Data - Monte Carlo Compatibility Check

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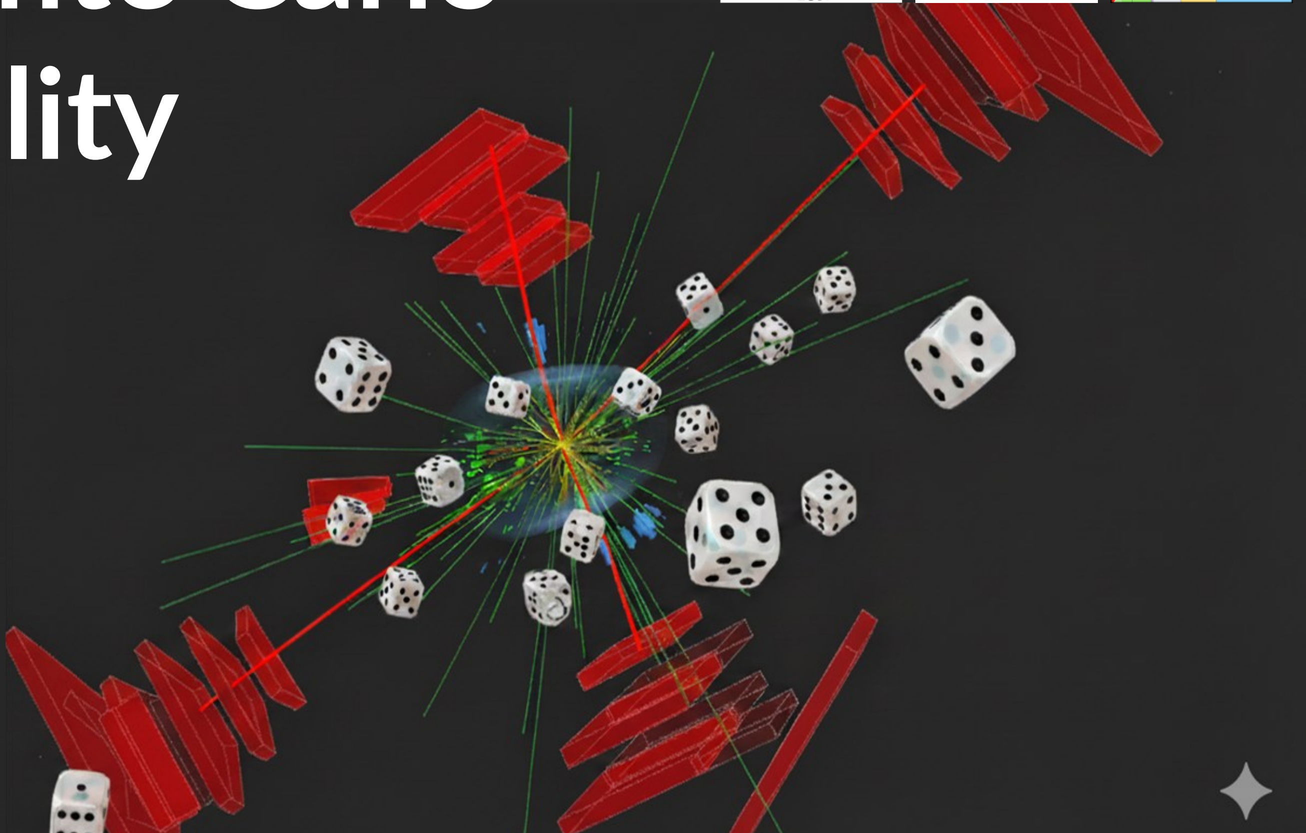
24 / 10 / 25



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Why Data–Monte Carlo Compatibility Matters — The Reality Check

- **Physics Goal:** Before any discovery or precision measurement, we must verify that *our detector and simulations agree on what the world looks like.*
- **Benchmark Channel:** The **Z → $\mu^+\mu^-$** process — clean, well-understood, and sensitive to detector and modelling differences.
- **The Question:** *Do our Monte Carlo templates truly represent what CMS recorded ?*
- **The Approach:**
  - Start with simple **shape tests (KS test)**
  - Move to **likelihood fits** to extract scaling parameters
  - Iterative KS tests with new scaling parameters
  - Introduce **shape morphing** to test systematic effects
- **End Goal:** Build a statistically consistent bridge between *simulation* and *reality.*

Data and Samples (Event Selection :Tag & Probe Method)

Data	DoubleMuon primary dataset in NANOAOD format from RunH of 2016
Signal	Simulated dataset ZToMuMu_M-50To120_TuneCP5_13TeV-powheg-pythia8
Background-1	Simulated dataset TTTo2L2Nu_TuneCP5_13TeV-powheg-pythia8
Background-2	Simulated dataset WJetsToLNu_TuneCP5_13TeV-madgraphMLM-pythia8
Background-3	Simulated dataset ZZTo2L2Nu_TuneCP5_13TeV_powheg_pythia8
Background-4	Simulated dataset ZZTo4L_M-1toInf_TuneCP5_13TeV_powheg_pythia8

Tag & Probe Method:

Event Selection:

- Event Trigger : HLT_IsoMu22_eta2p1
- MET p_T > 40 GeV
- nMuon >= 2

Electron Veto:

- Good electron : $[p_T^e > 10\ GeV, \eta^e < 2.5, no\ \mu\ within\ \Delta R = 0.4\ ]$
- If good electron, reject the event

Tag Selection:

- $p_T^\mu \geq 24\ GeV$
- $\eta^\mu < 2.1$
- $iso^\mu < 0.3$
- $[tight\ id]^\mu = 1$

Jet Veto:

- Good Jet : $[p_T^{Jet} > 30\ GeV, \eta^{Jet} < 4.7, no\ \mu\ within\ \Delta R = 0.4\ ]$
- If >3 good Jets, reject the event

Probe Selection:

- Probe_chrg * Tag_chrg < 0
- $\eta^\mu < 2.1$
- $M_{\{\mu^{Tag}\mu^{Probe}\}} < 2000\ GeV$

b-Jet Veto:

