

# Reinterpretation with model-agnostic likelihoods

## Constraining new physics with $B^+ \rightarrow K^+ \nu \bar{\nu}$ @ Belle II

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# What we dream of...





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... the PDF of observables  $x$  given theory parameters  $\theta$

$$p(x|\theta) = \int dz_d \int dz_p \underbrace{p(x|z_d)}_{\text{observables}} \underbrace{p(z_d|z_p)}_{\text{detector response}} \underbrace{p(z_p|\theta)}_{\text{prediction}}$$



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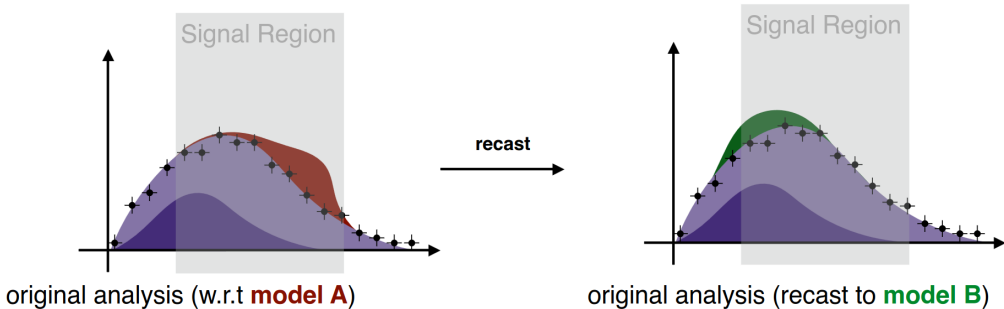
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Intractability forces us to approximate

$$\text{MC} \sim p(x|\theta)$$

**→ MC data is model dependent**

# What result would we get if we replace the signal model?



[\[source\]](#)



# Approaches to reinterpretation

## Recasting / simulation based reinterpretation

- Produce and analyse new MC samples
- Requires full analysis strategy
- Relatively accurate (analysis still optimized for original model)
- 🔥 Resource-heavy



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- Assumption: acceptances / efficiencies unaffected by kinematic shape differences
- ⚠️ Potentially biased results



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**Is accurate reinterpretation without new MC samples possible?**

♻️ **Yes, we can reweight samples or even histograms directly!**





# redist

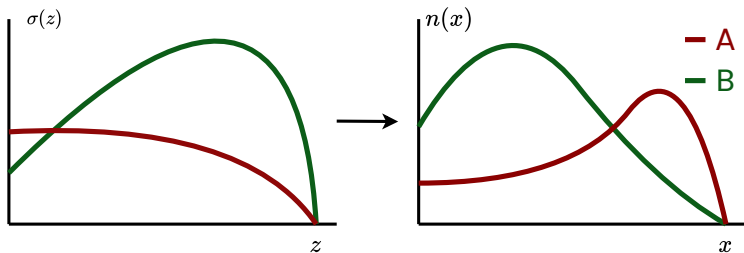
A novel reinterpretation method

[EPJC]

[github.com/lorenzennio/redist](https://github.com/lorenzennio/redist)

# Templates from kinematic predictions

$$n(x) = \int dz L \varepsilon(x|z) \sigma(z) = \int dz n(x, z).$$



$z$  – kinematic d.o.f.

$x$  – reconstruction / fitting variable(s)

