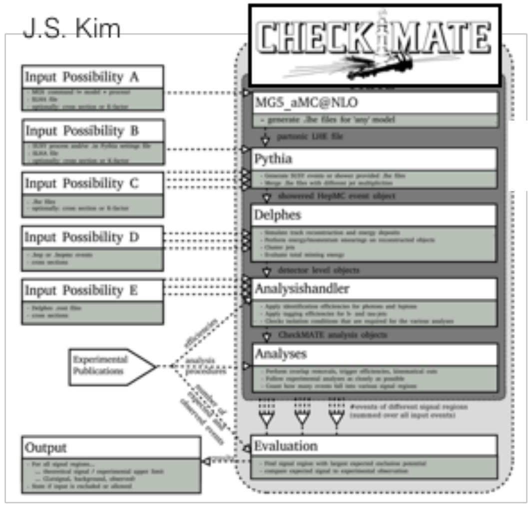
### New signal model
- UFO+param/proc/run card
- …

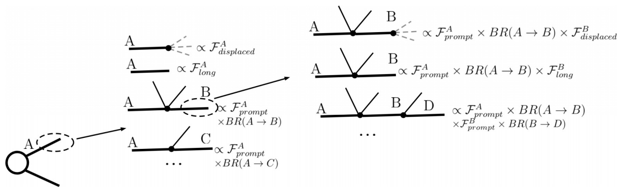
### MC generation
- MG5+Pythia
- Herwig
- Sherpa
- …

### Detector Simulation
- Full/Fast Geant4
- Delphes
- BuckFast
- Transfer functions
- …

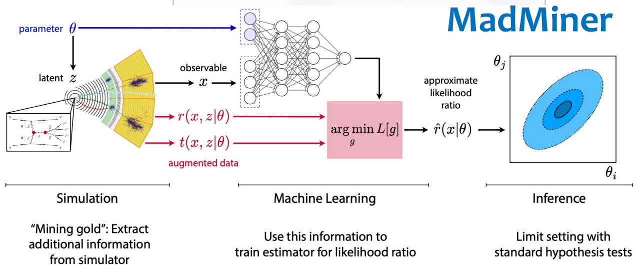
### Event Selection/categorisation
- Rivet
- MadAnalysis
- …

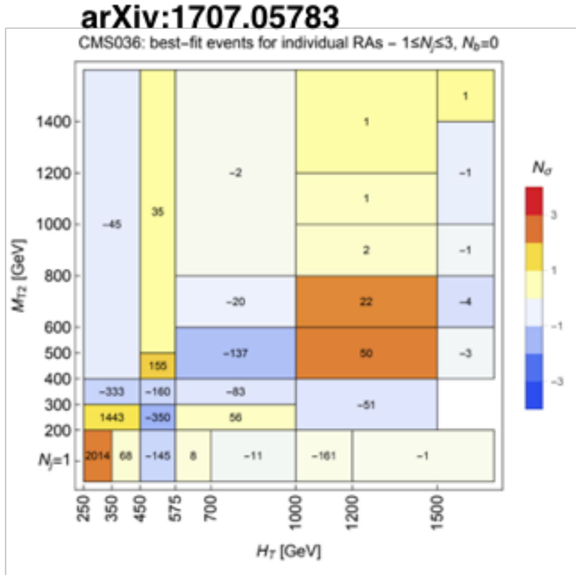


SModelS


- Counts/observables for signal process
- Statistical inference

# Calibration from experimental meta data

**Analysis descriptions needed to tune workflows**

- METADATA
  - MC Event Gen info (SLHA/UFO)
  - Code snippets / RIVET routines for analysis logic
  - BDT/ML algorithms where critical for the selection
- Efficiencies / Resolutions (in particular for LL searches) needed to calibrate detector simulation

ATLAS EXPERIMENT: https://twiki.cern.ch/twiki/bin/view/AtlasPublic

CMS: http://cms-results.web.cern.ch/cms-results/public-results/publications/

LHCb: http://lhcbproject.web.cern.ch/lhcbproject/Publications/LHCbProjectPublic/Summary_all.html

ALICE: https://twiki.cern.ch/twiki/bin/view/ALICEpublic/ALICEPublicResults

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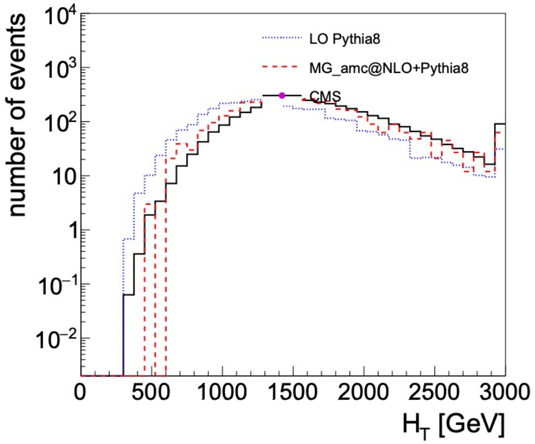
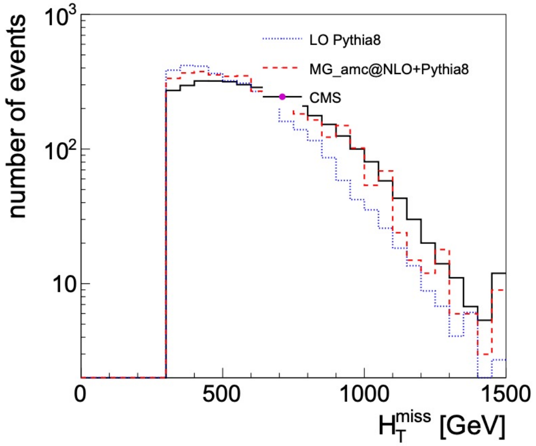
http://lhcbproject.web.cern.ch/lhcbproject/Publications/LHCbProjectPublic/Summary_all.html

https://twiki.cern.ch/twiki/bin/view/ALICEpublic/ALICEPublicResults

CMS-SUS-19-006 example (Jets+missing energy search)




Validation in MA5 by M. Mrowietz, S. Bein, J. Sonneveld

Table 1. Pre-selection cutflow for the T1qqqq-1300-100 simplified model.

| Cut | MA5 Pythia8 | MA5 Madgraph5 +Pythia8 | CMS | MA5 Pythia8 diff [%] | MA5 Madgraph5 +Pythia8 diff [%] | MA5 Pythia8 drop [%] | MA5 Madgraph5 +Pythia8 drop [%] | CMS drop [%] |
|---|---|---|---|---|---|---|---|---|
| $N_{jet} \geq 2$ | $100.0\pm^{0.0}_{0.0}$ | $100.0\pm^{0.0}_{0.1}$ | 100.0±0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| $H_T > 300$ | $100.0\pm^{0.0}_{0.0}$ | $100.0\pm^{0.0}_{0.1}$ | 100.0±0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| $H_T^{miss} > 300$ | $67.5\pm^{0.5}_{0.5}$ | $75.3\pm^{0.9}_{0.9}$ | 77.1±0.5 | 12.45 | 2.33 | 32.5 | 24.7 | 22.9 |
| $H_T > H_T^{miss}$ | $67.3\pm^{0.5}_{0.5}$ | $75.2\pm^{0.9}_{0.9}$ | 77.0±0.5 | 12.6 | 2.34 | 0.2 | 0.1 | 0.1 |
| NoIsoMuons | $67.3\pm^{0.5}_{0.5}$ | $75.1\pm^{0.9}_{0.9}$ | 76.9±0.5 | 12.48 | 2.34 | 0.0 | 0.1 | 0.1 |
| NoMuonsTracks | $67.2\pm^{0.5}_{0.5}$ | $75.1\pm^{0.9}_{0.9}$ | 76.8±0.5 | 12.5 | 2.21 | 0.1 | 0.0 | 0.1 |
| NoIsoElectrons | $67.2\pm^{0.5}_{0.5}$ | $75.0\pm^{0.9}_{0.9}$ | 76.5±0.5 | 12.16 | 1.96 | 0.0 | 0.1 | 0.3 |
| NoElectronsTracks | $67.1\pm^{0.5}_{0.5}$ | $75.0\pm^{0.9}_{0.9}$ | 76.1±0.5 | 11.83 | 1.45 | 0.1 | 0.0 | 0.4 |
| NoIsoTracks | $66.7\pm^{0.5}_{0.5}$ | $74.5\pm^{0.9}_{0.9}$ | 75.3±0.5 | 11.42 | 1.06 | 0.4 | 0.5 | 0.8 |
| NoIsoPhotons | $65.7\pm^{0.5}_{0.5}$ | $73.4\pm^{0.9}_{1.0}$ | 72.5±0.5 | 9.38 | -1.24 | 1.0 | 1.1 | 2.8 |
| $\Delta\Phi_{H_T^{miss},j1} > 0.5$ | $64.9\pm^{0.5}_{0.5}$ | $72.2\pm^{1.0}_{1.0}$ | 71.2±0.5 | 8.85 | -1.4 | 0.8 | 1.2 | 1.3 |
| $\Delta\Phi_{H_T^{miss},j2} > 0.5$ | $58.7\pm^{0.5}_{0.5}$ | $65.6\pm^{1.0}_{1.0}$ | 64.5±0.6 | 8.99 | -1.71 | 6.2 | 6.6 | 6.7 |
| $\Delta\Phi_{H_T^{miss},j3} > 0.3$ | $54.7\pm^{0.5}_{0.5}$ | $60.7\pm^{1.0}_{1.1}$ | 59.6±0.6 | 8.22 | -1.85 | 4.0 | 4.9 | 4.9 |
| $\Delta\Phi_{H_T^{miss},j4} > 0.3$ | $50.4\pm^{0.5}_{0.5}$ | $55.6\pm^{1.1}_{1.1}$ | 54.9±0.6 | 8.2 | -1.28 | 4.3 | 5.1 | 4.7 |