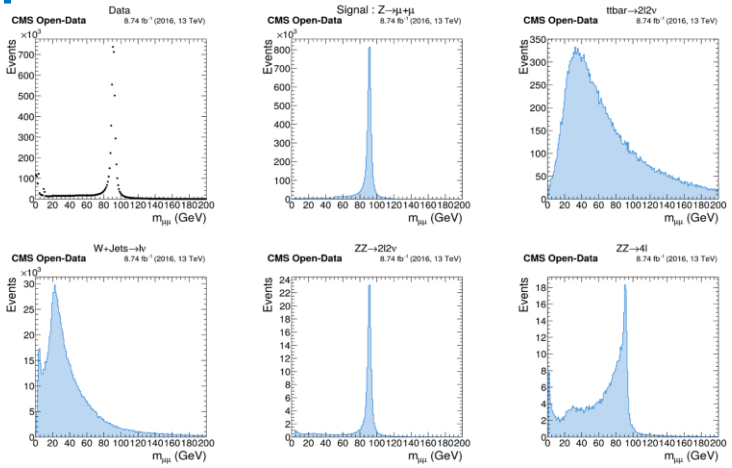
- Good b-Jet : $[p_T^{Jet} > 30\ GeV, \eta^{Jet} < 4.7, no\ \mu\ within\ \Delta R = 0.4, btag \geq 0.33\ ]$
- If good b-jet, reject the event.

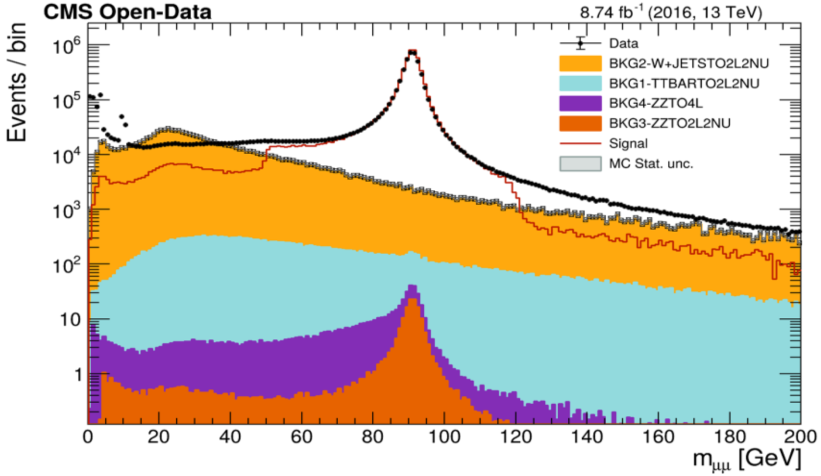
Trigger & Event Selection → Tag Selection → Probe Selection → Election Veto → Jet & b-Jet Veto → Store the observables in histograms

MC Normalization to Data Luminosity :

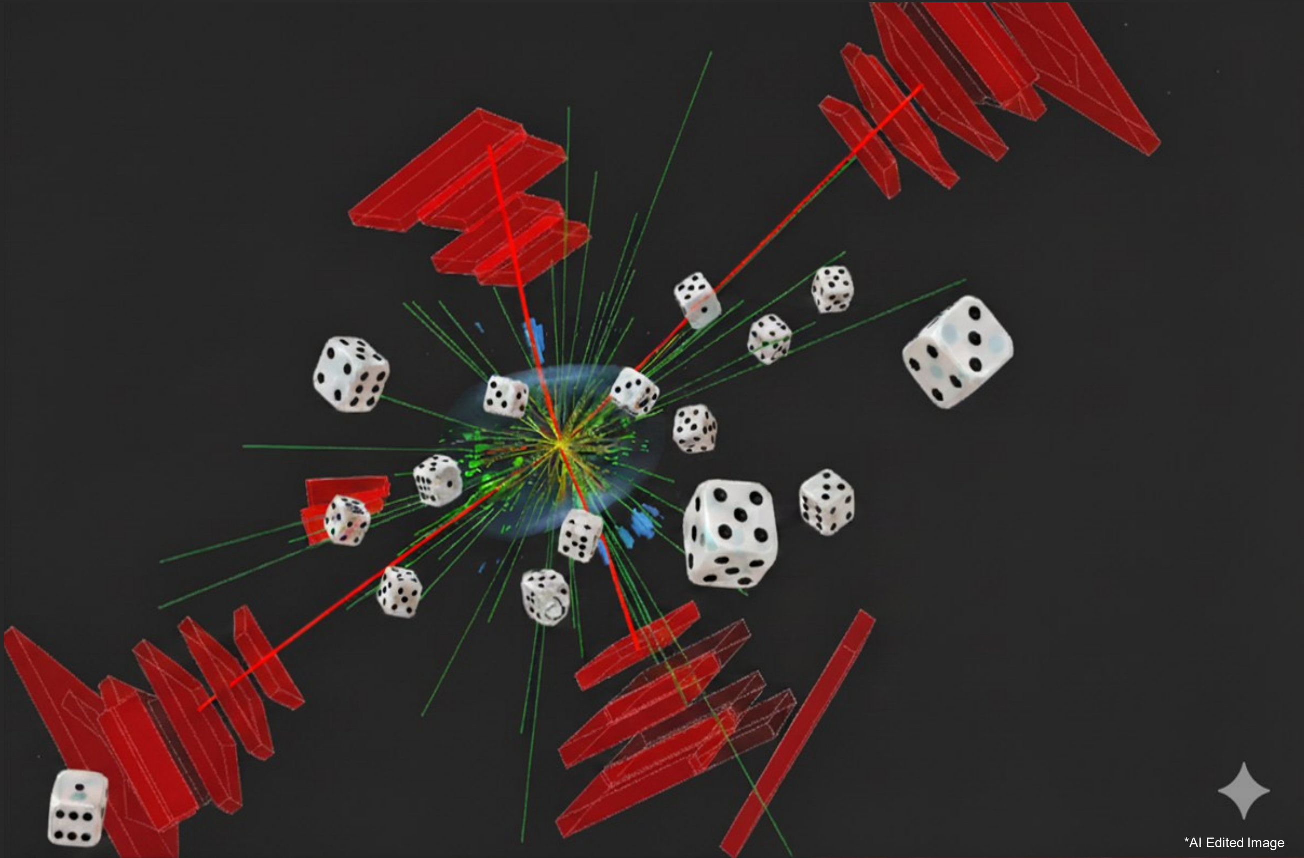
- MC samples are arbitrary number of events generated → randomize mixture of random numbers
- Real Process Info. (Randomness in reality) corresponds to a known **Integrated Luminosity** >> encoded in Data << MC (randomness implemented to mimic reality) should be look similar to Data if we know the process
- So, each MC event is assigned a **weight** = how many real events it represents ?
- Otherwise, our understanding ,  =  + 
- General formula : $w_{event} = w_{norm} \cdot (genWeight) \cdot w_{PU} \cdot w_{SF}^{\mu\mu} \cdot w_{prefire}$
- Where, $w_{norm} = \frac{L_{data}[fb^{-1}] \cdot \sigma[fb] \cdot \epsilon \cdot k}{\sum w}$
- Ensures **total MC yield** matches expected yield for **8.74 fb⁻¹ (2016, 13 TeV)**