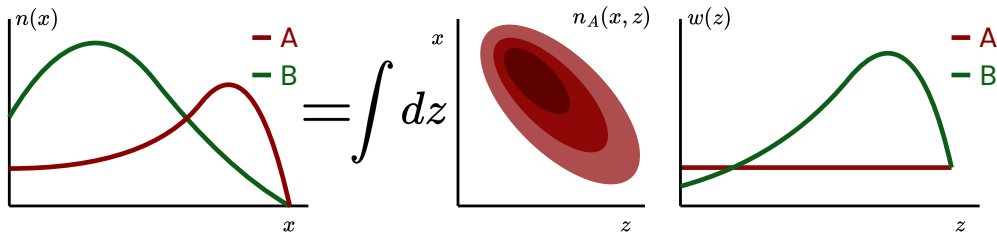
$L$  – luminosity

$\varepsilon(x|z)$  – conditional efficiency

$n(x, z)$  – joint number density

# Reweight to new model

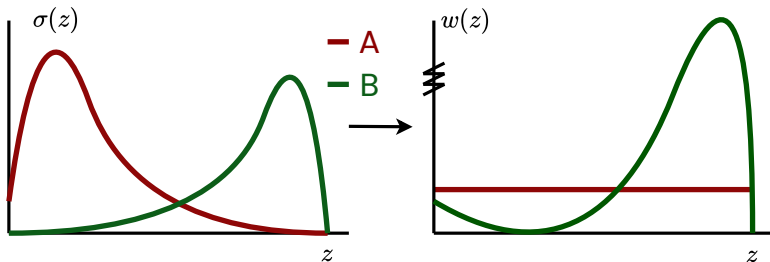
$$n_B(x) = \int dz L \varepsilon(x|z) \sigma_B(z) = \int dz L \varepsilon(x|z) \sigma_A(z) \frac{\sigma_B(z)}{\sigma_A(z)} = \int dz \underbrace{n_A(x, z)}_{\text{main object}} w(z)$$



$p(x|\theta)$  &  $n(x, z)$  = model-agnostic likelihood

# Method limitations

Substantial model changes  $\rightarrow$  large weights



Minimal requirement:

$$\text{supp}(\sigma_B) \in \text{supp}(\sigma_A)$$

Always possible to compare only in  $\text{supp}(\sigma_A)$



# Reinterpretation of $B^+ \rightarrow K^+ \nu \bar{\nu}$

# Evidence for $B^+ \rightarrow K^+ \nu \bar{\nu}$ – What next?



Belle II has found "**Evidence for  $B^+ \rightarrow K^+ \nu \bar{\nu}$  Decays**"

[arXiv:2311.14647](https://arxiv.org/abs/2311.14647) [hep-ex]

What does this really mean?

- This statement is based on the model

$$p(x|\text{SM})$$

- However, we cannot say much about

$$p(x|\text{NP})$$

# Benefit of combination



Total of 3 analyses

- ITA

$$\underbrace{p(x_{ITA}|\theta_{ITA})}_{\text{BDT}_2 \times a_{rec}^2}$$

- HTA

$$\underbrace{p(x_{HTA}|\theta_{HTA})}_{\text{BDTh}}$$

- ITA+HTA

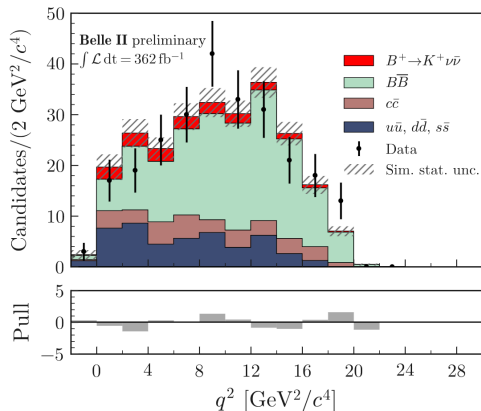
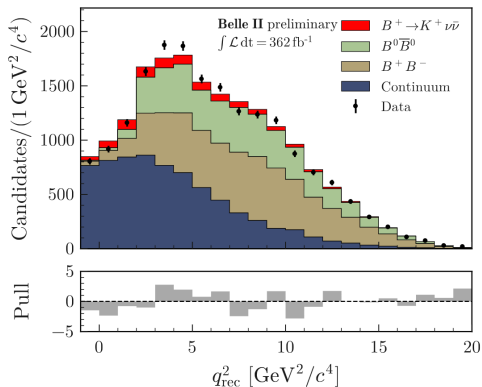
$$p(x|\theta) = \underbrace{p(x_{ITA}|\theta'_{ITA})}_{\text{BDT}_2 \times a_{rec}^2} \cdot \underbrace{p(x_{HTA}|\theta'_{HTA})}_{\text{BDTh}}$$

→ 10% increase in precision over ITA result

[arXiv:2311.14647](https://arxiv.org/abs/2311.14647) [hep-ex]



# There are always open questions...



Excess around  $3 \text{ GeV}^2 < q_{\text{rec}}^2 < 7 \text{ GeV}^2$  for ITA best-fit projection.

[arXiv:2311.14647](https://arxiv.org/abs/2311.14647) [hep-ex]





What if the  $B^+ \rightarrow K^+ \nu \bar{\nu}$  signal includes  
 $B^+ \rightarrow K^+ X$ ?