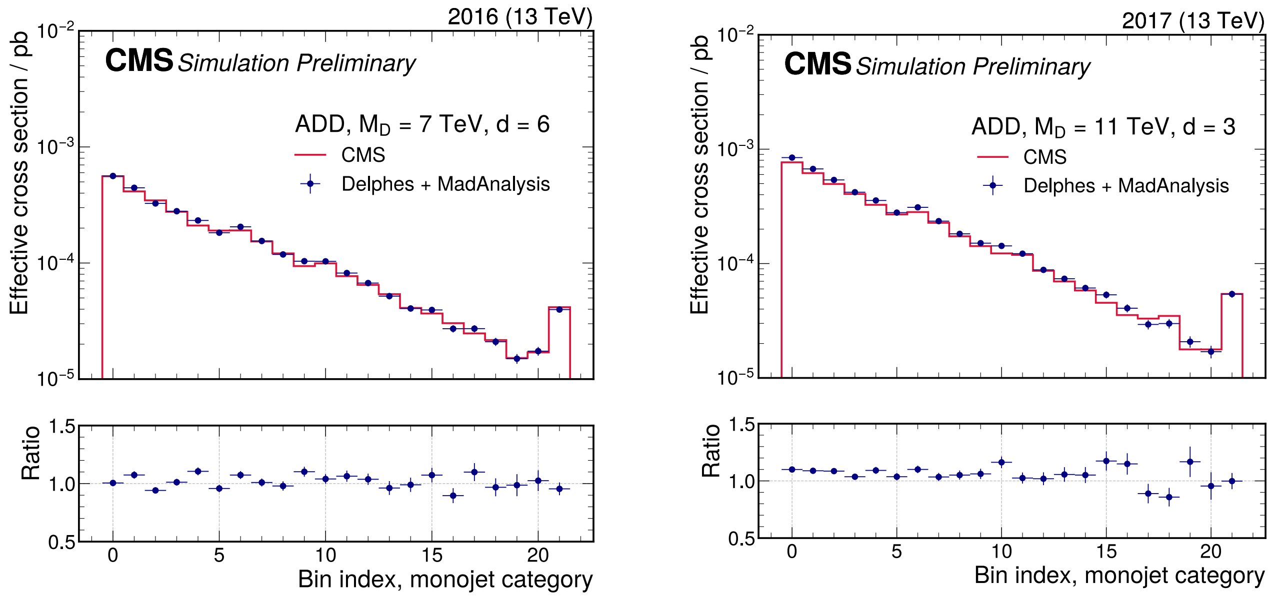
- Description of statistical methods
  - E.g validity of asymptotic approximations if used

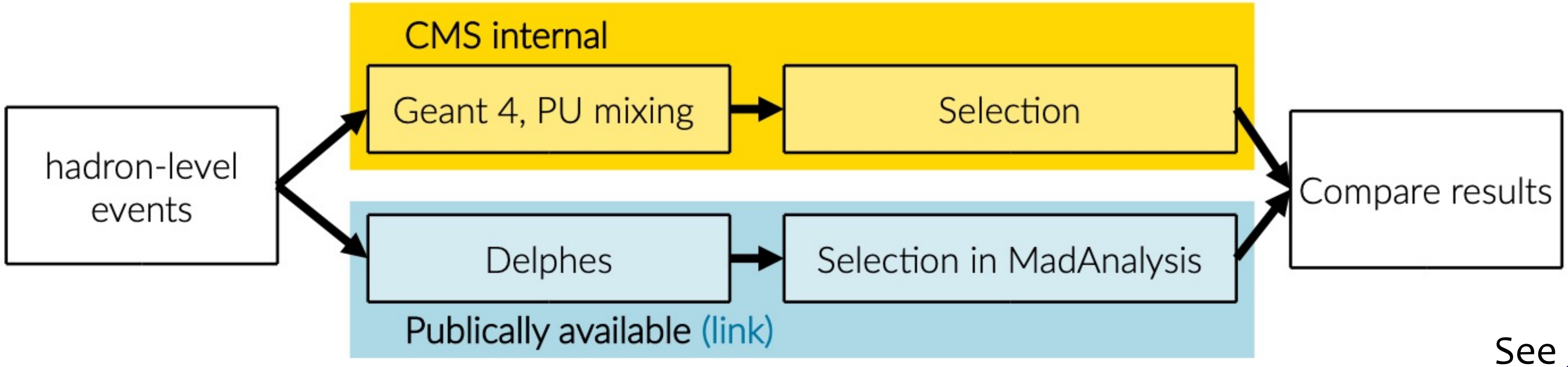
# Example from CMS (EXO-20-004)

*"Search for new particles in events with energetic jets and large missing transverse momentum in proton-proton collisions at 13 TeV" – Full Run-2 data update*

HepData entry

- Signal templates & cutflows
- Simplified likelihood inputs
- MC Generator configs for various signals + MadAnalysis implementation



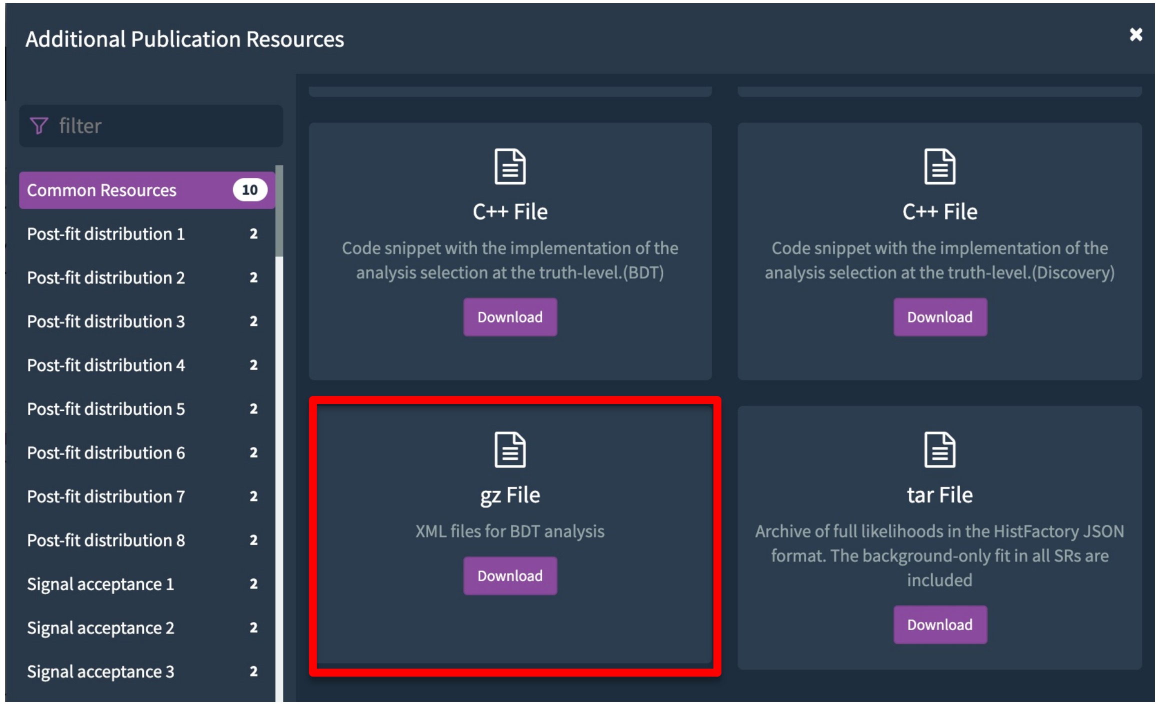



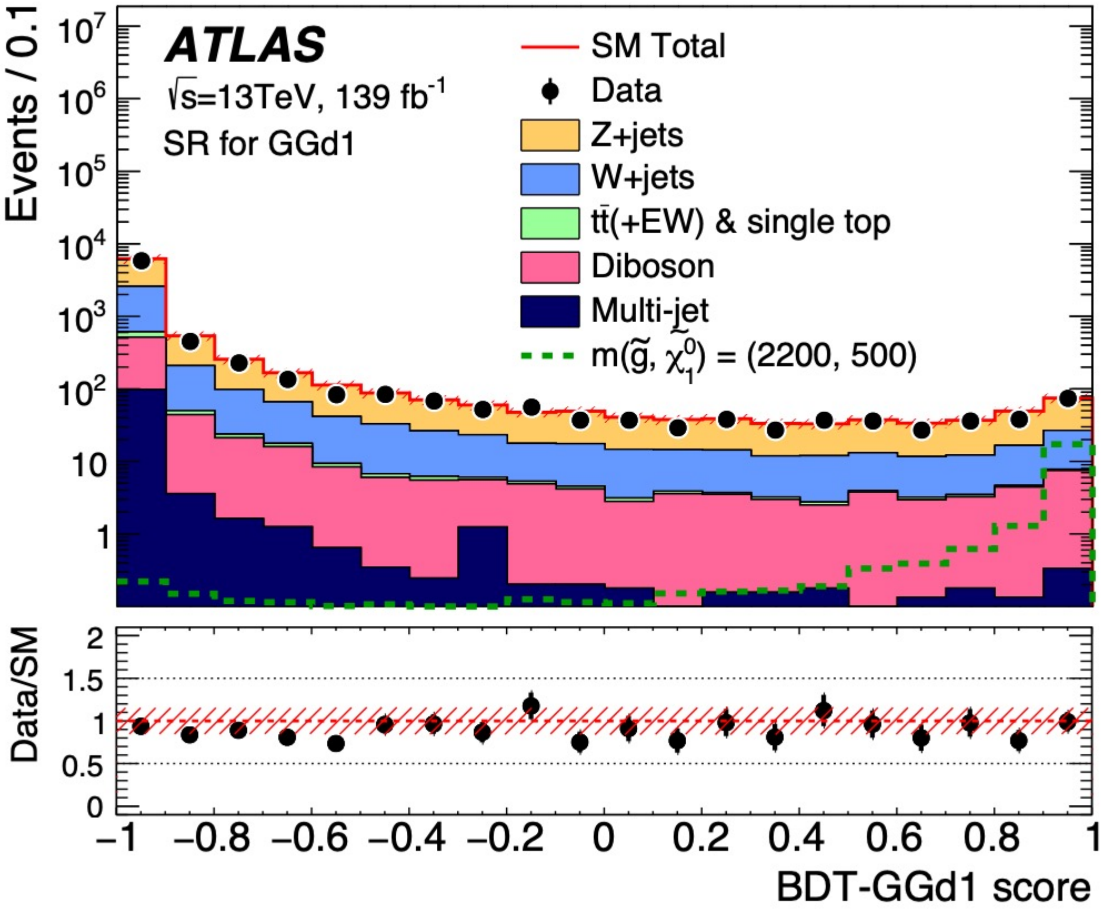

See RAMP talk by A. Albert

# Example from ATLAS (SUSY-2018-22)

*"Search for squarks and gluinos in final states with jets and missing transverse momentum using 139/fb of ps =13 TeV p p collision data with the ATLAS detector"*