Process	Cross-section (pb)	Events
Data	----	5025648
Signal : $Z \rightarrow \mu^{+} + \mu^{-}$	2008.4	5412870.60
Bkg-1 : $t\bar{t} \rightarrow 2\mu + 2\nu$	88.29	7928.12
Bkg-2 : $\mathrm{W} + \mathrm{Jets} \rightarrow \mu + \nu$	61529.7	173500.67
Bkg-3 : $\mathrm{ZZ} \rightarrow 2\mu + 2\nu$	0.564	155.67
Bkg-4 : $\mathrm{ZZ} \rightarrow 4\mu$	1.256	304.84





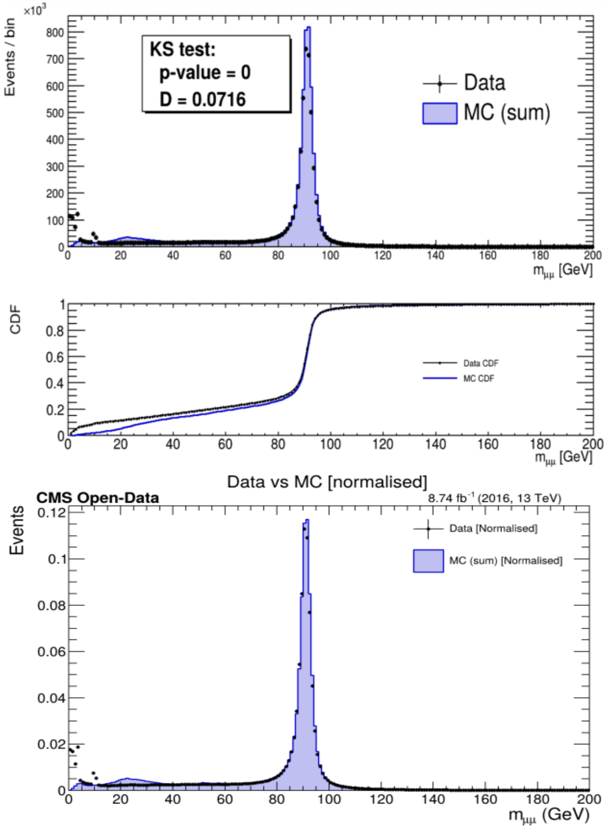
KS Test



Data–MC Comparison: Kolmogorov–Smirnov (K-S) Test

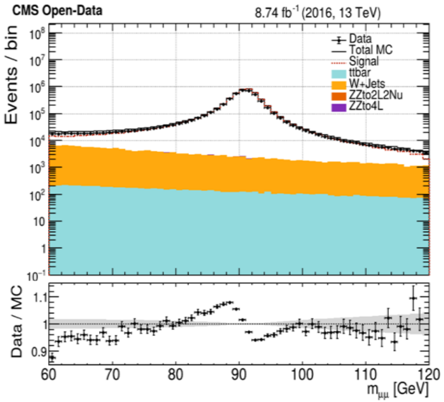
A **non-parametric statistical test** used to compare **two probability distributions** ⇒ Draws conclusion whether those **two PDFs** are drawn from the same underlying distribution or not.

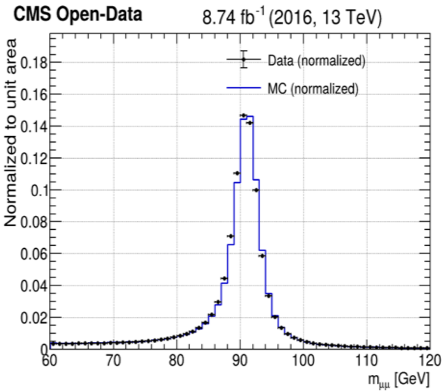
- **How it Works** :
  - The test is based on **empirical cumulative distribution functions (ECDFs)**.
  - For each PDF, the ECDF is given by : $F_n(x) = \frac{Number\ of\ data\ points \leq x}{Total\ number\ of\ points:\ n}$
  - KS Test Statistics : $D = \sup_x [F_n(x) - F_m(x)] = \sup_x [F_{Data}(x) - F_{MC}(x)]$ i.e, the largest vertical distance b/w 2 CDFs
  - P-value ≥ 0.05 → Good Agreement but P-value ≪ 0.05 → Significant Mismatch
- **Why it matters :**
  - Non-parametric, so no assumption about the form of distribution
  - Sensitive to difference in both **location (mean shift**) and **shape (skew)**
  - Used check Data-Monte Carlo agreement for generators and detector simulation validation
  - Comparison between different unfolding methods**.**

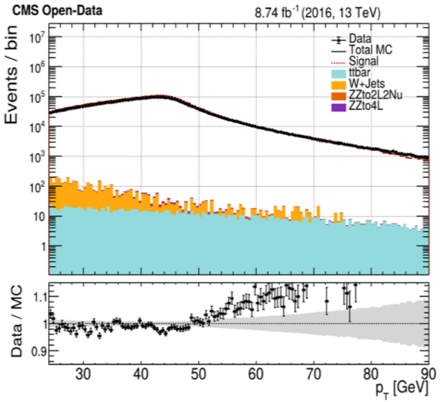


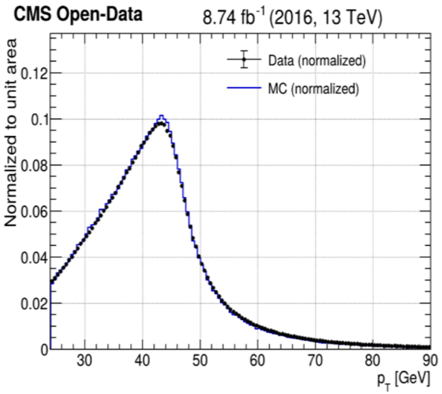
Result : Data and MC differ notably around the Z-peak region → indicates modeling or detector bias → motivates fit-based approach.