$X$  – light ( $m_X \leq m_B - m_K$ ) resonant boson, decaying invisibly or escaping undetected

See [arXiv:2311.14629 \[hep-ph\]](https://arxiv.org/abs/2311.14629), [arXiv:2312.12507 \[hep-ph\]](https://arxiv.org/abs/2312.12507) for first estimates.



# Ingredients for reinterpretation

1. Likelihood  $p(x|\theta)$
2. Joint number density  $n(x, z)$
3. Decay kinematics  $\rightarrow w(z)$

# 1. pyhf statistical model



A statistical model for multi-bin histogram-based analysis and its interval estimation.



**Likelihood** function for observed event counts  $n$  is

$$p(x|\theta) = p(n, a|\eta, \chi) = \underbrace{\text{Pois}(n|\nu(\eta, \chi))}_{\text{data likelihood}} \underbrace{c(a|\chi)}_{\text{constraint likelihood}}$$

Expected number of events are

$$\nu(\eta, \chi) = \kappa(\eta, \chi) \left( \nu^0(\eta, \chi) + \Delta(\eta, \chi) \right).$$

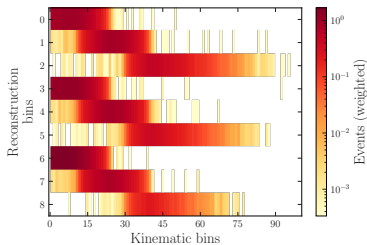
Use `redist` for bin weights  $\kappa(\eta, \chi) = n_B(\eta, \chi) / n_A$ .

# 2. Joint number density

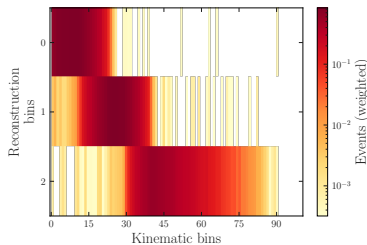
The main object for reinterpretation,  $n(x, z)$ .  
→ This should be published by collaborations.



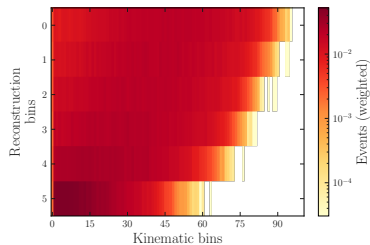
ITA 1



ITA 2



HTA



Kinematic binning:  $q_{gen}^2 = [-1, (0, 22.885, 100)] \text{ GeV}^2$

# 3. Decay kinematics

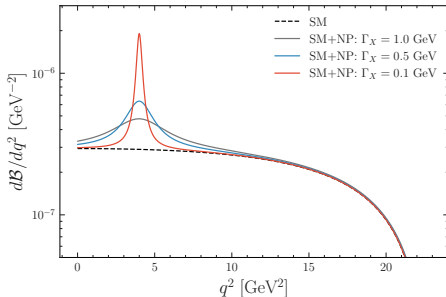
- Model as sharp resonance peak,

$$\frac{d\mathcal{B}}{dq^2} = \frac{d\mathcal{B}_{SM}}{dq^2} + \mu_X p_{RBW}(q^2; m_X, \Gamma_X) \cdot 10^{-6},$$

with the PDF

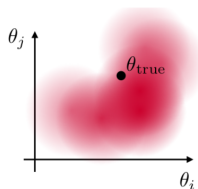
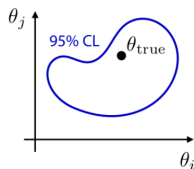
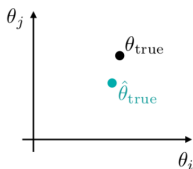
$$p_{RBW}(q^2; m_X, \Gamma_X) = \frac{k}{(q^2 - m_X^2)^2 + m_X^2 \Gamma_X^2}$$

- **Free parameters** are  $\mu_X, m_X$  (and  $\Gamma_X$ )
- Bound by resolution  $\Gamma_X > 0.1$  GeV



Model shown for  $\mu_X = 1, m_X = 2$  GeV.

# What do we want to learn?



Gilles Louppe @ PHYSTAT-SBI 2024

- **Frequentist:** Find  $\hat{\theta}$  maximising  $p(x|\theta)$ . Build confidence interval.
- **Bayesian:** Compute posterior  $p(\theta|x) \propto p(x|\theta)p(\theta)$ . Obtain credible intervals.