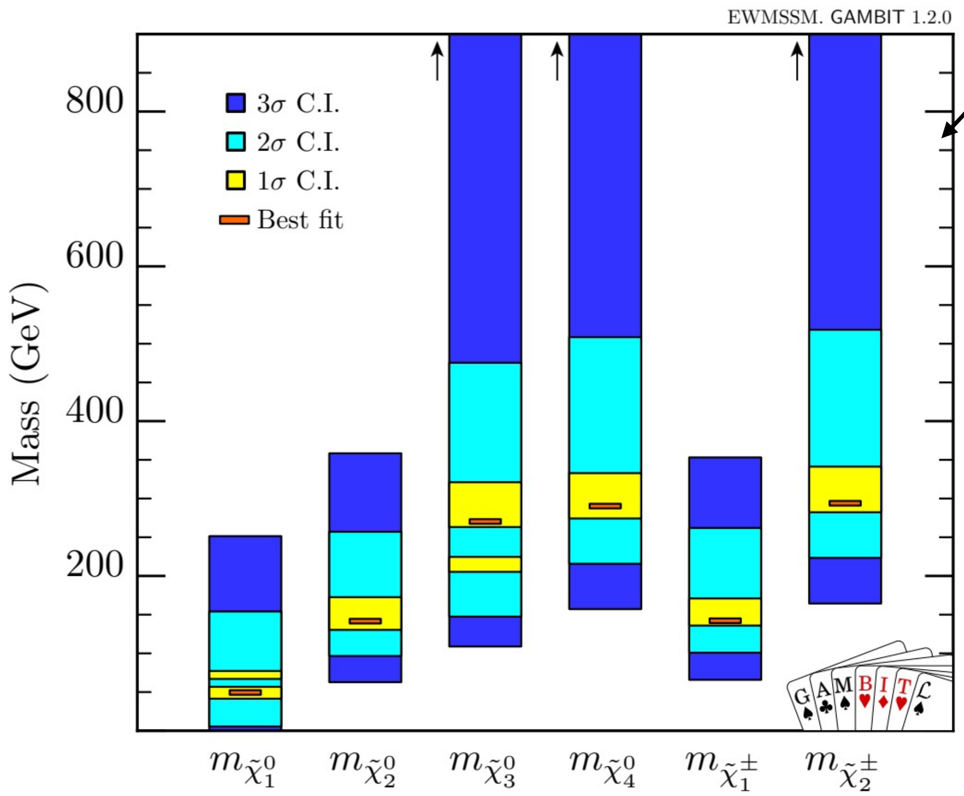
HepData entry
- Full likelihood model
- Analysis snippet codes
- XML for evaluating BDT weights



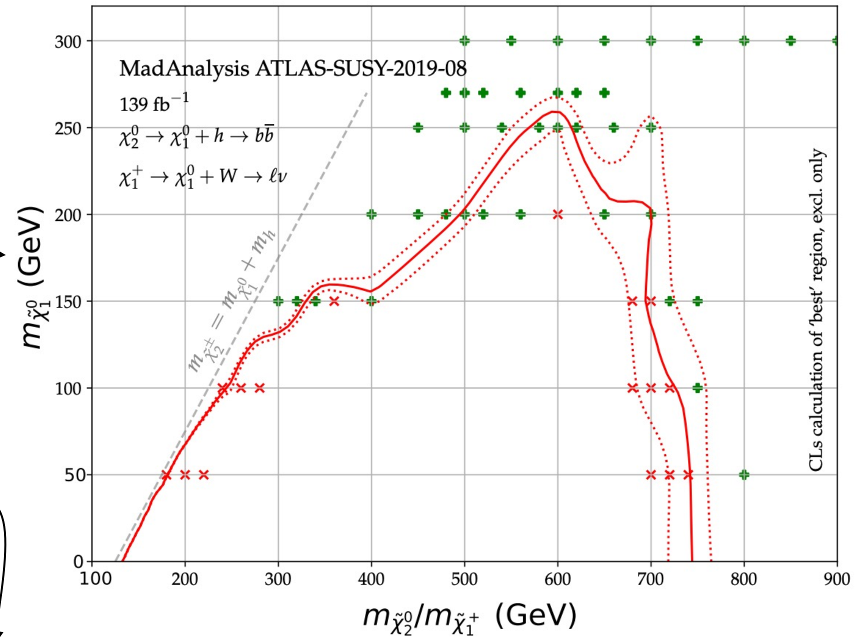



# Re-interpretations in the wild

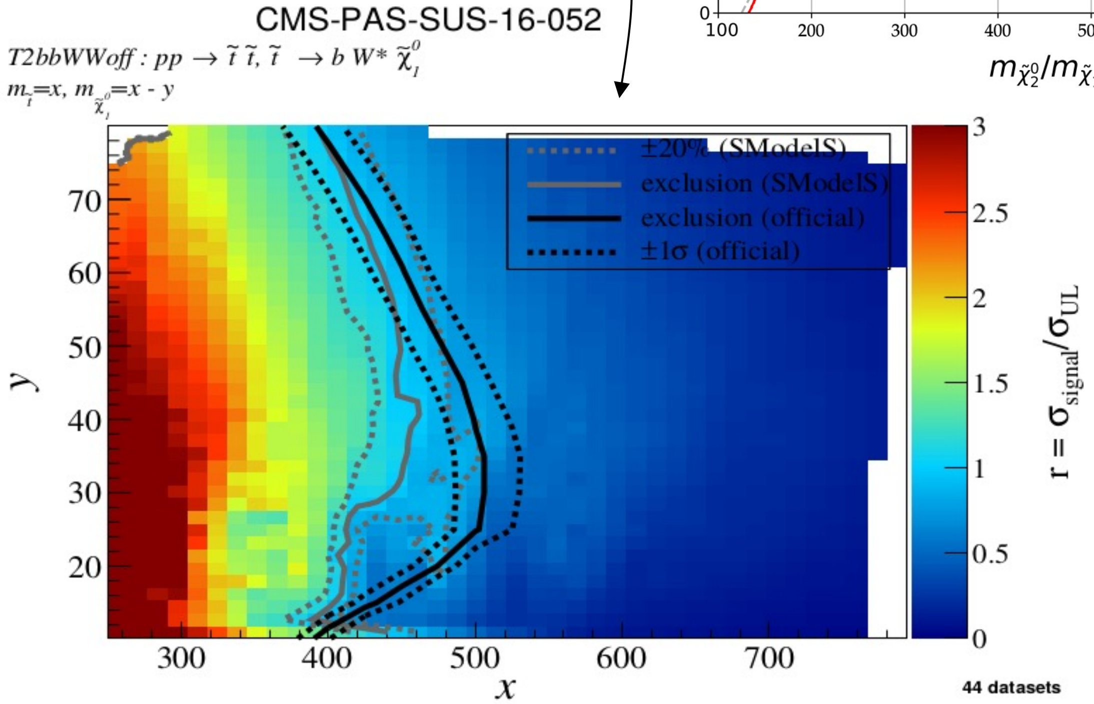
LHC+LEP constraints on neutralino/charginos with Gambit, using combination ATLAS+CMS results (simplified likelihood where available)




SUSY exclusions using full (ATLAS) likelihoods in MadAnalysis5




SUSY exclusion contours in SModelS using (linear) simplified (CMS) likelihood




More studies on use of full/simplified likelihoods in LesHouches19 report

# Preservation

Preservation of data is vital for longevity of LHC results

## Science 2061

- Many members of the generation who may wish to re-analyze the LHC Run 3 data in 2061 have yet to be born.
- That generation may wish to re-analyze these data simultaneously with old LSST and LIGO data using BSM models that they invent from which (with the help of their AI assistants) they are able to compute testable predictions for LHC, LSST, and LIGO data.
- Now ask yourself: What are we doing wrong, or what are we forgetting, that risks thwarting such heroic efforts forty year hence?

H. Prosper Reinterp2021

**Publishing likelihoods** is a step in that direction

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## CERN announces new open data policy in support of open science

**A new open data policy for scientific experiments at the Large Hadron Collider (LHC) will make scientific research more reproducible, accessible, and collaborative**

11 DECEMBER, 2020

Data storage solutions at the CERN data centre (Image: CERN)

https://home.cern/news/press-release/knowledge-sharing/cern-announces-new-open-data-policy-support-open-science

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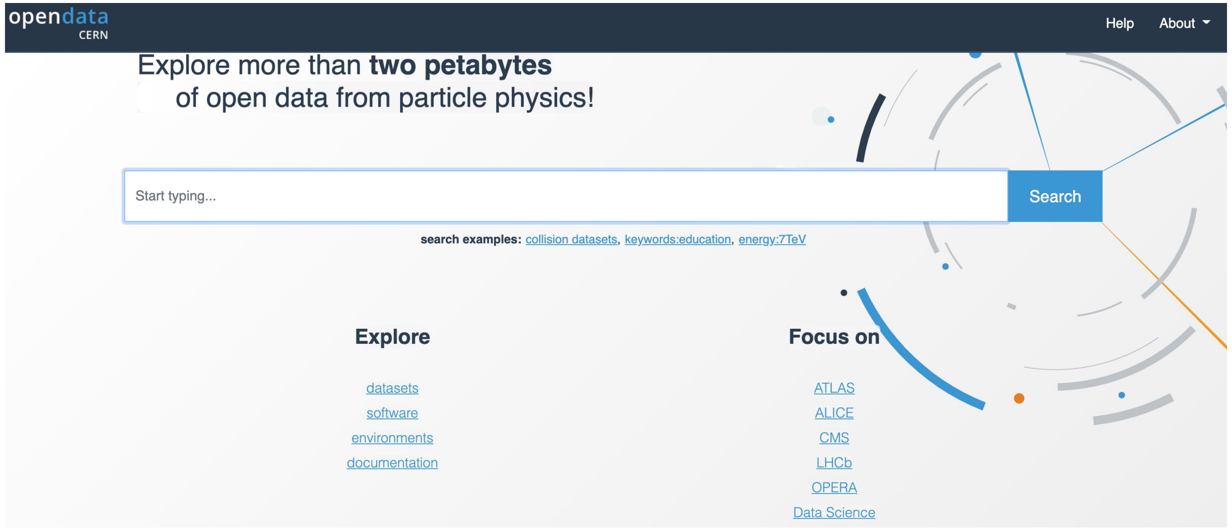
H. Prosper [Reinterp2021]

Larger efforts to preserve data and analysis workflows are underway at the LHC experiments …




Software / environments preserved via containers (docker)
Large scale analysis possible via
- [CMS analysis in the cloud]
- [Reana]

# Conclusions

## Can we really "Re"-interpret data from the LHC?

### Long answer, ***yes but*** …

- Beware of approximations in unfolded measurements
  - Signal acceptance/response compared to SM.
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https://twiki.cern.ch/twiki/bin/view/LHCPhysics/InterpretingLHCresults

latest workshop:
https://indico.cern.ch/event/982553/

Tutorials:

SModelS 2.0
Tue 11 am

SMEFTsim
Wed 10 am

MARTY
Wed 11 am

CheckMATE
Thu 10 am

MadAnalysis 5
Thu 11 am

MadMiner
Thu 3:30 pm

pyhf
Thu 4:30 pm

Contur
Fri 11 am

*New series* for ECRs to showcase re-interpretable analyses
→ https://indico.cern.ch/category/14155/