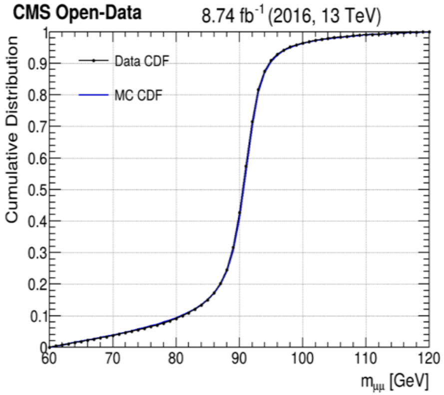
Kolmogorov–Smirnov (K-S) Test of different Observables











Kolmogorov-Smirnov Test Results

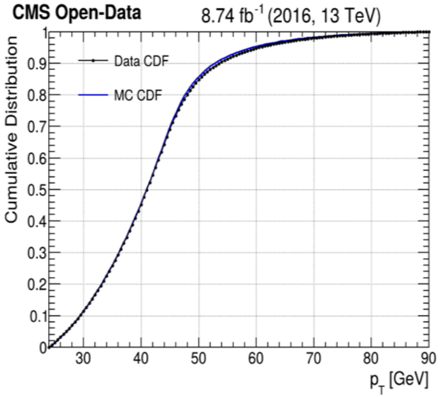
Analysis window: [60.0, 120.0] GeV

KS statistic D = 0.01767

Asymptotic p-value = 0

Signal strength: μ_{sig} = 1.0000

Background scales: β = [1.000, 1.000, 1.000, 1.000]



Kolmogorov-Smirnov Test Results

Analysis window: [24.0, 90.0] GeV

KS statistic D = 0.01111

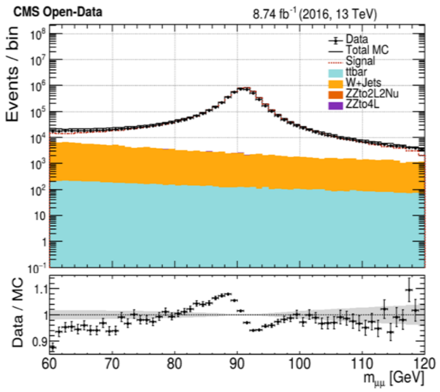
Asymptotic p-value = 0

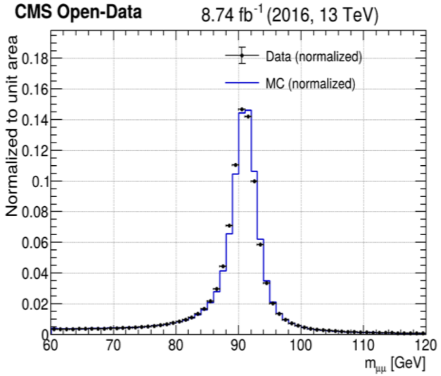
Signal strength: μ_{sig} = 1.0000

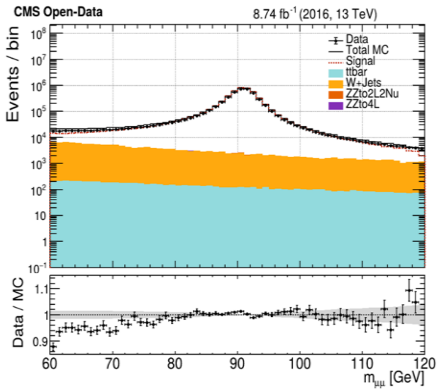
Background scales: β = [1.000, 1.000, 1.000, 1.000]

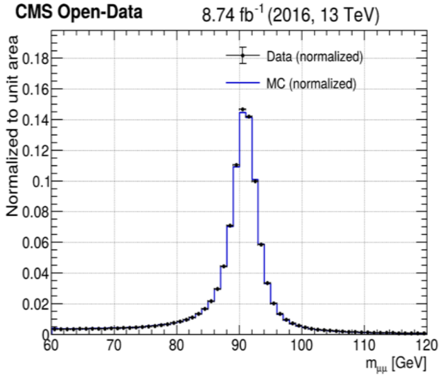
Kolmogorov–Smirnov (K-S) Test : Scope of Improvement ??

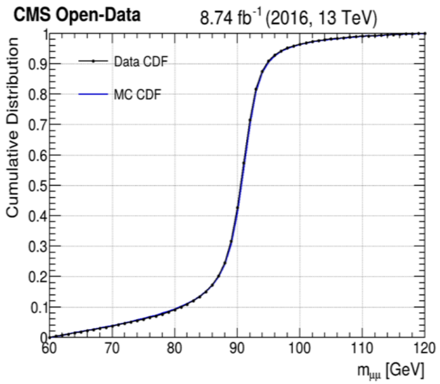
- Made a *12% shift of bin-contents of to the consecutive left* bins → Shape Improves !!
- Also the μ_{sig} *and* $\beta's$ are **ASSUMED to 1**











Kolmogorov-Smirnov Test Results

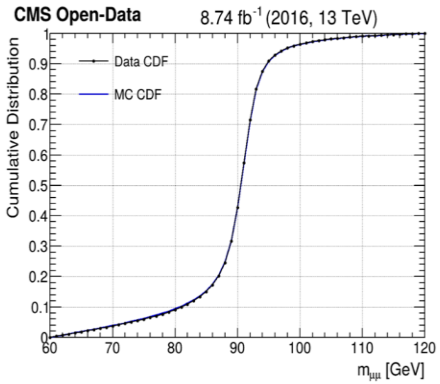
Analysis window: [60.0, 120.0] GeV

KS statistic D = 0.01767

Asymptotic p-value = 0

Signal strength: μ_{sig} = 1.0000

Background scales: β = [1.000, 1.000, 1.000, 1.000]