## Bayesian inference more insightful for multiple, correlated POIs.

Posterior model simply from pyhf likelihood:

$$p(\eta, \chi|n, a) \propto \underbrace{\text{Pois}(n|\nu(\eta, \chi))}_{\text{data likelihood}} \underbrace{p(\chi|a)}_{\text{constraint prior}} \underbrace{p(\eta)}_{\text{unconstraint prior}}$$

# $B^+ \rightarrow K^+ X$ marginal posterior

- 1d and 2d marginalized posterior

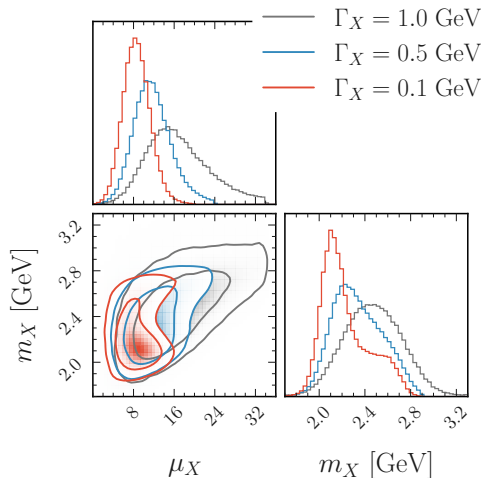
$$p(\eta|n, a) = \int d\chi \, p(\eta, \chi|n, a)$$

- Uniform priors for POIs
- **Credible intervals** (95%) from  $\Gamma_X = 0.1 \text{ GeV}$

$$B(B^+ \rightarrow K^+ X) \in [0.34, 1.4] \times 10^{-5}$$

$$m_X \in [1.9, 2.7] \text{ GeV}$$

- Consistent with results of [arXiv:2311.14629](https://arxiv.org/abs/2311.14629) [hep-ph],  
[arXiv:2312.12507](https://arxiv.org/abs/2312.12507) [hep-ph]

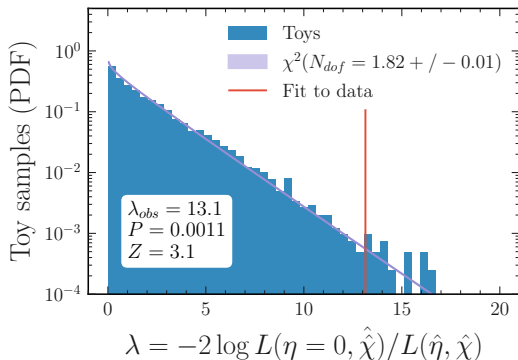




# Model comparison



# Pointwise: P-value



- Toy study for  $\Gamma_X = 0.1$  GeV model, 10k toys
- **Significance of  $Z = 3.1$  over SM+background**



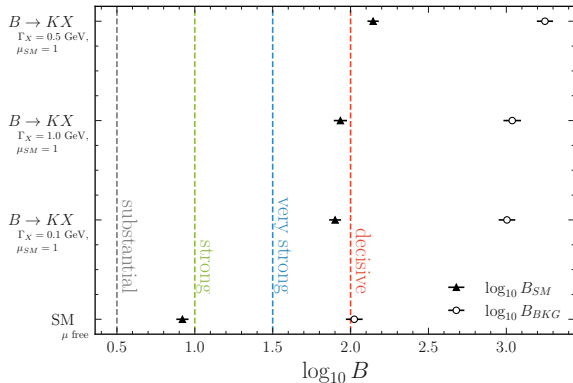
# Averaged: Bayes factor

Compare the probabilities of the observed data being produced by a given model.

$$p(\theta|x, M) = \frac{p(x|\theta, M) p(\theta|M)}{p(x|M)}$$

$$p(x|M) = \int d^n\theta p(x|\theta, M) p(\theta|M)$$

$$B_M = \frac{p(x|M')}{p(x|M)}$$



→  $B \rightarrow KX$  models dominate over SM.

⚠ Average likelihood in the *full* parameter space → prior dependent

# Summary



## Reinterpretability is important

- Necessary for **bias-free inference** on BSM parameters.
- Enables **combinations** with other channels and/or experiments.

