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Non-Parametric Data-Driven Background Modelling using Conditional Probabilities

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UNIVERSITY OF BIRMINGHAM

erc

Exclusive Higgs

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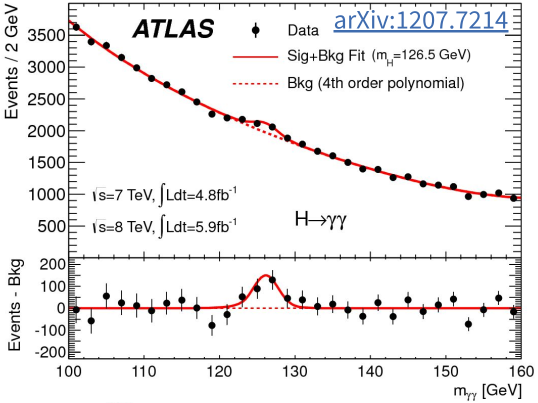
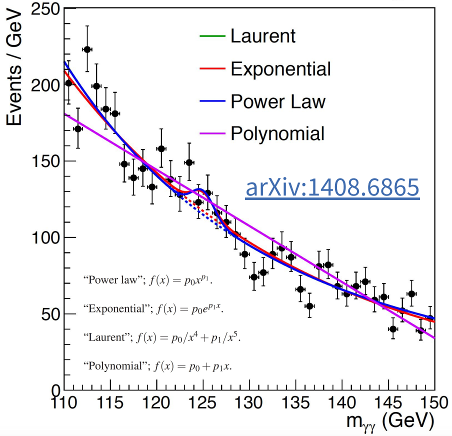
Motivation

➔ **Background modelling** is one of the main challenges in particle physics analyses

➔ Common techniques of background modelling:

- **MC simulation:**
  - Not always possible to model background with sufficient accuracy
  - Often computationally costly to produce large samples → significant statistical uncertainties
- **Parametric Models:**
  - Does the true shape belong to the family of curves parametrised by the chosen function?
    - Taken into account as **"spurious signal"** systematic uncertainty [1, 2]
    - Discrete **profiling of an ensemble of parametric forms** [3, 4, 5]





[arXiv:1207.7214 (1), arXiv:2007.07830 (2), arXiv:1408.6865 (3), arXiv:2002.06398 (4), arXiv:2009.04363 (5)]

Background Modelling

➔ Non-parametric data-driven background modelling:

Background Modelling

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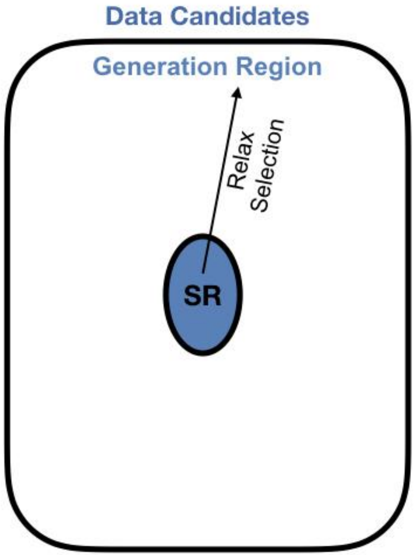
1. Obtain sample of data events enriched in background by relaxing event selection requirements (**Generation Region**)



Background Modelling

➔ Non-parametric data-driven background modelling:

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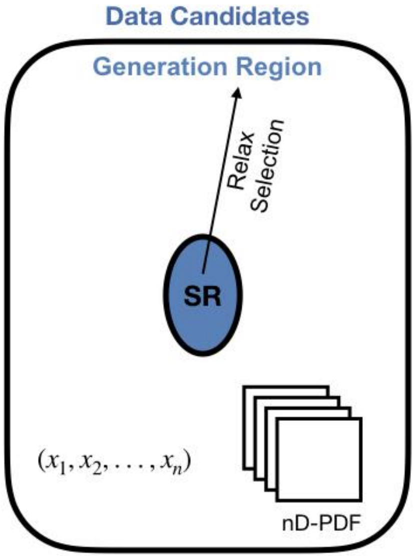

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1. Obtain sample of data events enriched in background by relaxing event selection requirements (**Generation Region**)
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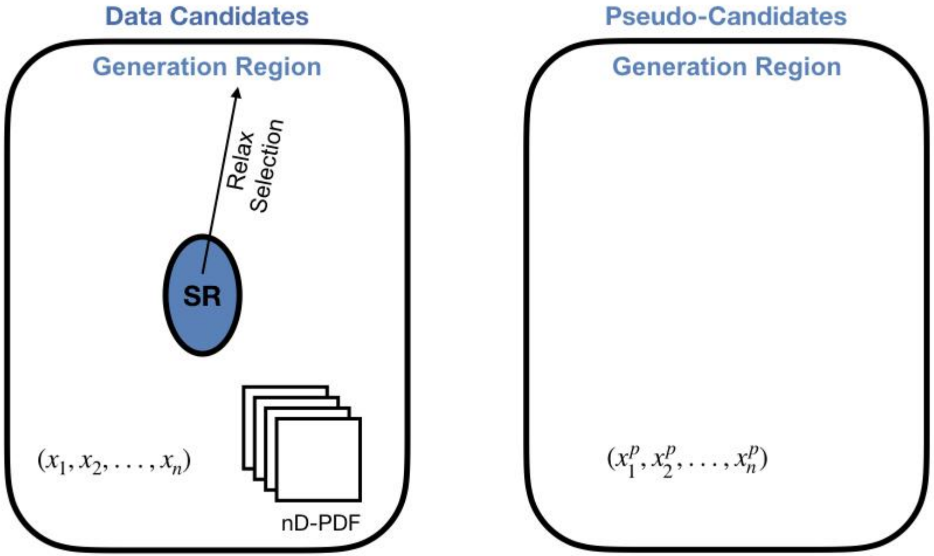
3. Generate sample of pseudo-candidates