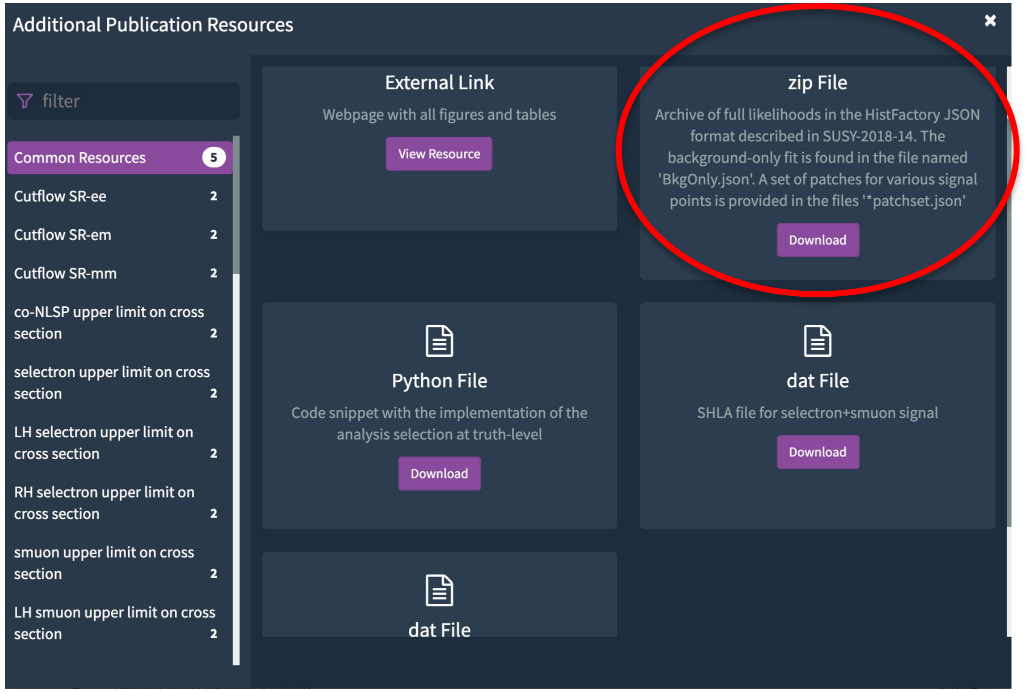
info-LHC-interpretation@cern.ch

# Thanks!

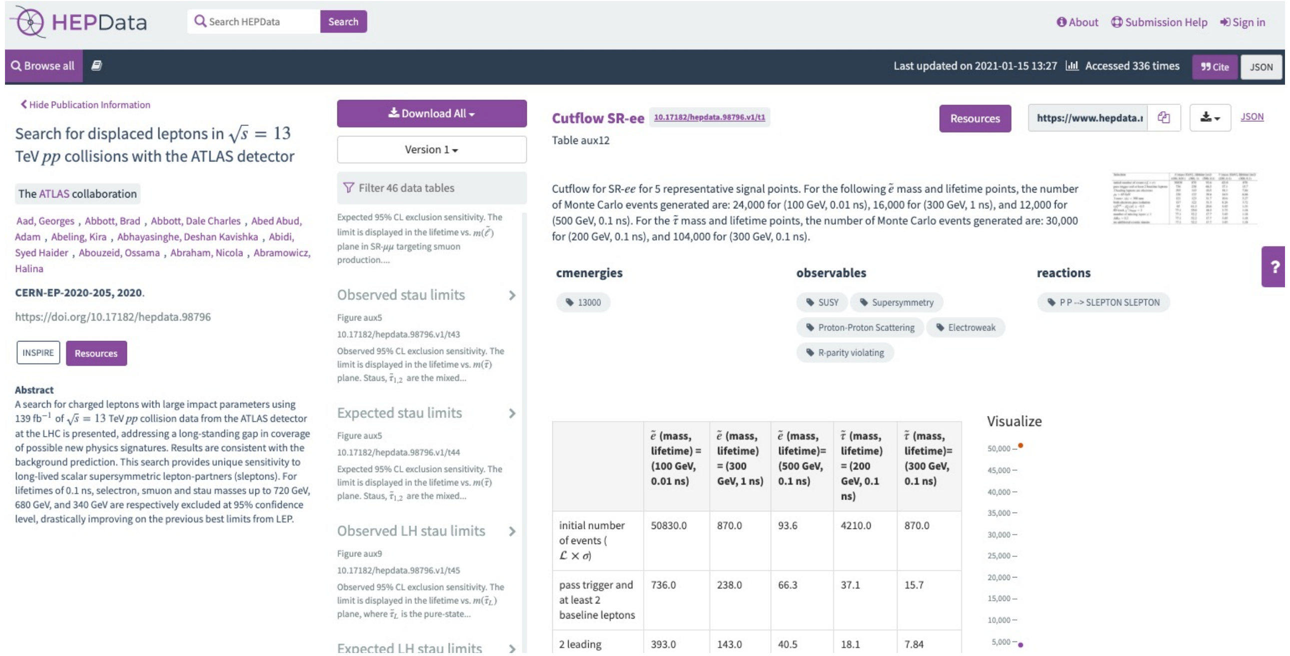
Backup

# HepData for published likelihoods

https://www.hepdata.net/record/ins1748602




Search for bottom-squark pair production with the ATLAS detector in final states containing Higgs bosons, $b$-jets and missing transverse momentum



# Binned likelihood parameterization in pyHF

$$f(\boldsymbol{n}, \boldsymbol{a} \,|\, \boldsymbol{\eta}, \boldsymbol{\chi}) = \underbrace{\prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Pois}\left(n_{cb} \,|\, \nu_{cb}\left(\boldsymbol{\eta}, \boldsymbol{\chi}\right)\right)}_{\substack{\text{Simultaneous measurement}\\ \text{of multiple channels}}} \underbrace{\prod_{\chi \in \boldsymbol{\chi}} c_{\chi}(a_{\chi} \,|\, \chi)}_{\substack{\text{constraint terms}\\ \text{for ``auxiliary measurements''}}},$$

- Analysis-specific model terms describing channels with observed events $n_{cb}$ given expected events $\nu_{cb}(\boldsymbol{\eta},\boldsymbol{\chi})$.
- Analysis-independent constraint terms for constrained parameters $\boldsymbol{\chi}$.

$$\nu_{cb}\left(\boldsymbol{\phi}\right) = \sum_{s \in \text{samples}} \nu_{scb}\left(\boldsymbol{\eta}, \boldsymbol{\chi}\right) = \sum_{s \in \text{samples}} \underbrace{\left(\prod_{\kappa \in \boldsymbol{\kappa}} \kappa_{scb}\left(\boldsymbol{\eta}, \boldsymbol{\chi}\right)\right)}_{\text{multiplicative modifiers}} \left(\nu_{scb}^{0}\left(\boldsymbol{\eta}, \boldsymbol{\chi}\right) + \underbrace{\sum_{\Delta \in \boldsymbol{\Delta}} \Delta_{scb}\left(\boldsymbol{\eta}, \boldsymbol{\chi}\right)}_{\text{additive modifiers}}\right)$$

- Sample rates $\nu_{scb}$ with nominal rate $\nu^{0}_{scb}$
- Additive and multiplicative rate modifiers $\boldsymbol{\Delta}(\boldsymbol{\phi})$ and $\boldsymbol{\kappa}(\boldsymbol{\phi})$

E. Schanet, *Re-interp 2021*

# Simplified likelihood log-likelihood

$$\ln\big(L_{\mathrm{S}}(\mu,\boldsymbol{\theta})\pi(\boldsymbol{\theta})\big) = \sum_{I}^{P}\left[n_I^{\mathrm{obs}}\ln\left(\mu n_{s,I}+n_{b,I}(\boldsymbol{\theta})\right)-\left(\mu n_{s,I}+n_{b,I}(\boldsymbol{\theta})\right)-n_I^{\mathrm{obs}}!\right] \tag{B.1}$$

$$-\frac{1}{2}\boldsymbol{\theta}^{\mathrm{T}}\boldsymbol{\rho}^{-1}\boldsymbol{\theta}-\frac{P}{2}\ln 2\pi$$

$$\frac{\partial\ln L_{\mathrm{S}}}{\partial\mu} = \sum_{I}^{P}\left(\frac{n_I^{\mathrm{obs}}}{\mu n_{s,I}+n_{b,I}(\boldsymbol{\theta})}-1\right)\cdot n_{s,I} \tag{B.2}$$

$$\frac{\partial\ln L_{\mathrm{S}}}{\partial\theta_A} = \left(\frac{n_A^{\mathrm{obs}}}{\mu n_{s,A}+n_{b,A}(\boldsymbol{\theta})}-1\right)\cdot\left(b_A+2c_A\theta_A\right)-\sum_{I}^{P}\rho_{AI}^{-1}\,\theta_I\ , \tag{B.3}$$