→ Increases **impact** of results.

## Reinterpretation can be easy (**redist**)

- Only requires **likelihood** and  $n(\mathbf{x}, \mathbf{z})$  (or MC samples with kinematic information).
- **FAST**
- $\mathbf{B} \rightarrow K\nu\bar{\nu}$  **reinterpretation i.t.o.**  $\mathbf{B} \rightarrow KX$ 
  - High significance model ( $Z = 3.1$ ) with potential explanation for the observed excess in data.
  - Credible intervals (95%)

$$BR(B^+ \rightarrow K^+X) \in [0.34, 1.4] \times 10^{-5} \quad m_X \in [1.9, 2.7] \text{ GeV}$$

- **pyhf** model and  $n(\mathbf{x}, \mathbf{z})$  to be published by Belle II (under internal review)



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[B2Documents] [method paper]



# $B \rightarrow KX$ posterior

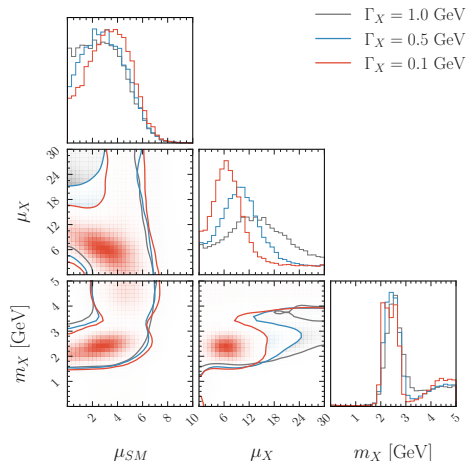
- Based on ITA+HTA likelihood
- Priors are uniform with support

$$0 \leq \mu_{SM} \leq 10$$

$$0 \leq \mu_X \leq 20$$

$$0 \leq m_X \leq 4.8 \text{ GeV}$$

- Contours encompass 68% and 95% of samples
- 3 different  $\Gamma_X$  cases
- bound by resolution  $\Gamma_X > 0.1 \text{ GeV}$
- consistent with results of [arXiv:2311.14629](https://arxiv.org/abs/2311.14629) [hep-ph]

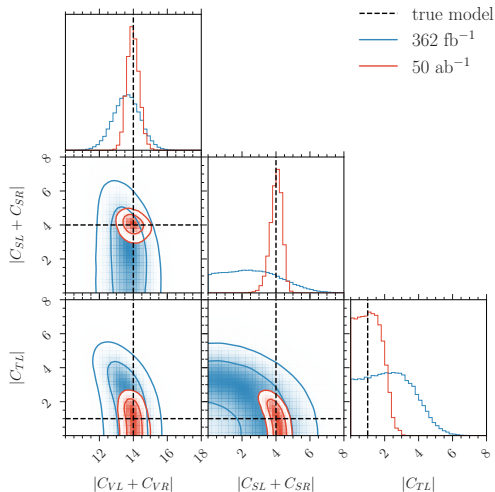




# $B^+ \rightarrow K^+ \nu \bar{\nu}$ toy study

- Weak effective theory  $\sigma(z|\psi)$ ,  
 $\psi = \{C_i\}$  (models B)
- Analysis assumes SM (model A)
  - $C_{VL} \simeq 6.6, C_i = 0 \quad \forall \quad i \neq VL$
- "Data" contains new physics

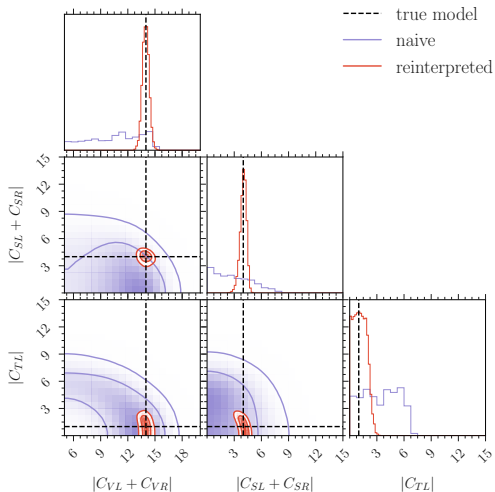
[arXiv:2402.08417 \[hep-ph\]](https://arxiv.org/abs/2402.08417)