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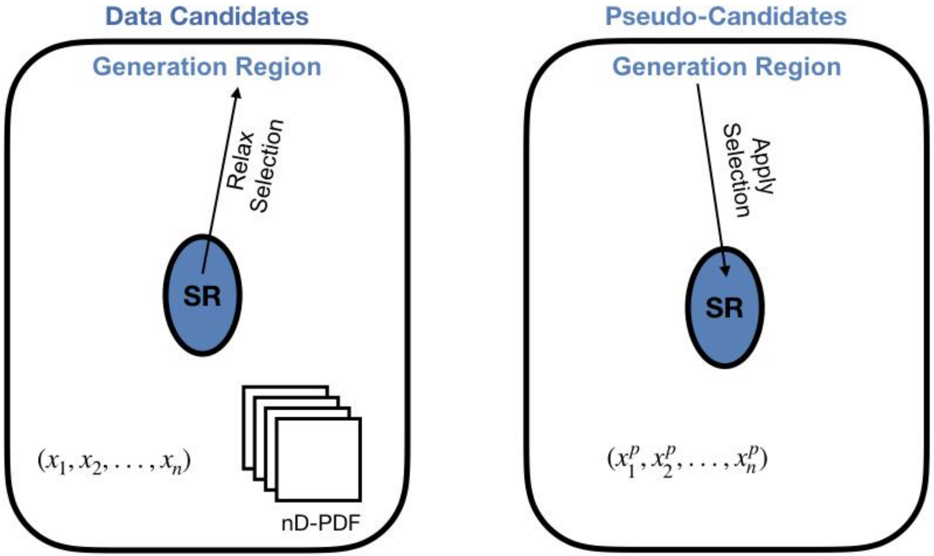

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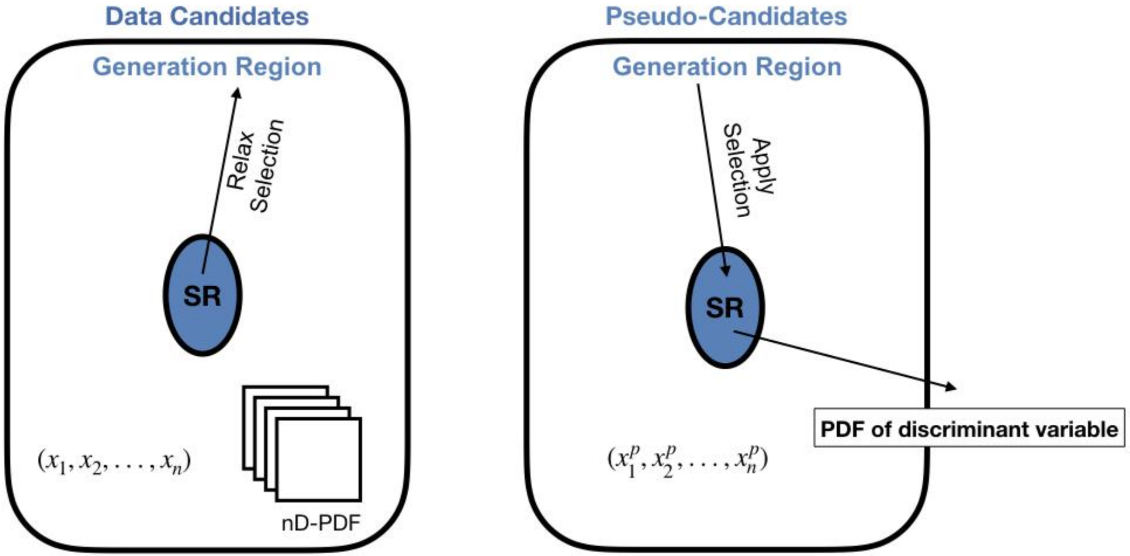

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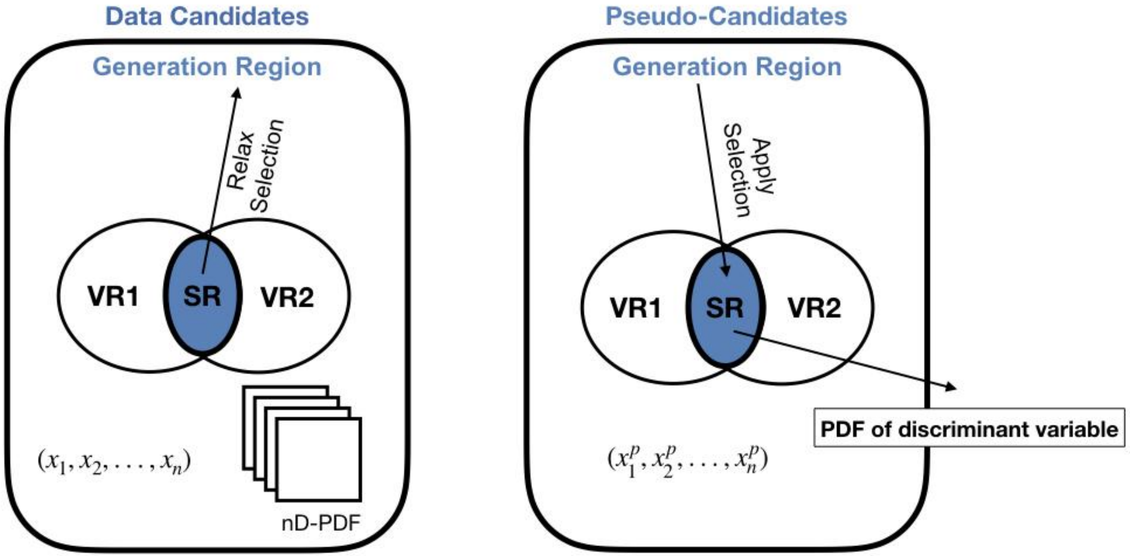
   - Intermediate **Validation Regions** to check method