# Analytic simplified likelihood coefficients

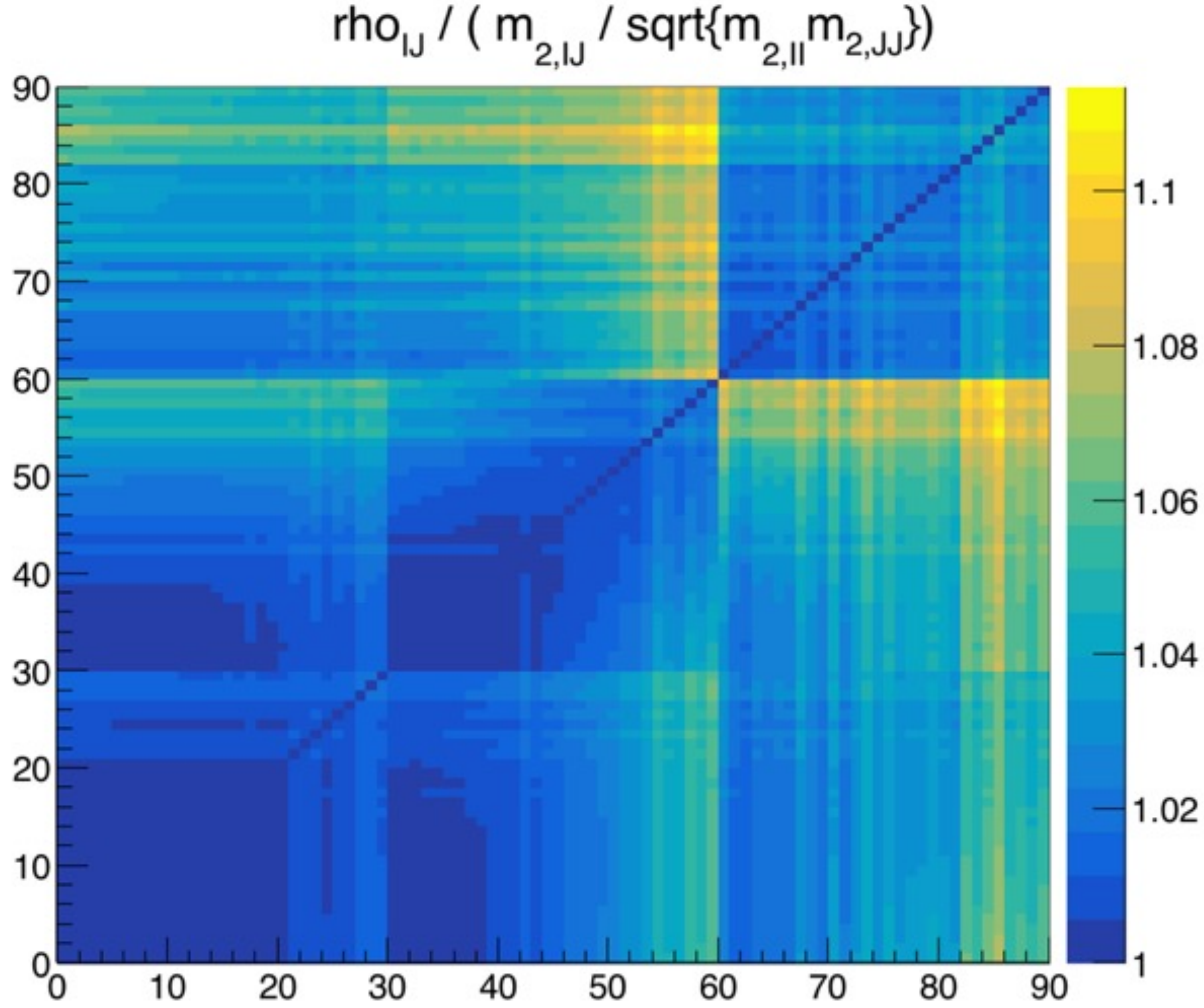
$$a_I = n_I^0 \left( 1 + \mathrm{tr}\,\Delta_{2,I} - \frac{1}{6}\sum_{i=1}^{N} \gamma_i (\Delta_{1,I,i})^3 + O(\Delta^4) \right) \, ,$$

$$b_I = a_I \left( \Delta_{1,I}^{\mathrm{T}} . \Delta_{1,I} + 2\sum_{i=1}^{N} \gamma_i \Delta_{1,I,i} \Delta_{2,I,i} + O(\Delta^4) \right)^{1/2} \, ,$$

$$\rho_{IJ} = \frac{a_I a_J}{b_I b_J} \left( \Delta_{1,I}^{\mathrm{T}} . \Delta_{1,J} + \sum_{i=1}^{N} \gamma_i (\Delta_{1,I,i} \Delta_{2,J,i} + \Delta_{1,J,i} \Delta_{2,I,i}) \right) + O(\Delta^4) \, ,$$

$$c_I = \frac{a_I}{6} \sum_{i=1}^{N} \gamma_i (\Delta_{1,i})^3 + O(\Delta^4) \, ,$$

# Corrections to correlations




NSL definition of correlation modified due to skew term

Ratio of ρIJ to linear correlation shows up to 15% correction in toy model

# Unfolded measurements for BSM searches

Measurements of SM processes with same final state as BSM signature useful for reinterpretation

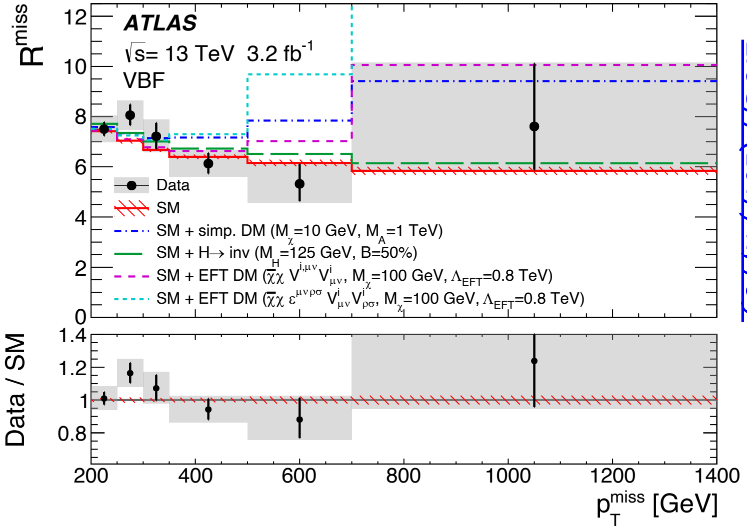
D. Price

$$R_{\text{miss}} = \frac{\sigma(\not{p}_T + \text{jets})}{\sigma(Z(\to \ell^+\ell^-) + \text{jets})} = \frac{1}{C_Z}\frac{N(\not{p}_T + \text{jets})}{N(Z(\to \ell^+\ell^-) + \text{jets})}$$

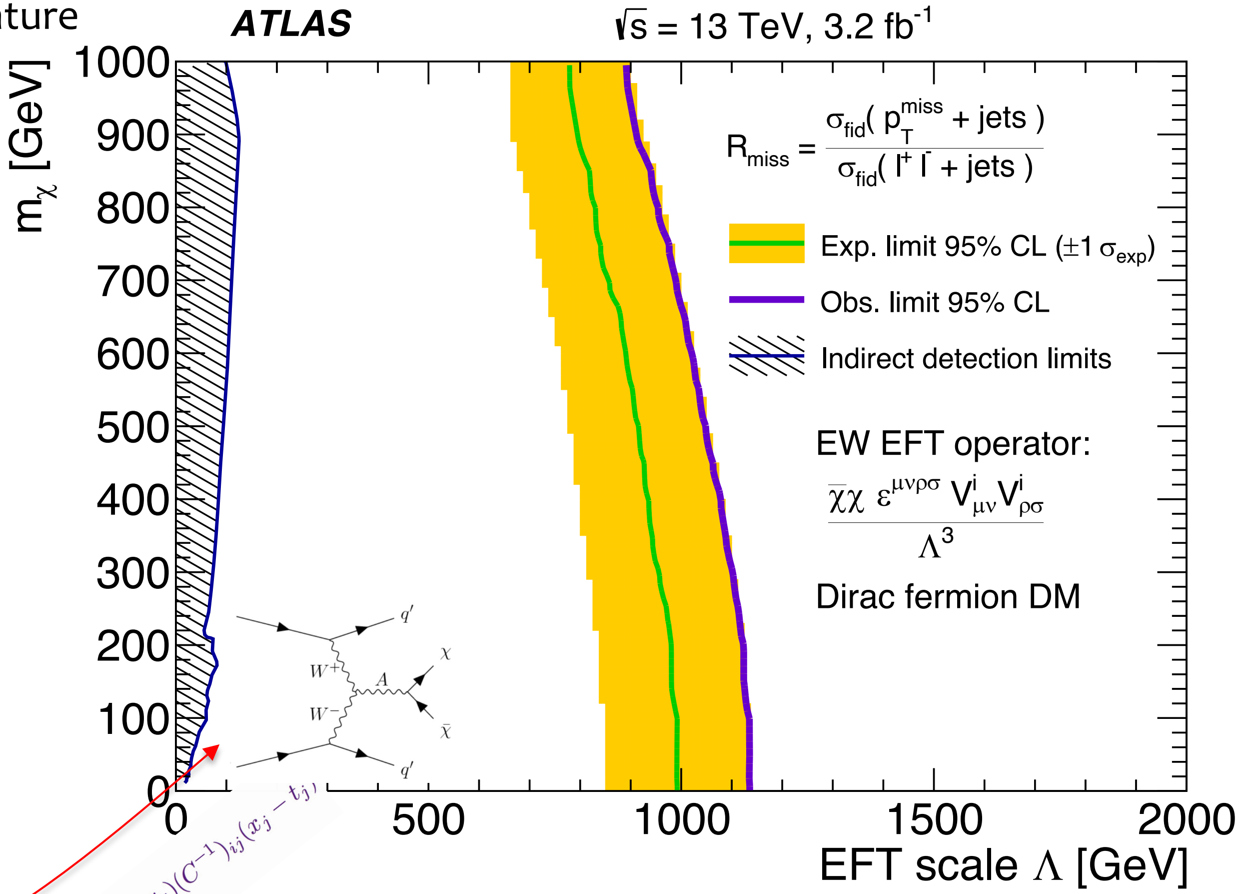
Number of background-subtracted events in MET+jets signal region

Correction factor accounting for detector resolution and efficiency

Number of background-subtracted events in l⁺l⁻+jets signal region




EPJC77 (2017) 11, 765

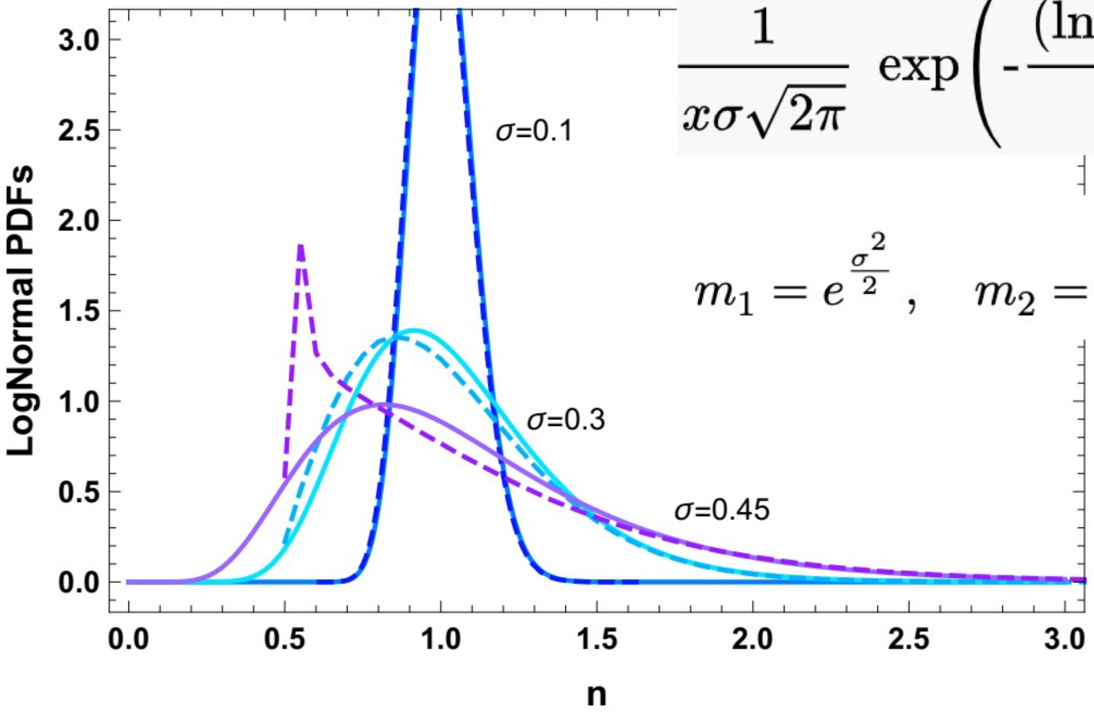



$$\chi^2 = \sum_{i,j}^{n} (x_i - t_i)(C^{-1})_{ij}(x_j - t_j)$$

Correlations ***between bins and different observables*** (can be estimated using bootstrapping).