# The necessity for reinterpretation

- naive reinterpretation = simple BR rescaling
- biased posterior

[arXiv:2402.08417 \[hep-ph\]](https://arxiv.org/abs/2402.08417)



# HistFactory model



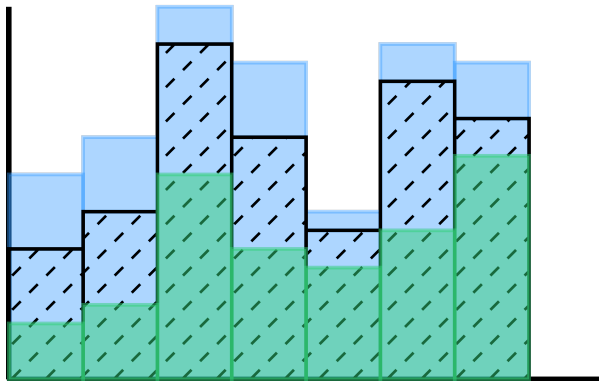
Likelihood function for observed event counts  $n$  is

$$L(n, a|\eta, \chi) = \underbrace{\prod_{c \in \text{channels}} \prod_{b \in \text{bins}} \text{Pois}(n_{cb}|\nu_{cb}(\eta, \chi))}_{\text{multiple channels}} \underbrace{\prod_{\chi \in \mathcal{X}} c_{\chi}(a_{\chi}|\chi)}_{\text{constraint terms}}$$

Expected number of events per channel per bin are

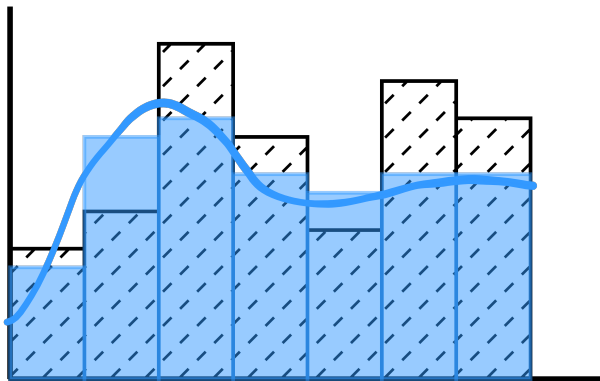
$$\nu_{cb}(\eta, \chi) = \sum_{s \in \text{samples}} \underbrace{\prod_{\kappa \in \kappa} \kappa_{scb}(\eta, \chi)}_{\text{multiplicative modifiers}} (\nu_{scb}^0(\eta, \chi) + \underbrace{\sum_{\Delta \in \Delta} \Delta_{scb}(\eta, \chi)}_{\text{additive modifiers}}).$$

# Modifiers





# Custom modifiers



# Modifiers and constraints



Description	Modification	Constraint Term $c_\chi$	Input
Uncorrelated Shape	$\kappa_{scb}(\gamma_b) = \gamma_b$	$\prod_b \text{Pois}(r_b = \sigma_b^{-2}   \rho_b = \sigma_b^{-2} \gamma_b)$	$\sigma_b$
Correlated Shape	$\Delta_{scb}(\alpha) = f_p(\alpha   \Delta_{scb,\alpha=-1}, \Delta_{scb,\alpha=1})$	$\text{Gaus}(a = 0   \alpha, \sigma = 1)$	$\Delta_{scb,\alpha=\pm 1}$
Normalisation Unc.	$\kappa_{scb}(\alpha) = g_p(\alpha   \kappa_{scb,\alpha=-1}, \kappa_{scb,\alpha=1})$	$\text{Gaus}(a = 0   \alpha, \sigma = 1)$	$\kappa_{scb,\alpha=\pm 1}$
MC Stat. Uncertainty	$\kappa_{scb}(\gamma_b) = \gamma_b$	$\prod_b \text{Gaus}(a_{\gamma_b} = 1   \gamma_b, \delta_b)$	$\delta_b^2 = \sum_s \delta_{sb}^2$
Luminosity	$\kappa_{scb}(\lambda) = \lambda$	$\text{Gaus}(l = \lambda_0   \lambda, \sigma_\lambda)$	$\lambda_0, \sigma_\lambda$
Normalisation	$\kappa_{scb}(\mu_b) = \mu_b$		
Data-driven Shape	$\kappa_{scb}(\gamma_b) = \gamma_b$		