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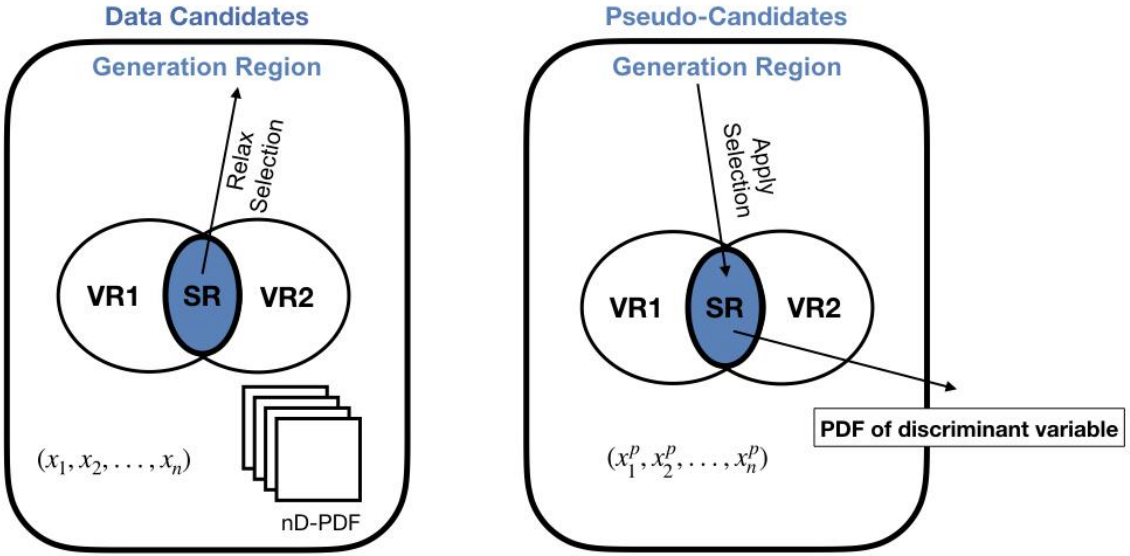
Today will present 2 implementations of the method

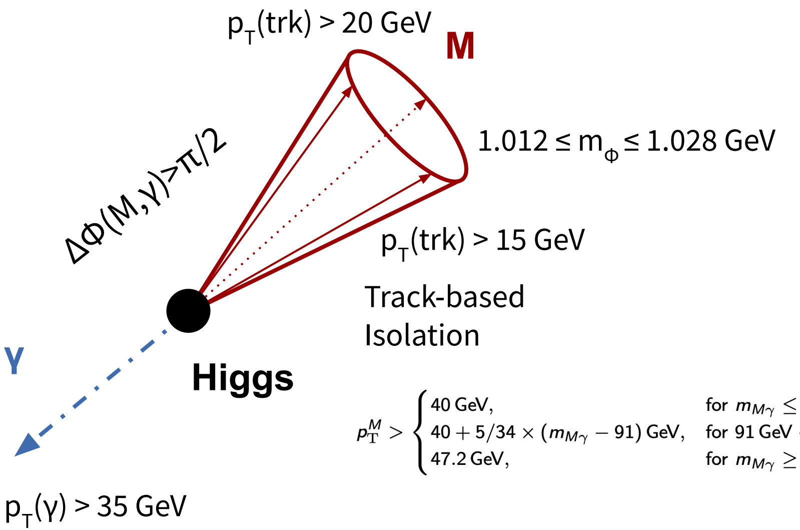


Ancestral Sampling

Case Study: H→Φγ

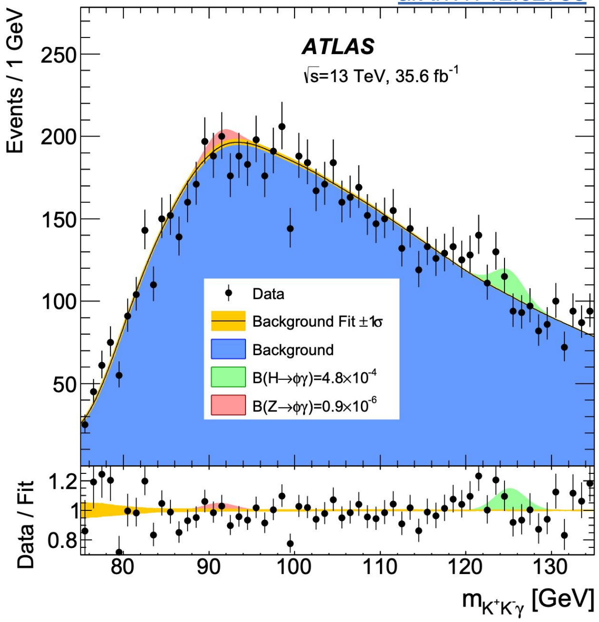
➔ H→ϕ(K⁺K⁻)γ has potential to probe **Higgs coupling to strange quark**

- **Distinct experimental signature**: pair of collimated high-p_T isolated tracks recoiling against isolated photon
- Main background : **photon + jet** and **dijet**
  - difficult to model accurately using MC - ideal use case for method
  - **photon + jet MC sample** used to exemplify model application



$$p_T^M > \begin{cases} 40\ \text{GeV}, & \text{for } m_{M\gamma} \le 91\ \text{GeV} \\ 40 + 5/34 \times (m_{M\gamma} - 91)\ \text{GeV}, & \text{for } 91\ \text{GeV} < m_{M\gamma} < 140\ \text{GeV} \\ 47.2\ \text{GeV}, & \text{for } m_{M\gamma} \ge 140\ \text{GeV} \end{cases}$$

arXiv:1712.02758



Building the model for H→Φγ

Relax Selection

Obtain Conditional PDFs

Generate pseudo candidates

Apply Selection

1. Relax $p_T(M)$ and Iso(M) requirements

Region	**$p_T(M)$ cut**	**Iso(M) cut**
GR	x	x
VR1	✓	x
VR2	x	✓
SR	✓	✓

Building the model for H→Φγ

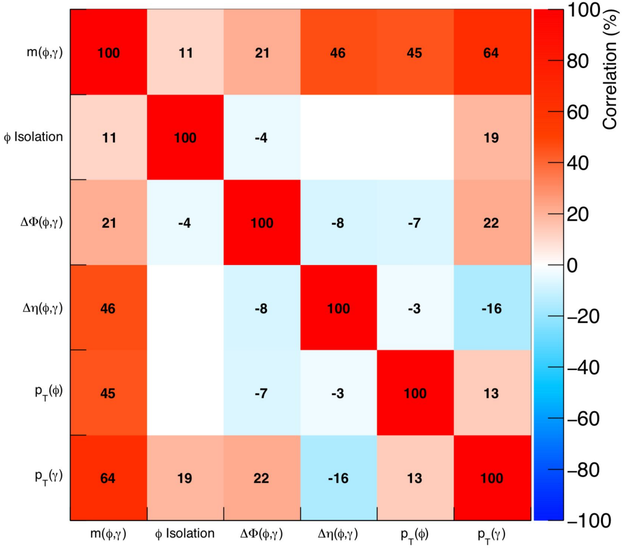
Relax Selection

Obtain Conditional PDFs

Generate pseudo candidates

Apply Selection

2. Build PDFs of relevant **kinematic** and **isolation** variables in generation region - we need the ϕ and γ 4-momentum vectors to ultimately obtain **m(ϕγ)** + Iso(ϕ)
   - 1D, 2D and 3D **histograms** to be sampled from in generation step
   - only most important correlations are explicitly described