Unfolded measurements used outside of experiments (eg Contur)

# SL approximation for a log-normal




$$\frac{1}{x\sigma\sqrt{2\pi}}\;\exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right)$$

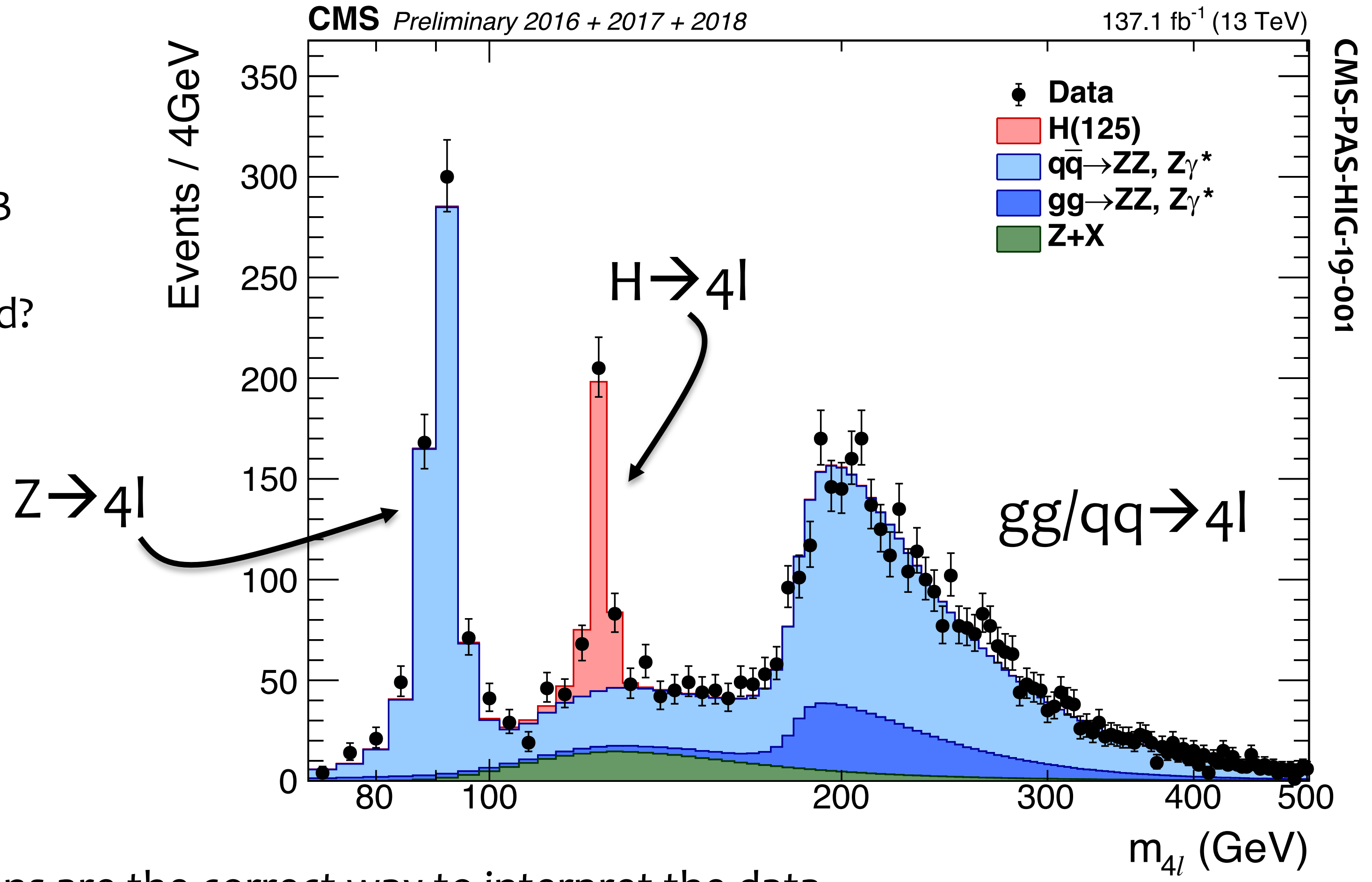
$$m_1 = e^{\frac{\sigma^2}{2}}, \quad m_2 = e^{2\sigma^2} - e^{\sigma^2}, \quad m_3 = e^{\frac{9\sigma^2}{2}} - 3e^{\frac{5\sigma^2}{2}} + 2e^{\frac{3\sigma^2}{2}}$$

**Figure 1**. The log normal PDFs and corresponding normal approximations for $\sigma = 0.1$, 0.3 and 0.45 are shown in blue, cyan and purple respectively. Solid curves show the true distributions, dashed curves show the approximate distributions.

# Signal or background

In measurements we are used to thinking of **Signal** / **Background**

How to account for S-B interference if already background subtracted?



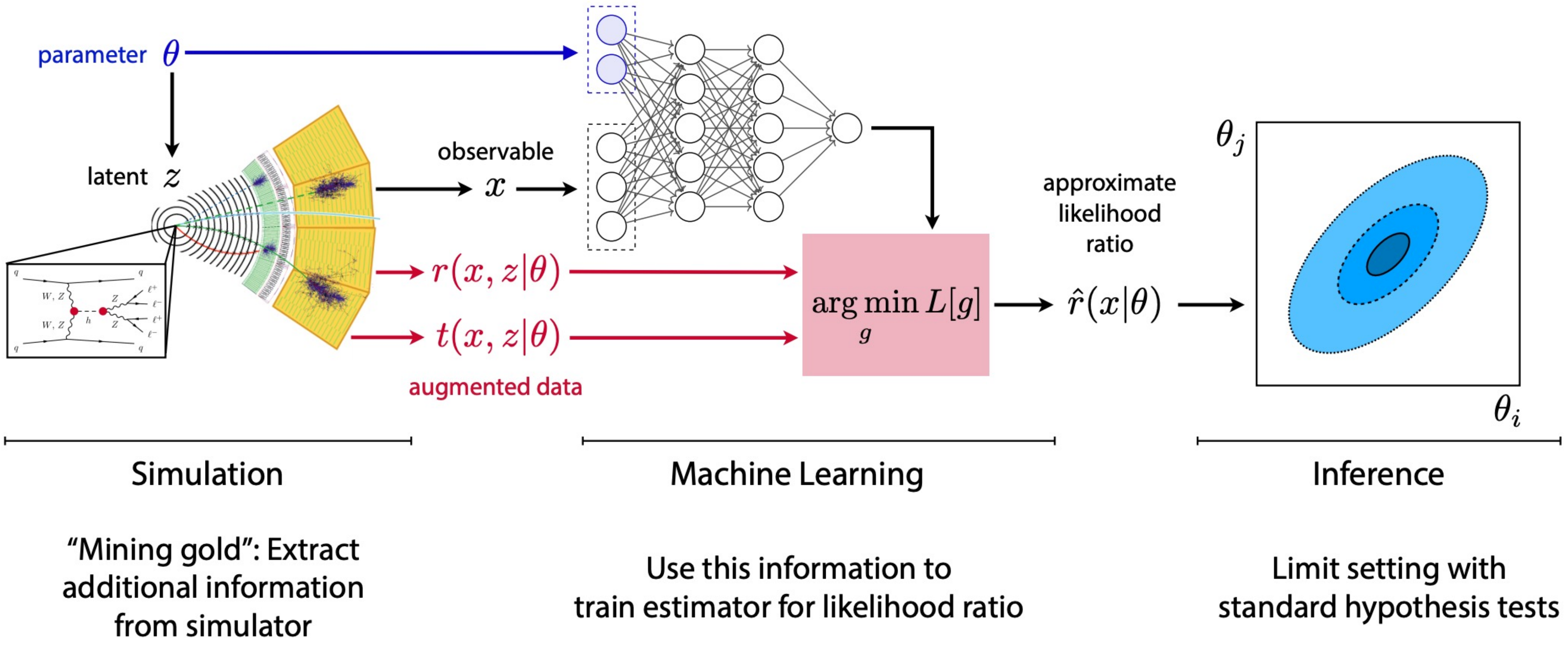

Full pp→4l combinations are the correct way to interpret the data

→Need to consider *all* contributions together

e.g unfolded

# Automating the workflow!

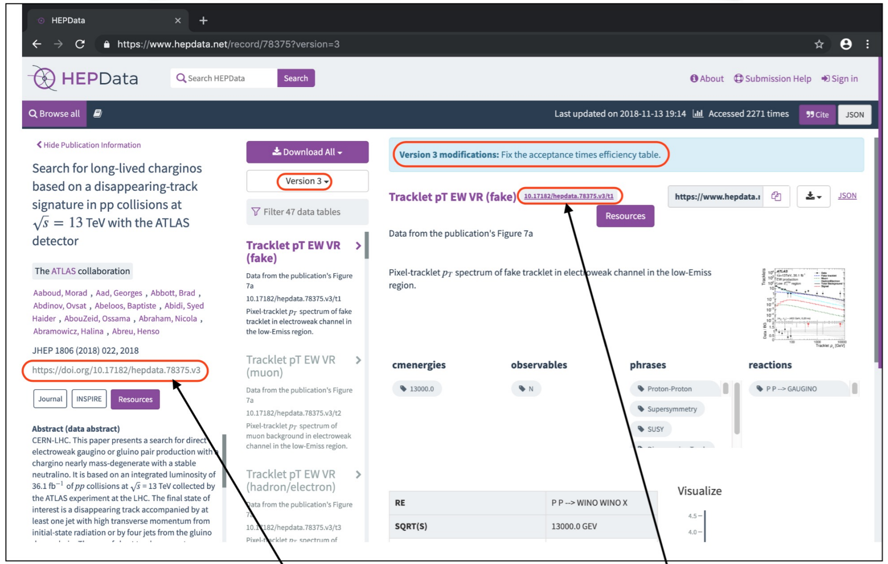
The future @ LHC could be to perform optimal analyses and inference that can be packaged up and preserved in totality!