Kolmogorov-Smirnov Test Results

Analysis window: [60.0, 120.0] GeV

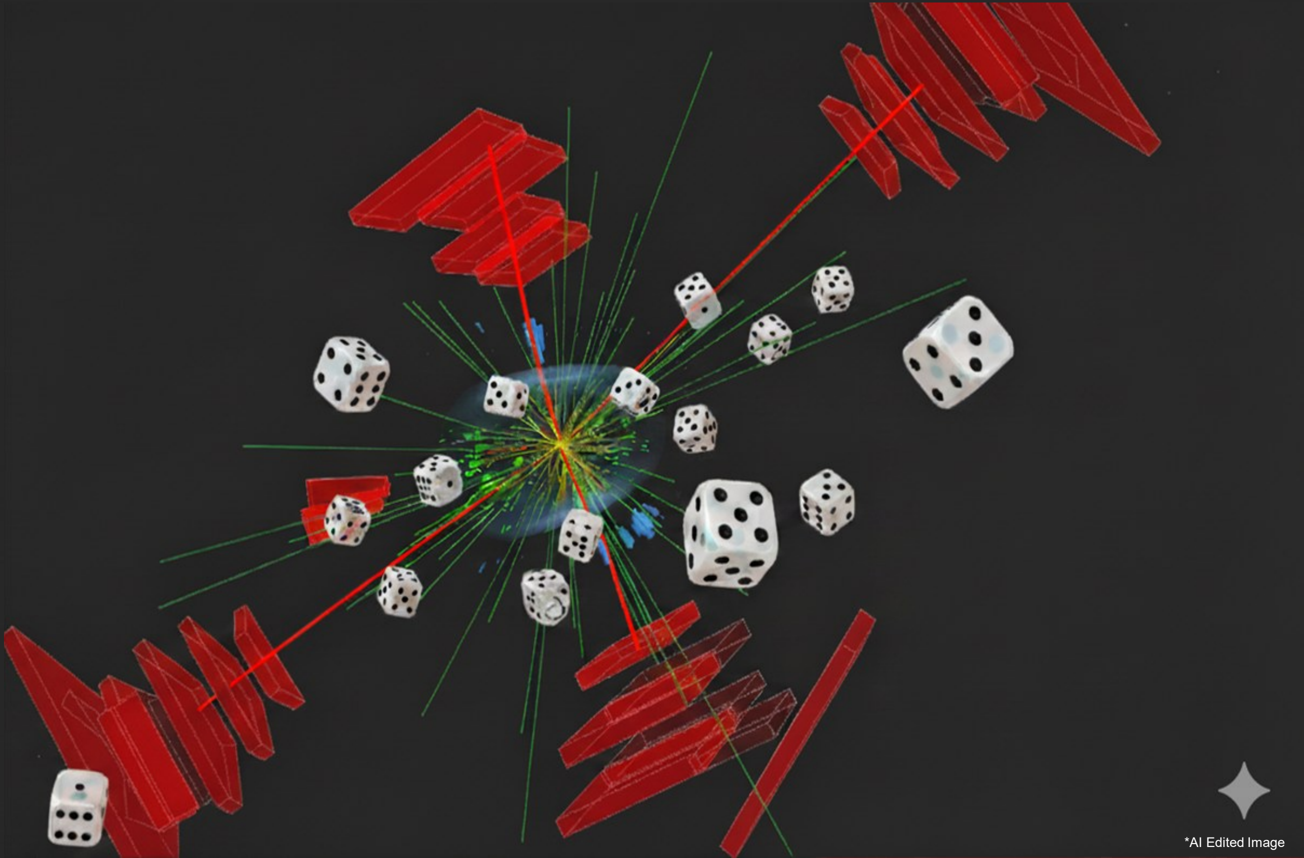
KS statistic D = 0.00390

Asymptotic p-value = 8.9606e-13

Signal strength: μ_{sig} = 1.0000

Background scales: β = [1.000, 1.000, 1.000, 1.000]

Template Fit



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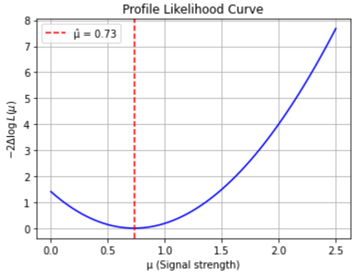
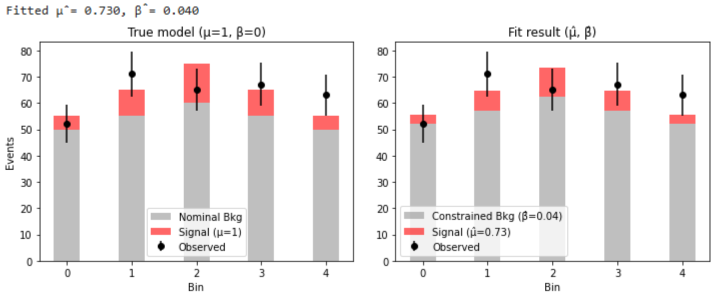
Template Fit Framework — Estimating Signal Strength