$p_T(\phi)$	$p_T(\gamma)$

$p_T(\gamma)$	ϕ Iso

$p_T(\phi)$	$p_T(\gamma)$	$\Delta\Phi(\phi,\gamma)$

$\Delta\Phi(\phi,\gamma)$	$\Delta\eta(\phi,\gamma)$

Building the model for H→Φγ

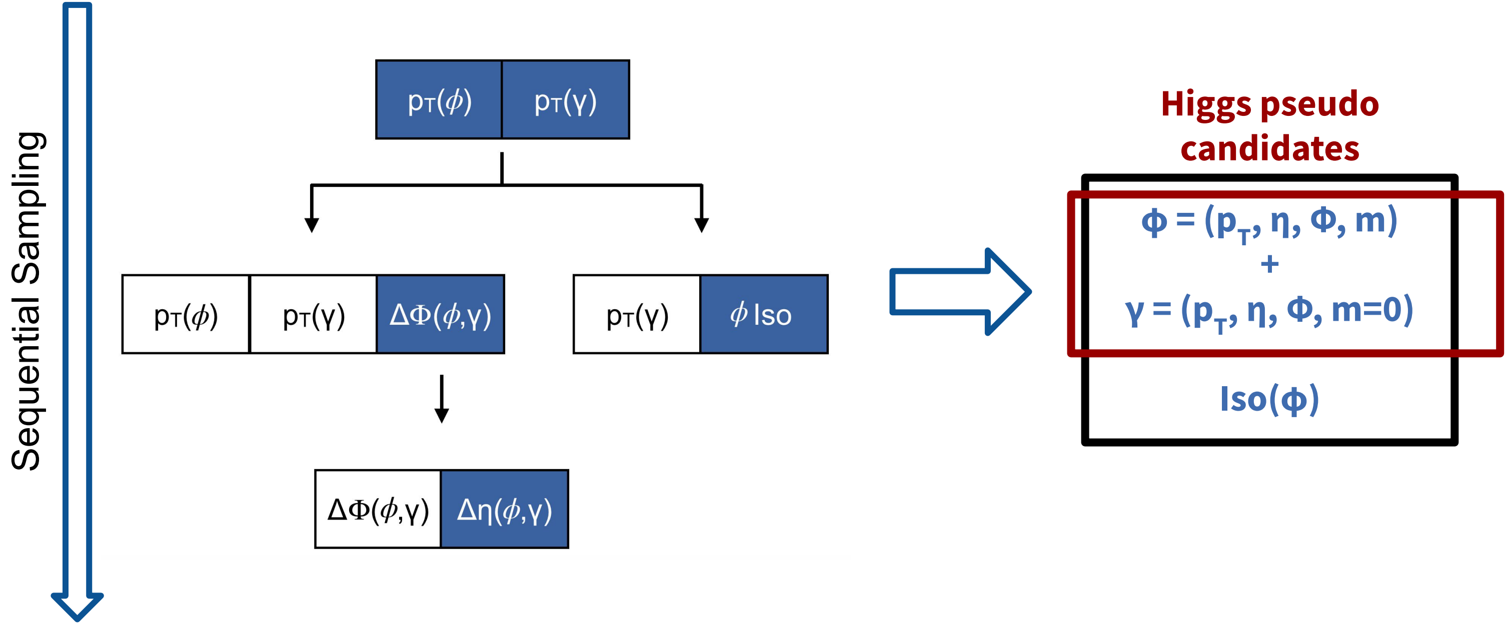
Relax Selection

Obtain Conditional PDFs

Generate pseudo candidates

Apply Selection

3. **Sample** from PDFs and construct pseudo-candidates
   - each pseudo-candidate is defined by the ϕ and γ 4-momentum vectors, and an associated Φ isolation variable