Sourced from https://github.com/diana-hep/madminer.
Excellent tutorial by K. Cramner: https://indico.cern.ch/event/982553/contributions/4220018/attachments/2185603/3706682/MadMiner-tutorial-reinterp-2021.pdf

# HepData

Digitized versions of results/additional information in HepData



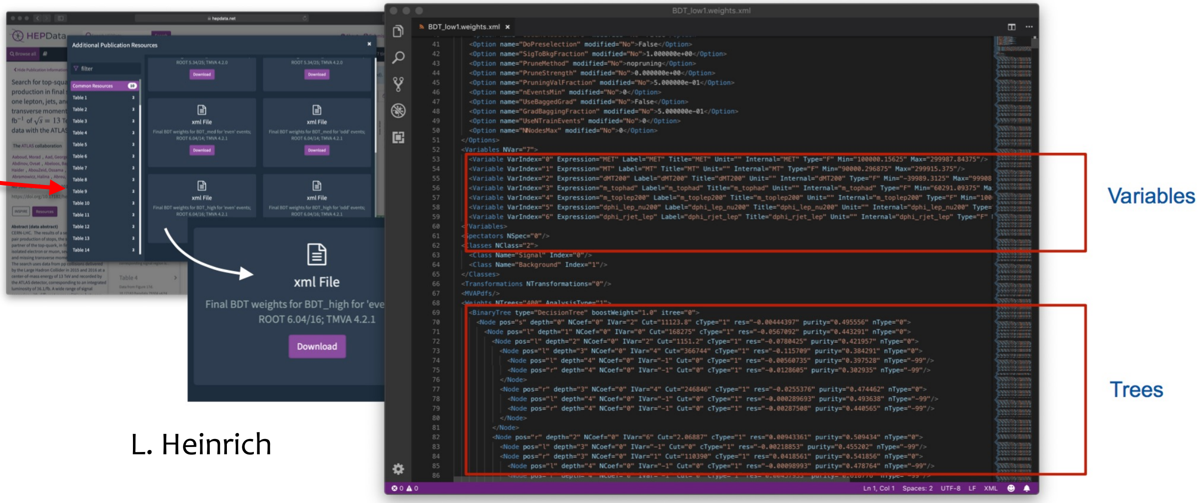

G. Watt

**Supports:**

- Tabulated data (yields, exclusion/likelihood contours)
- Efficiency maps
- Covariance matrices (SL)
- Error (sources) breakdowns
- Code snippets
  - C++ codes with analysis routines → eg for use with CheckMate, Rivet, MadAnalysis …

- DOIs minted for whole record and each table via DataCite.

XML for use with ML routines (in TMVA)




L. Heinrich

**Future development:** support for Neural Networks

- LWTNN: https://github.com/lwtnn/lwtnn
- ONNX: https://onnx.ai/

# Re-interpretation frameworks

Writeup contains a (non-exhaustive) list of existing re-interpretation frameworks for searches at the LHC

- Further details about each workflow, describing type of experimental input and key outputs given in report
- Typically our searches can be used for at least one of them, but the more information we provide, the more of them can use it!

| Package | Refs. | Experimental inputs | Event input | Detector simulation | Inference/Output |
|---|---|---|---|---|---|
| GAMBIT (ColliderBit) | 12, 99–101 | Cut-flows, analysis logic, object-level efficiency functions, observed event numbers in signal regions, background covariance matrices | particle | BuckFast (smearing & efficiencies) | Detector-level distributions, signal region efficiencies, simplified likelihood for calculating exclusion limits/contours |
| CheckMATE | 95, 96 | Cut-flows, analysis logic, object-level efficiency functions, observed event numbers in signal regions | particle, parton | Delphes | Detector-level distributions, signal region efficiencies, ratio of predicted to excluded cross-section |
| MadAnalysis 5 | 17–19, 97, 98 | Cut-flows, analysis logic, object-level efficiency functions, observed event numbers in signal regions, background covariance matrices, JSON likelihoods | particle | Delphes; customisable smearing | Detector-level distributions, signal region efficiencies, $1-\mathrm{CL}_s$ values |
| Rivet | 48, 49 | Cut-flows, analysis logic, detector smearing & efficiency functions | particle | Customisable smearing | Truth/detector-level distributions |
| Contur | 61 | Unfolded (particle-level) differential cross-sections via Rivet | particle | N/A | Exclusion contours in BSM model space |
| ADL interpreters: adl2tnm, CutLang | 20, 53, 54 | analysis logic, external functions of complex variables, object or event level efficiencies | particle | External (Delphes, CMS and ATLAS simulations) | cutflows, event-by-event weights per region, histograms |
| Recast | 8 | Experiment-specific formats | parton | Experiment-owned (fast) simulation | *p*-values, upper limits, likelihood values |

# Implementing analyses validation

Great effort to validate analyses implemented in MA5

**CMS analyses, 13 TeV**

| Analysis | Short Description | Implemented by | Code | Validation note | Version |
|---|---|---|---|---|---|
| CMS-SUS-16-033 | Supersymmetry in the multijet plus missing energy channel (35.9 fb-1) | F. Ambrogi and J. Sonneveld | Inspire | PDF | v1.7/Delphes3 |
| CMS-SUS-16-039 | Electroweakinos in the SS2L, 3L and 4L channels (35.9 fb-1) | B. Fuks and S. Mondal | Inspire | PDF | v1.7/Delphes3 |
| CMS-SUS-16-048 | Compressed electroweakinos with soft leptons (35.9 fb-1) | B. Fuks<br>J.Y. Araz | MA5 dataverse<br>MA5 dataverse | Sec. 19 in 2002.12220<br>Sec. 5.3 in 2006.09387 | v1.8/Delphes3<br>v1.8/SFS |
| CMS-SUS-16-052 | SUSY in the 1l + jets channel (36 fb-1) | D. Sengupta | Inspire | PDF | v1.6/Delphes3 |
| CMS-SUS-17-001 | Stops in the OS dilepton mode (35.9 fb-1) | S.-M. Choi, S. Jeong, D.-W. Kang *et al.* | Inspire | PDF | v1.6/Delphes3 |
| CMS-SUS-19-006 | SUSY in the HT/missing HT channel (137 fb-1) | M. Mrowietz, S. Bein, J. Sonneveld | MA5 dataverse | PDF | v1.8/Delphes3 |
| CMS-EXO-16-010 | Mono-Z-boson (2.3 fb-1) | B. Fuks | Inspire | PDF | v1.6/Delphes3 |
| CMS-EXO-16-012 | Mono-Higgs (2.3 fb-1) | S. Ahn, J. Park, W. Zhang | Inspire | PDF | v1.6/Delphes3 |
| CMS-EXO-16-022 | Long-lived leptons (2.6 fb-1) | J. Chang | Inspire | PDF | v1.7/Delphes3 |
| CMS-EXO-17-015 | Leptoquarks + dark matter in the 1mu+1jet+met channel (77.4 fb-1) | A. Jueid and B. Fuks | MA5 dataverse | PDF | v1.8/Delphes3 |
| CMS-EXO-17-030 | Pairs of trijet resonances (35.9 fb-1) | Y. Kang, J. Kim, J. Choi, S. Yun | MA5 dataverse | PDF | v1.8/Delphes3 |
| CMS-HIG-18-011 | Exotic Higgs decay in the 2 muons + 2 b-jet channel via 2 pseudoscalars (35.9 fb-1) | J.B. Lee and J. Lee | MA5 dataverse | PDF | v1.8/Delphes3 |
| CMS-TOP-17-009 | SM four-top analysis (35.9 fb-1) | L. Darmé and B. Fuks | Inspire | PDF | v1.7/Delphes3 |
| CMS-TOP-18-003 | SM four-top analysis (137 fb-1) | L. Darmé and B. Fuks | MA5 dataverse | PDF | v1.8/Delphes3 |

CMS Delphes 3 parametrisation cards for EXO-16-010 and SUS-17-001, EXO-16-012, EXO-16-022, EXO-17-015, EXO-17-030, SUS-16-039, SUS-16-041, SUS-16-052, SUS-19-006, HIG-18-011, TOP-17-009 and TOP-18-003.
The SFS detector parametrisations can be obtained from the MA5 dataverse links, together with the corresponding analysis codes.

# Power of unfolding

Inspired by P. Owen @ Reinterp2021

## A good example - |V$_{cb}$|

- Early 2017, Belle measures |V$_{cb}$|. BELLE-CONF-1612

**Precise determination of the CKM matrix element $|V_{cb}|$ with $\bar{B}^0 \to D^{*+} \ell^- \bar{\nu}_\ell$ decays with hadronic tagging at Belle**

The Belle Collaboration: A. Abdesselam, I. Adachi, K. Adamczyk, H. Aihara, S. Al Said, K. Arinstein, Y. Arita, D. M. Asner, T. Aso, H. Atmacan, V. Aulchenko, T. Aushev, R. Ayad, T. Aziz, V. Babu, I. Badhrees, S. Bahinipati, A. M. Bakich, A. Bala, Y. Ban, V. Bansal, E. Barberio, M. Barrett, W. Bartel, A. Bay, P. Behera, M. Belhorn, K. Belous, M. Berger, F. U. Bernlochner, D. Besson, V. Bhardwaj, B. Bhuyan, J. Biswal, T. Bloomfield, S. Blyth, A. Bobrov, A. Bondar, G. Bonvicini, C. Bookwalter, C. Boulahouache, A. Bozek, M. Bračko, N. Braun, F. Breibeck, J. Brodzicka, T. E. Browder, E. Waheed, D. Červenkov, M.-C. Chang, P. Chang, Y. Chao, V. Chekelian, A. Chen, K.-F. Chen, P. Chen, B. G. Cheon, K. Chilikin, R. Chistov, K Cho, V. Chobanova, S.-K. Choi, Y. Choi, D. Cinabro, J. Crnkovic, J. Dalseno, M. Danilov, N. Dash, S. Di Carlo, J. Dingfelder, Z. Doležal, D. Dossett, Z. Drásal, A. Drutskoy, S. Dubey, D Dutta, K. Dutta, S. Eidelman, D. Epifanov, S.Falke, H. Farhat, J. E. Fast, M. Feindt, T. Ferber, A. Frey, O. Frost, B. G. Fulsom, V. Gaur, N. Gabyshev, S. Ganguly, A. Garmash, M. Gelb, J. Gemmler, D. Getzkow, R. Gillard, F. Giordano, R. Glattauer, Y. M. Goh, P. Goldenzweig, B. Golob et al. (363 additional authors not shown)

*(Submitted on 6 Feb 2017 (v1), last revised 14 Feb 2017 (this version, v2))*

The precise determination of the CKM matrix element $|V_{cb}|$ is important for carrying out tests of the flavour sector of the Standard Model. In this article we present a preliminary analysis of the $\bar{B}^0 \to D^{*+} \ell^- \bar{\nu}_\ell$ decay mode and its charge conjugate, selected in events that contain a fully reconstructed $B$-meson, using 772 million $e^+ e^- \to \Upsilon(4S) \to B\bar{B}$ events recorded by the Belle detector at KEKB. Unfolded differential decay rates of four kinematic variables fully describing the $\bar{B}^0 \to D^{*+} \ell^- \bar{\nu}_\ell$ decay in the $B$-meson rest frame are presented. We measure the total branching fraction $\mathcal{B}(\bar{B}^0 \to D^{*+} \ell^- \bar{\nu}_\ell) = (4.95 \pm 0.11 \pm 0.22) \times 10^{-2}$, where the errors are statistical and systematic respectively. The value of $|V_{cb}|$ is determined to be $(37.4 \pm 1.3) \times 10^{-3}$. Both results are in good agreement with current world averages.

$$\frac{d\Gamma}{dq^2}(B \to D\ell\nu) \propto \underbrace{G_F^2 |V_{cb}|^2}_{\text{EW}} \underbrace{f(q^2)^2}_{\text{QCD}}$$

- Measurement and unfolded data published.