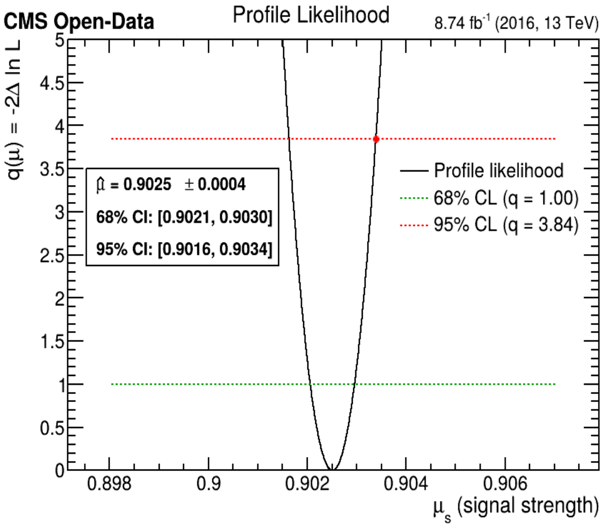
- We have binned hist. Data and MC templated for process (Signal & Backgrounds)
- For each bin (say in $\mathrm{i^{th}}$ bin of $\mathrm{m_{\mu\mu}}$ histogram), the expected event is $\boldsymbol{\nu_i(m_{\mu\mu}) = \mu_s \cdot s_i(m_{\mu\mu}) + \sum_{k\,\in bkg_s} \beta_k \cdot b_{k,i}(m_{\mu\mu})}$
  - Where $\boldsymbol{s_i, b_{k,i}}$ are signal and background shape templates respectively (MC yields per bin, possibly deformed by shape nuisances ϕ)
  - $\boldsymbol{\mu_s}$ is the signal strength scaling (parameter if interest)
  - $\boldsymbol{\beta_k}$ is the background scaling factors (can be treated as nuisance)
- Likelihood:
  - For observed count n_i, $\boldsymbol{P(n_i \mid \nu_i) = \dfrac{e^{-\nu_i}\, \nu_i^{n_i}}{n_i\,!}}$
  - $\boldsymbol{L_{primary}(\mu_s\,, \beta, \phi) = \prod_{i=1}^{N_{bins}} Pois\,(n_i \mid \nu_i(\mu_s\,, \beta, \phi))}$
  - $\boldsymbol{L_{auxiliary}(\eta) = \prod_k \pi_k(\beta_k) \cdot \prod_j \pi_j(\phi_j) \cdot (MC - stat\ constraints)}$
    - $\boldsymbol{\pi(\beta_k) = \begin{cases} N(1, \sigma_k)\ \ (\,Gaussian\ Constriant) \\ LogNormal(1, \sigma_k)\ \ (Positive, multiplicative\ constraint) \end{cases}}$
    - With $\boldsymbol{\sigma_k = 0.10\ \rightarrow 10\%\ prior\ uncertainty}$
  - Full likelihood : $\boldsymbol{L(\mu_s\,, \beta, \phi) = L_{primary} \cdot L_{aux}}$.
- Profiling :
  - To estimate μ_s, profile all nuisances :
    - $\boldsymbol{\hat{\hat{\eta}}(\,\mu_s) = \arg\max_{\eta} L(\mu_s, \eta)\ ,\ \ \widehat{\mu_s}, \hat{\eta} = arg\,max_{\mu_s,\eta}\, L}$
    - This lets the data pull nuisances within their constrain, avoiding bias and giving realistic uncertainties.





Constraints on Backgrounds to Nominal with Uncertainty, Singal is kept Free

- We trust our background predictions reasonably well; constrained with Gaussian priors (σ = 10%)
- Only the main component = Signal float freely
- Parameters $\begin{cases} \mu_s \; [\, free\ to\ float \,] \\ \beta_k \; [constrained\ by\ \pi(\beta_k)\,] \end{cases}$

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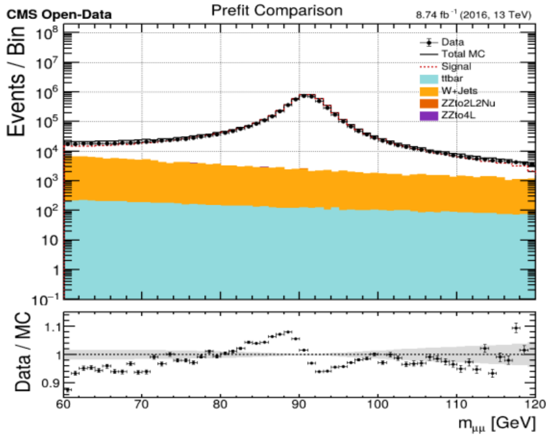
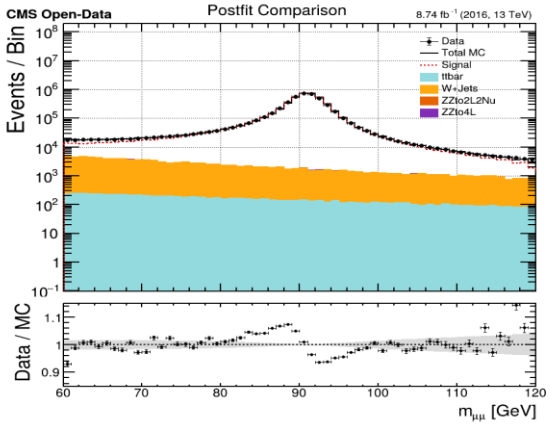
========================================
Fitting
========================================