Building the model for H→Φγ

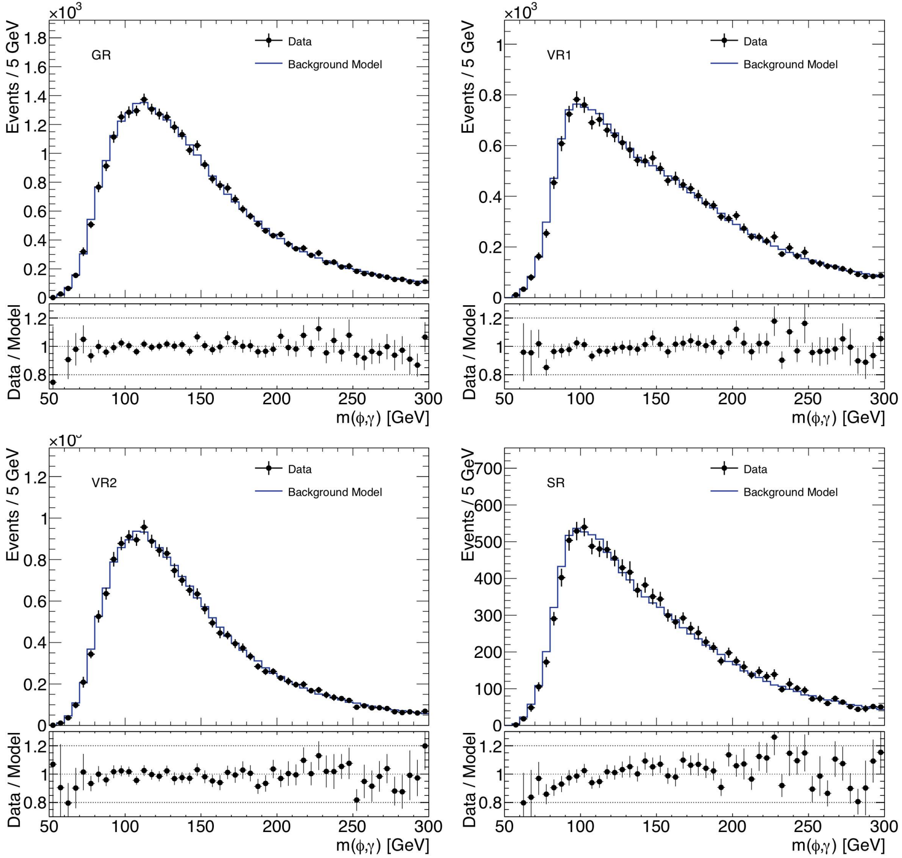
Relax Selection

Obtain Conditional PDFs

Generate pseudo candidates

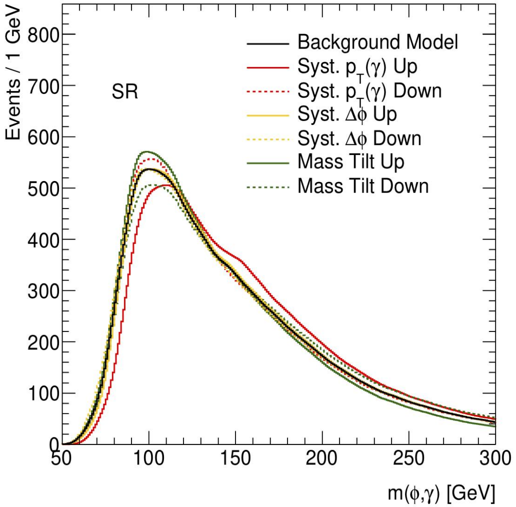
Apply Selection

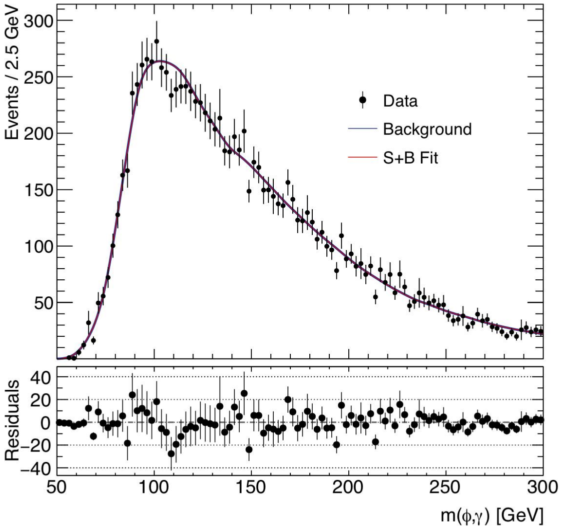
4. Apply $p_T(M)$ and Iso(M) requirements to sample of pseudo-candidates
   - obtain PDF of **m(ϕγ)** for statistical analysis in Signal and Validation Regions



Implementation in Statistical Analysis

- ➔ **Systematic uncertainties** are provided through variations of the nominal PDFs
  - ◆ selected to capture different modes of potential deformations of the background shape
- ➔ Maximum likelihood fit to invariant mass
  - ◆ each variation controlled by a nuisance parameter - directly constrained by data in fit





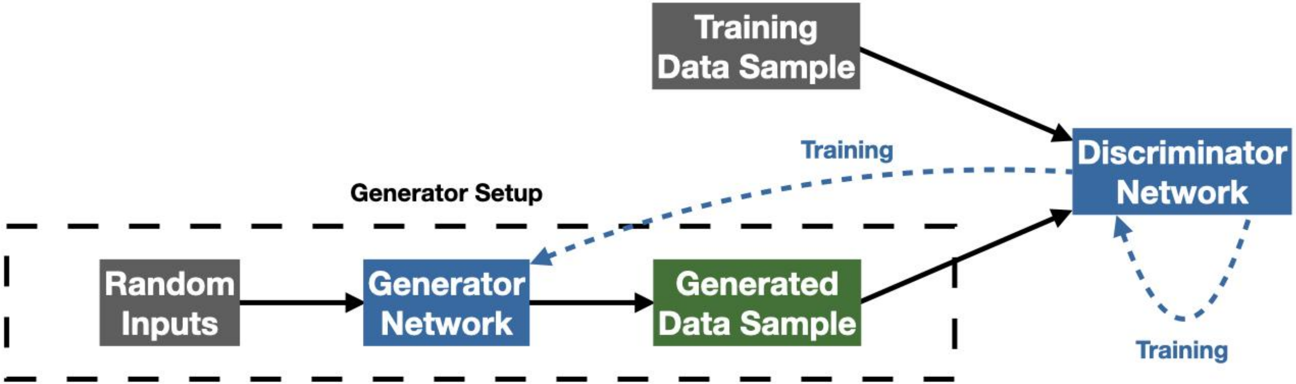
Parameter	Value	Uncertainty $(\pm 1\sigma)$
μ_{signal}	-0.03	± 0.55
μ_{bkgd}	1.01	± 0.01
Shape: $p_T(\gamma)$ shift	0.27	± 0.15
Shape: $\Delta\Phi(\phi,\gamma)$ tilt	0.26	± 0.43
Shape: $m(\phi,\gamma)$ tilt	0.11	± 0.24

Conditional Generative Adversarial Networks

Generative Adversarial Networks

➔ Challenge for ancestral sampling:
  - application in multivariate analyses
  - signal region blinding