- ~6 weeks later, two papers posted, fitting that data with different parameterisation of the form factors.

**fresh look at the determination of |V_cb| from B-> D^* l nu**

nte Bigi, Paolo Gambino, Stefan Schacht

*mitted on 17 Mar 2017 (v1), last revised 26 Apr 2017 (this version, v2))*

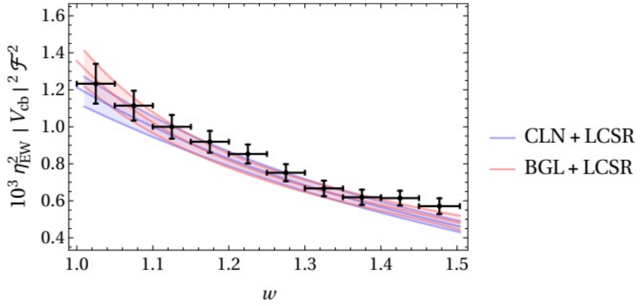
We use recent Belle results on $\bar{B}^0 \to D^{*+} l^- \bar{\nu}_l$ decays to extract the CKM element $|V_{cb}|$ with two different but well-founded parameterizations of the form factors. We show that the CLN and BGL parameterizations lead to quite different results for $|V_{cb}|$ and provide a simple explanation of this unexpected behaviour. A long lasting discrepancy between the inclusive and exclusive determinations of $|V_{cb}|$ may have to be thoroughly reconsidered.

**del-Independent Extraction of $|V_{cb}|$ from $\bar{B} \to D^* \ell \bar{\nu}$**

amin Grinstein, Andrew Kobach

*nitted on 23 Mar 2017 (v1), last revised 7 Jun 2017 (this version, v2))*

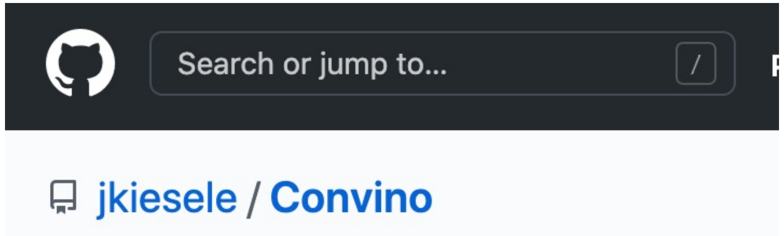
e fit the unfolded data of $\bar{B}^0 \to D^{*+} \ell \bar{\nu}$ from the Belle experiment, where $\ell \equiv e, \mu$, using a method independent of heavy quark symmetry to extrapolate to zero-recoil and extract the lue of $|V_{cb}|$. This results in $|V_{cb}| = (41.9\,^{+2.0}_{-1.9}) \times 10^{-3}$, which is robust to changes in the theoretical inputs and very consistent with the value extracted from inclusive semileptonic $B$ cays.



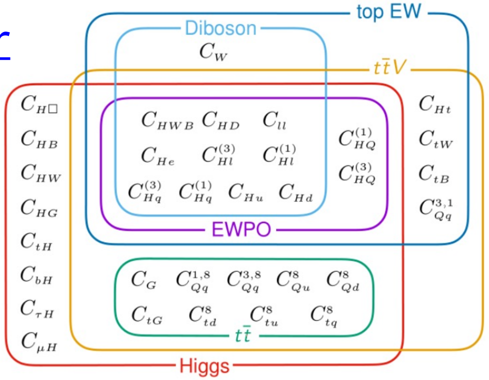

**e FF parameterisation much more important than expected, a conclusion not possible without the release of data.**

# Measurements for re-interpretation

Combining unfolded measurements with Convino




FitMaker



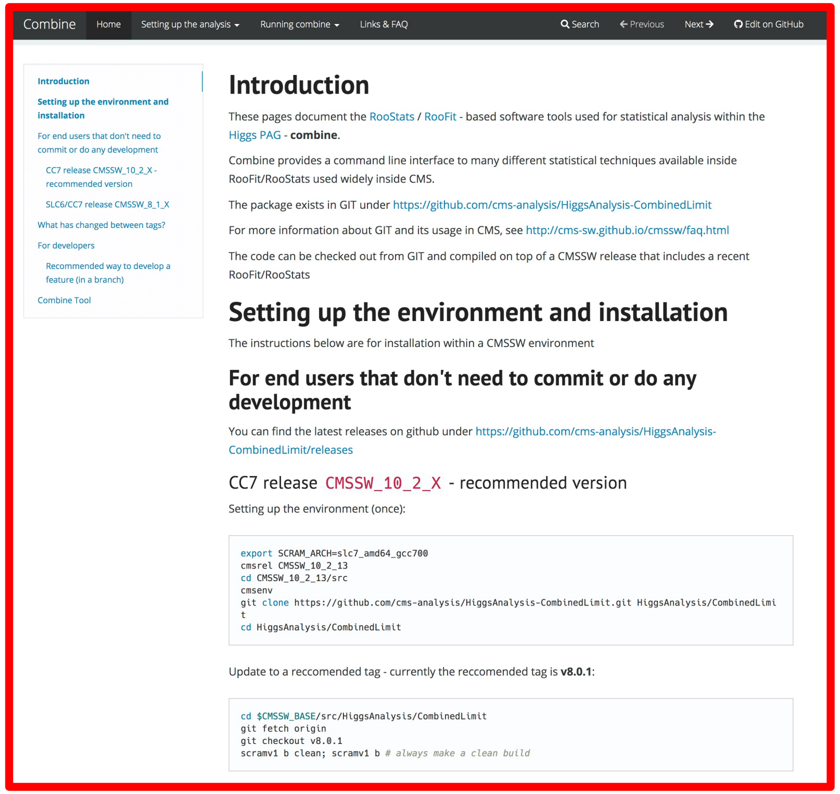

| Package | Refs. | Experimental inputs | Model input | Inference/Output |
|---|---|---|---|---|
| SModelS | 33, 35, 36 | Simplified-model cross-section upper limits and efficiency maps from SUSY searches, background covariance matrices | SLHA or LHE (any BSM model with $Z_2$-like symmetry) | Ratio of predicted to excluded cross-section, exclusion CL (if efficiency maps are available) |
| HiggsBounds | 90, 91 | Model independent (exp. and obs.) 95% CL upper limits and exclusion likelihoods from BSM Higgs searches | masses, widths, cross-sections and BRs (or effective couplings) of all Higgs bosons | Ratio of predicted to excluded cross-section, allowed/excluded at 95% CL, $\chi^2$ for specific searches |
| ZPEED | 92 | Observed event numbers in signal regions, background predictions, detector resolution and efficiencies | Model parameters | Likelihood values |
| DarkCast | 93 | Simplified-model production mechanism, cross-section upper limits or ratio map of observed to expected cross-sections for dark photon searches | couplings of new gauge bosons to the SM fermions | 95% CL exclusion limits on couplings |
| DarkEFT | 104 | 95% CL exclusion limits on dark sector searches and rare meson decay BRs | effective couplings for 4-fermion operators | 95% CL exclusion limits on the effective coupling |

Table II. Summary of public frameworks for the reinterpretation of searches and measurements (continued). The columns summarise the major inputs from the experiments used for the reinterpretation, the model inputs, and the principle outputs in terms of performing statistical inference.

# Workhorses in experiments

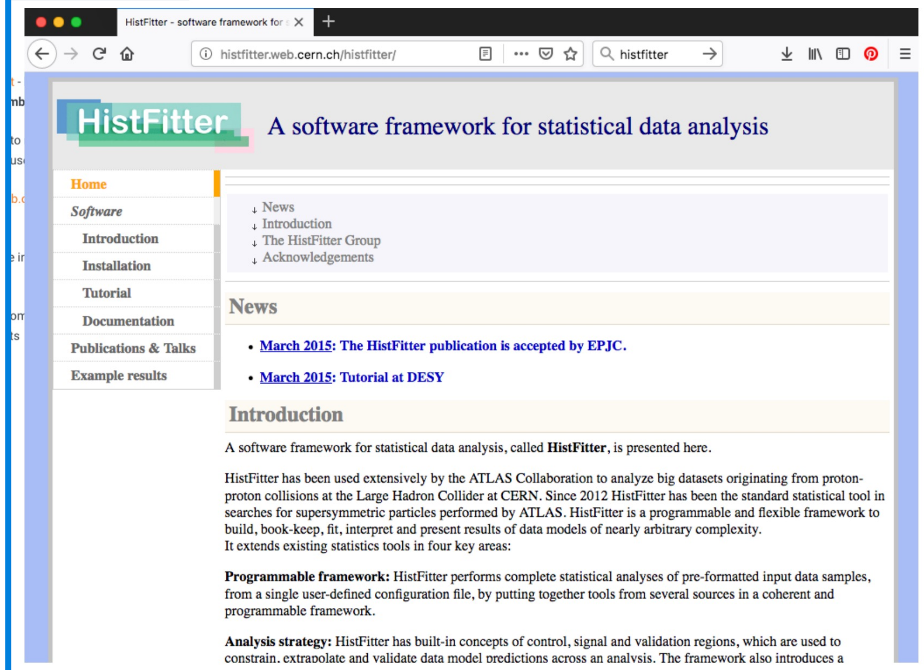
Building & organizing complicated analyses/combinations via higher level tools in **CMS** and **ATLAS**

Many additional tools for validation of results in these packages…




http://cms-analysis.github.io/HiggsAnalysis-CombinedLimit/

http://histfitter.web.cern.ch/histfitter/




Other tools also used:

- https://diana-hep.org/pyhf/ - python based, GPU accel.+auto-diff (tensorflow)
- https://github.com/jkiesele/Convino – combining differential measurements
- https://jrbourbeau.github.io/pyunfold/ - iterative unfolding