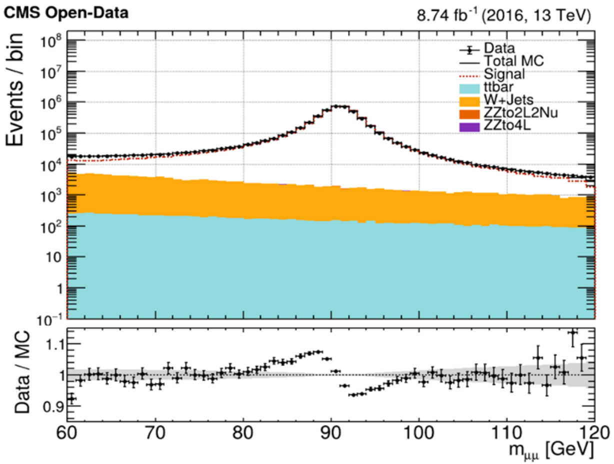
Best-fit μ = 0.902525 ± 0.000448
β1 = 1.2007 ± 0.0984
β2 = 0.7320 ± 0.0073
β3 = 0.9453 ± 0.1011
β4 = 0.9773 ± 0.1008
```

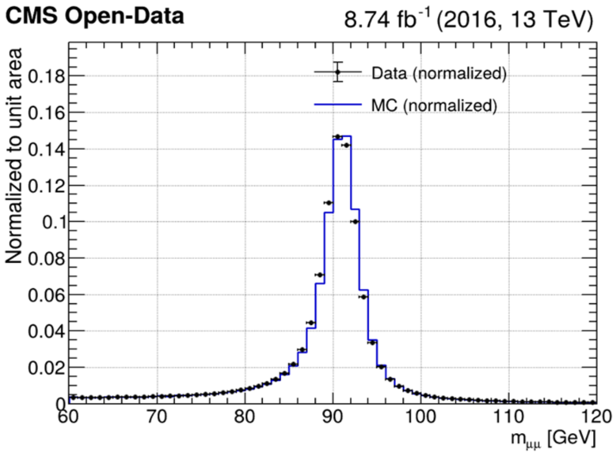


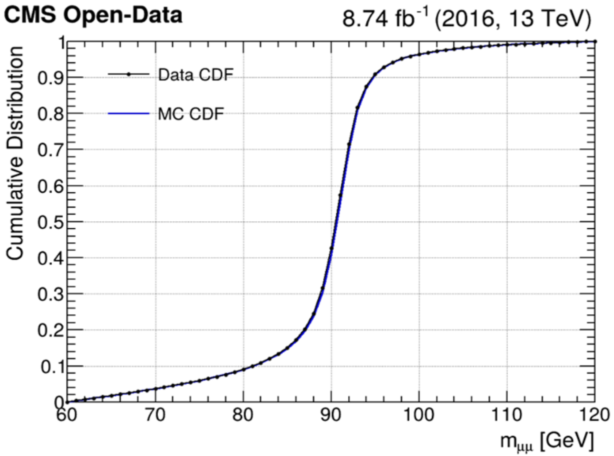


Allowing μ_s to float improves the overall shape agreement, but residual mismatch near Z-mass remains — hinting at small shape bias

Post-fit Validation : KS Test







Kolmogorov-Smirnov Test Results

Analysis window: [60.0, 120.0] GeV

KS statistic D = 0.01871

Asymptotic p-value = 0

Signal strength: μ_{sig} = 0.9025

Background scales: β = [1.201, 0.732, 0.945, 0.977]

- **KS test after fit:**
- D = 0.0187, p = 0 → Data and MC still not statistically compatible
- Agreement improved but not perfect → likely due to **mass-scale or shape modeling differences**

Shape Adjustment — 12 % Left Shift of Signal Template

[Testing possible mass-scale bias around Z peak]

Goal: Investigate whether a small **mass-scale bias** in simulation can explain the Data–MC shape mismatch.

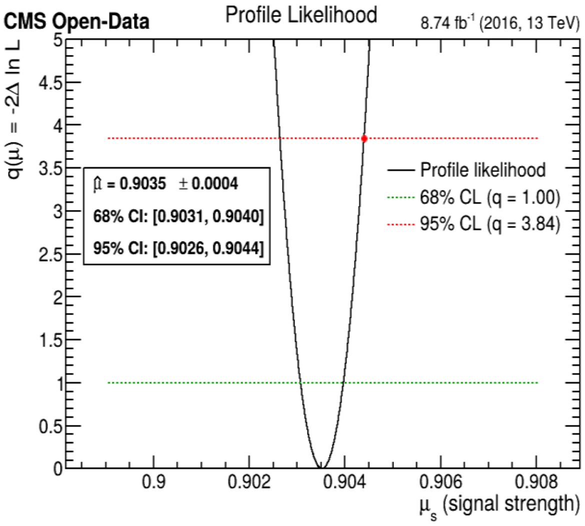
Approach:

- Shift the **signal template** by 12 % toward lower mass
- Keep backgrounds **Gaussian-constrained** (σ = 10 %)
- Allow $\boldsymbol{\mu_s}$ (signal strength) to float freely

Interpretation:

- Fit quality improved compared to nominal
- KS test shows better Data–MC compatibility

Result: Applying a 12 % left shift aligns the Z peak and improves both fit and Data–MC consistency.

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Fitting
====================================

Best-fit μ = 0.903537 ± 0.000448
β1 = 1.2667 ± 0.0986
β2 = 0.7060 ± 0.0073
β3 = 0.9445 ± 0.1011
β4 = 0.9465 ± 0.1009
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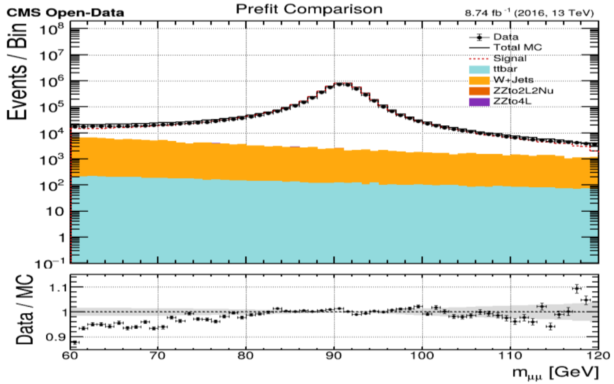
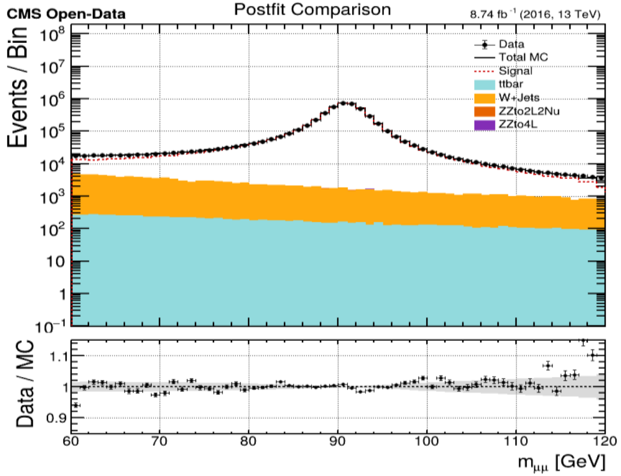
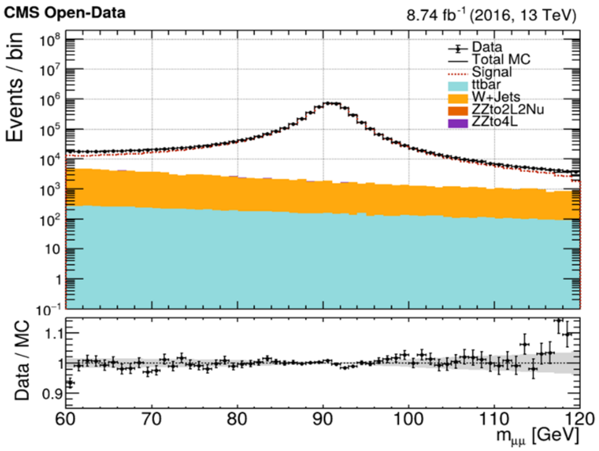
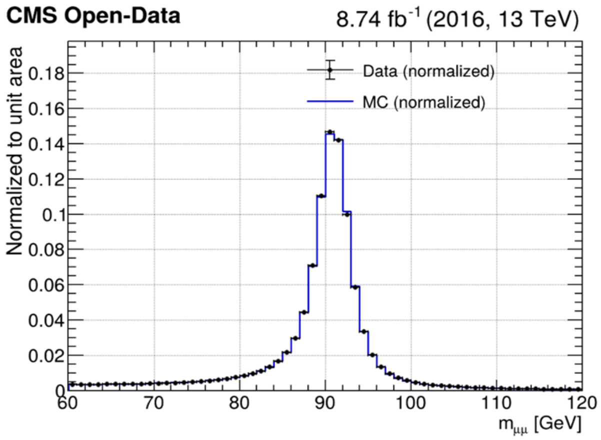
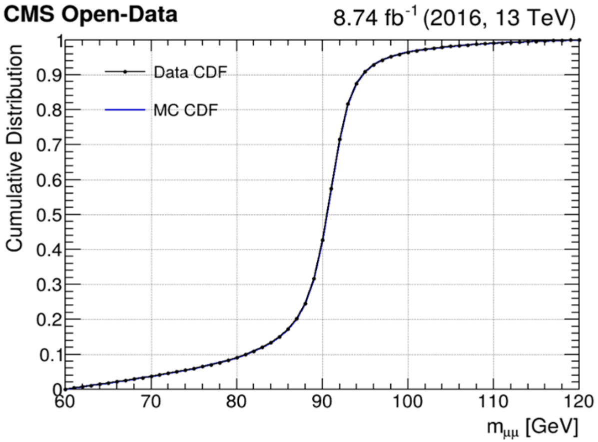