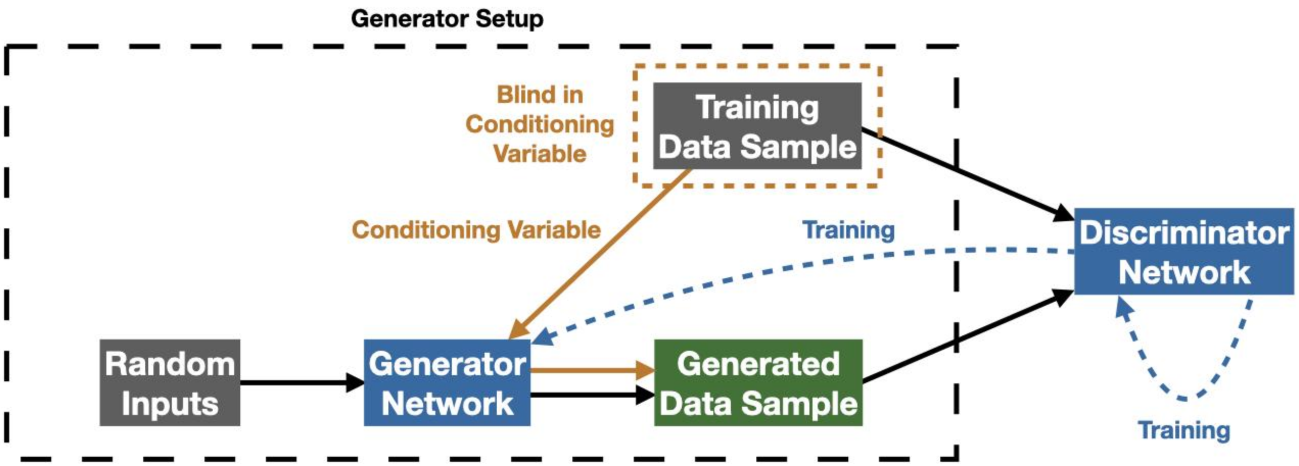
➔ Generalisation of method: use **GANs trained on data** to produce background model
  - **Generator** - learns generative model from data sample
  - **Discriminator** - simultaneously trained to discriminate the generator output from data



Conditional Generative Adversarial Networks

➔ Possible **signal contamination** in training data:

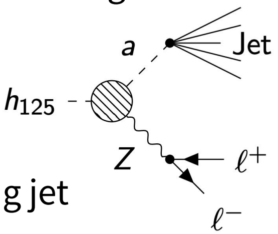
- **Condition** GAN (cGAN) on a blinding variable, allowing **SR to be blinded during training** - cGAN extrapolates prediction into SR



Case Study: H→Za

➔ Light pseudo-scalars produced in Higgs decays feature in BSM theories like two-Higgs-doublet model and the 2HDM with additional scalar singlet

➔ Search for **H→Z(ll)+a**, with a→hadrons:
- Main background: **Z + jets**
- background discrimination relies on **MVA** techniques, using jet substructure variables
- ideal case study for implementation of background modelling using cGANs
  - systematics arising by limited stats in MC simulation (arXiv:2004.01678)
  - use of MVA techniques makes it impractical to use ancestral sampling



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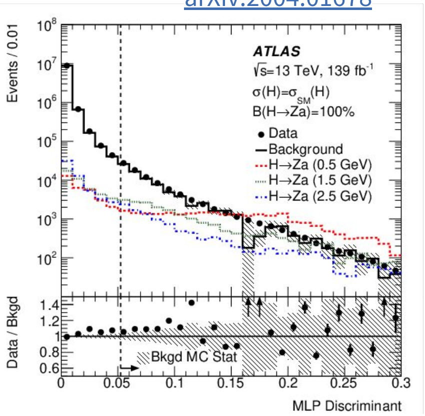
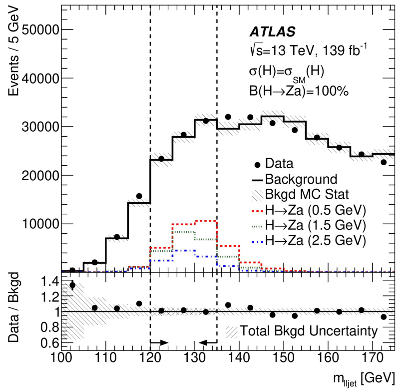




➔ **Z + jets MC sample** used to exemplify model application

Building the model for H→Za

Relax Selection

Obtain Conditional PDFs

Generate pseudo candidates

Apply Selection

1. Remove MLP-based selection
   - **& blind signal region** to avoid signal contamination

Use $m_{\mu\mu j}$ as blinding variable

⇩

123 GeV ≤ $m_{\mu\mu j}$ ≤ 135 GeV blinded

Building the model for H→Za

Relax Selection

Obtain Conditional PDFs

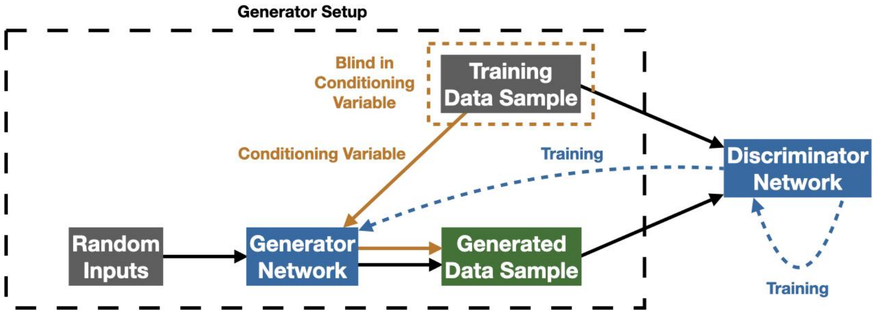
Generate pseudo candidates

Apply Selection

2. cGans trained using **blinded data**
   - learn generative model of the conditional probability distribution of the data, given value of blinding variable
   - Use **ensemble** of cGANs and take average:
     - 100 cGANs trained, 5 best based on χ^2 metric kept for analysis

Generator and discriminator:

- 5 layers x 256 hidden nodes with leaky ReLU activation function
- binary cross entropy loss function and L2 regularisation



Building the model for H→Za

Relax Selection

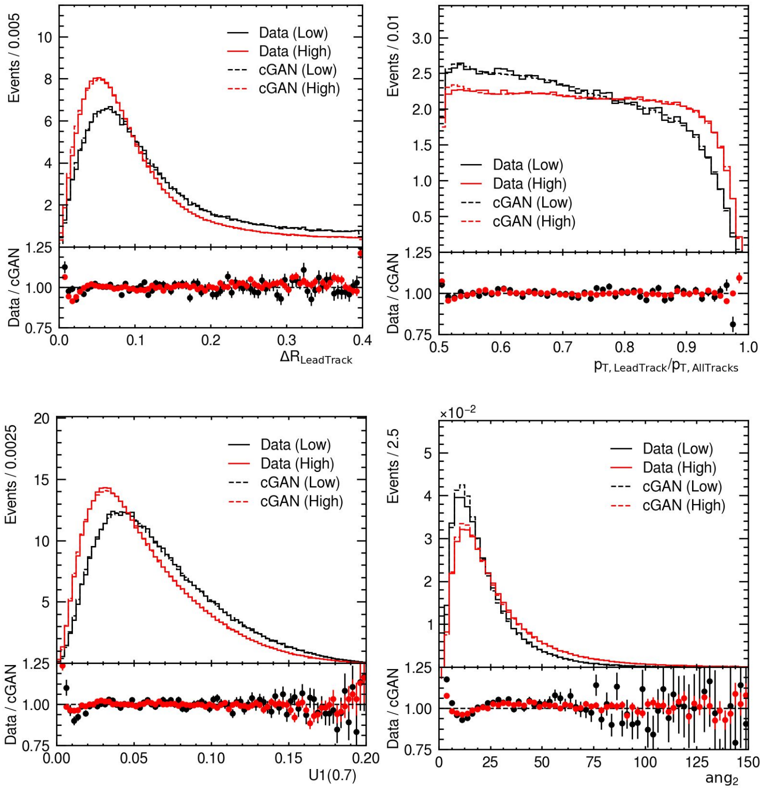
Obtain Conditional PDFs

Generate pseudo candidates

Apply Selection

3. Input inclusive distribution of the conditioning variable into cGAN:
   - cGAN **extrapolates** the conditional generative model into signal region
   - obtain prediction of **MLP input variables**

$m_{\mu\mu j}$ sidebands



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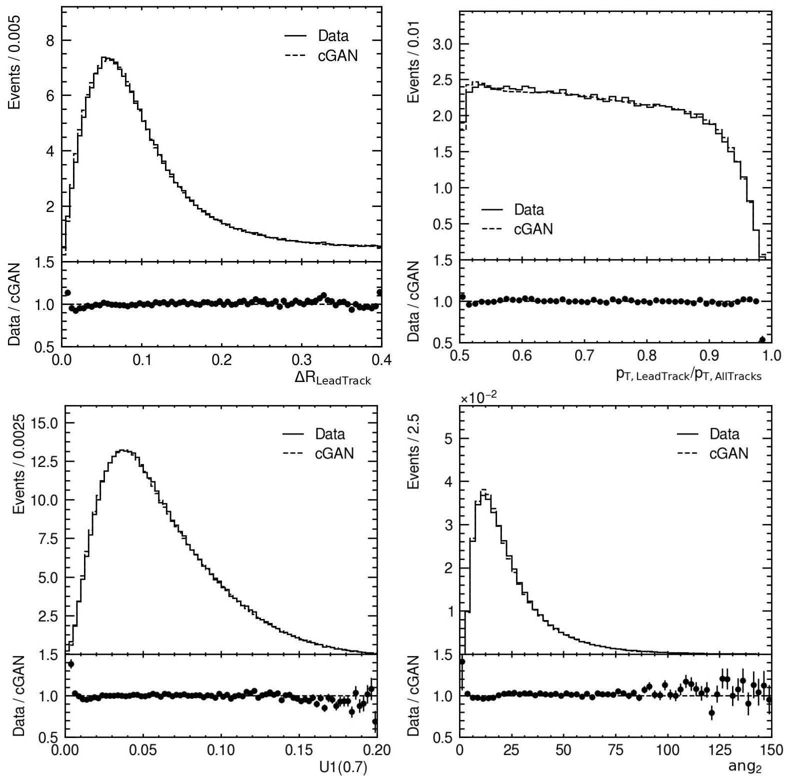
$m_{\mu\mu j}$ SR



Building the model for H→Za

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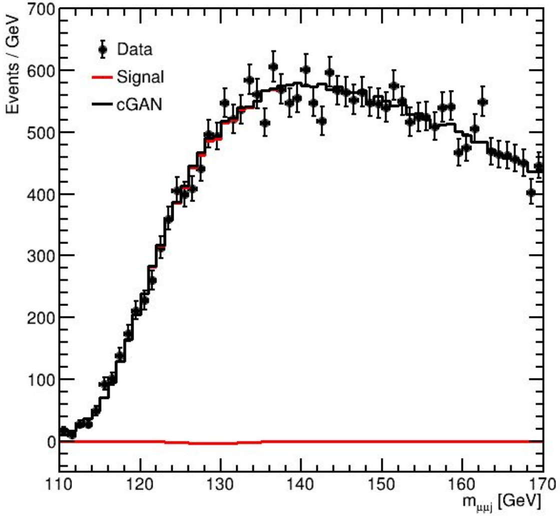
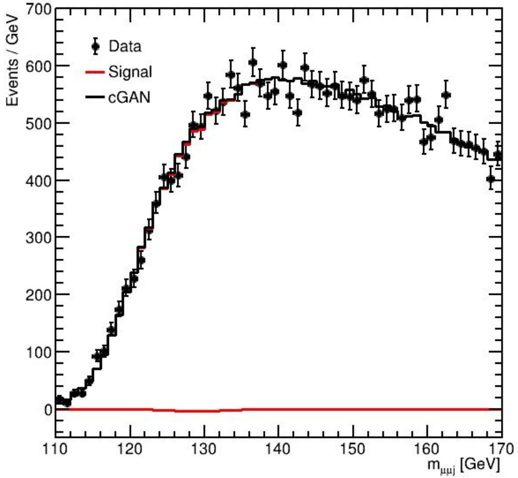
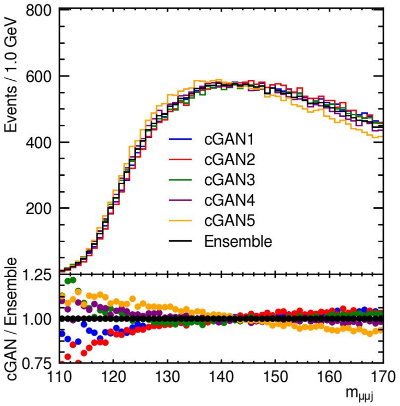
4. Apply MLP selection to pseudo-candidates sample
   - obtain PDF of $\mathbf{m}_{\mu\mu j}$ in SR for statistical analysis

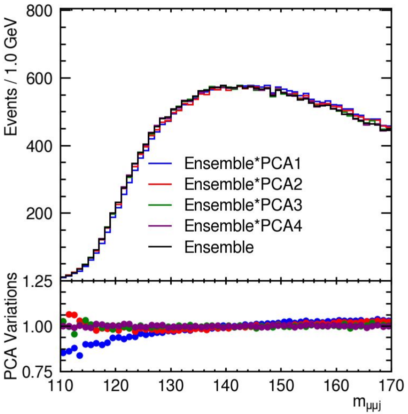


Implementation in Statistical Analysis

- ➔ **Systematic uncertainties** are provided through shape variations:
  - ◆ Differences between ensemble and individual cGANs
  - ◆ Principal component analysis performed to orthogonalise differences
- ➔ Maximum likelihood fit to Higgs invariant mass
  - ◆ each variation controlled by a nuisance parameter - directly constrained by data in fit







Parameter	Value	Uncertainty ($\pm 1\sigma$)
μ_{signal}	-0.003	± 0.010
μ_{bkgd}	1.001	± 0.008
Shape uncertainty 1	-0.36	± 0.27
Shape uncertainty 2	-0.31	± 0.52

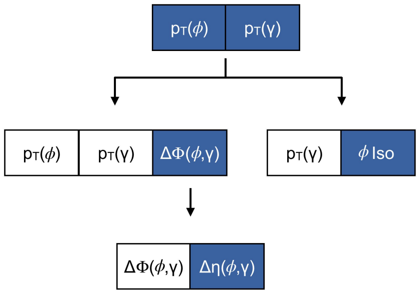
Summary

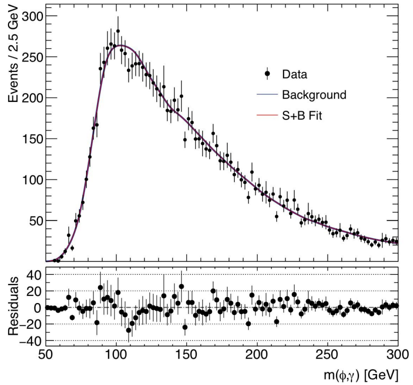
➔ A novel **non-parametric**, **data-driven** background modelling technique was presented
- Addresses typical shortcomings of often employed background modelling techniques
- Dataset from a **relaxed event selection** to create a model based on **conditional probabilities**
- Two distinct ways of building the conditional PDF:

arXiv:2112.00650

Ancestral sampling

- Sample from histograms of relevant variables in data, built with respect to most important correlations
- Already used in multiple analysis! [Phys. Rev. Lett. 114 (2015) 121801, Phys. Rev. Lett. 117, 111802 (2016), JHEP 07 (2018) 127, Phys. Lett. B 786 (2018) 134]





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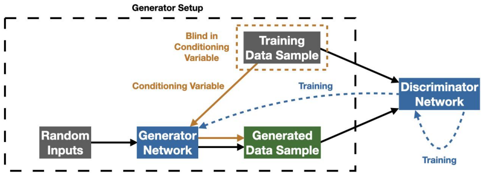
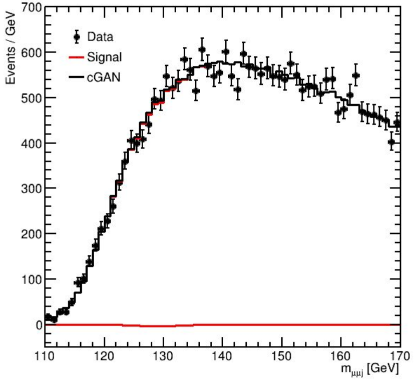
- **Condition** GAN (cGAN) on a blinding variable, allowing **SR to be blinded during training**





BACK-UP

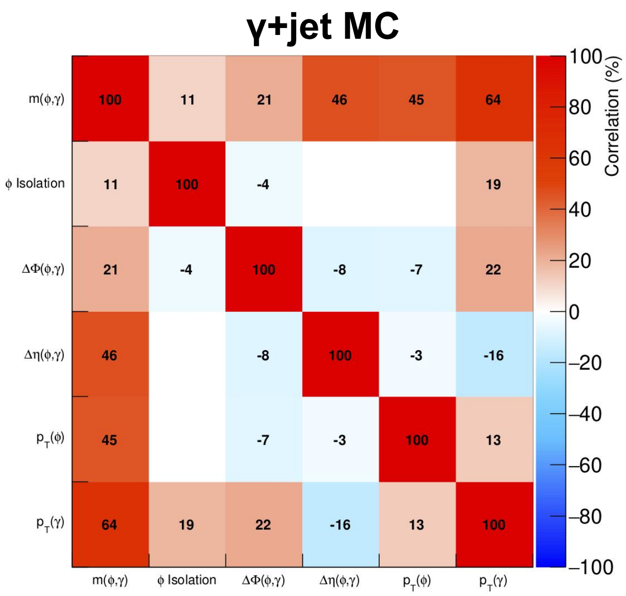
Building the model for H→Φγ

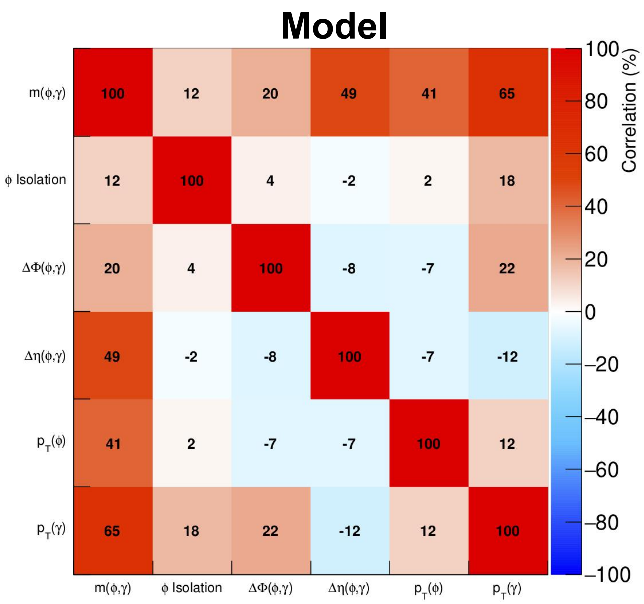
Relax Selection

Obtain Conditional PDFs

Generate pseudo candidates

Apply Selection





Ancestral Sampling

➔ Background model is **robust under signal contamination**
- ◆ Signal Injection tests to evaluate robustness