Post-fit Validation — Improved Data–MC Agreement







Kolmogorov-Smirnov Test Results

Analysis window: [60.0, 120.0] GeV

KS statistic D = 0.00141

Asymptotic p-value = 0.047568

Signal strength: μ_{sig} = 0.9035

Background scales: β = [1.267, 0.706, 0.945, 0.947]

- The **KS p-value rises from ≈ 0 → 0.05**, confirming better shape consistency.
- Indicates a small **mass-scale mismatch** between Data and MC — corrected by shifting signal.

After shape adjustment, Data and MC are statistically consistent within 5 % level.

Unconstrained Background Fit

Goal : Test whether freeing background normalizations can improve the overall fit and Data–MC agreement.

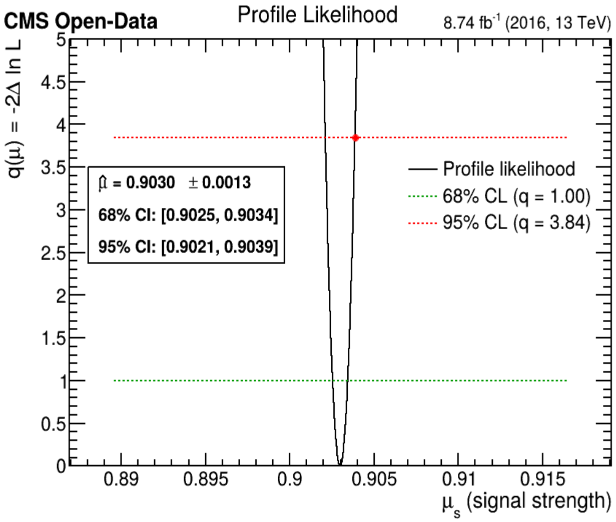
Setup:

- Backgrounds $\beta_{1,2,3,4}$ allowed to float (some unconstrained, some with 10% prior)
- Signal strength μ_s **free to float**

Interpretation:

- Fit still converges near $\mu_s \approx 0.90$
- Uncertainty increases as expected
- Backgrounds adjust within reasonable physical range
- Expect further KS improvement

Result: Letting background yields float freely improves shape flexibility and slightly enhances post-fit agreement, without biasing μ_s.

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Building RooFit model (generalized background constraints)
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Constraint: bkg1 is FREE (no Gaussian).
Constraint: bkg2 is FREE (no Gaussian).
Constraint: bkg3 constrained with Gaussian σ = 0.100
Constraint: bkg4 constrained with Gaussian σ = 0.100

==============================================================
Fitting (μ profiled; selected backgrounds free)
==============================================================

Best-fit μ = 0.903696 ± 0.001341
β1 = 0.0000 ± 4.9656  [FREE]
β2 = 0.7574 ± 0.0584  [FREE]
β3 = 0.9478 ± 0.0543  [Gauss 10%]
β4 = 0.9501 ± 0.0548  [Gauss 10%]
μ^(MINOS) = 0.902992  -0.000449 +0.000447
```
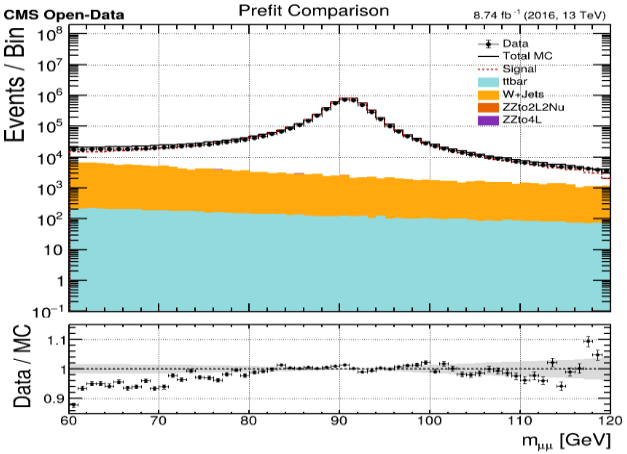
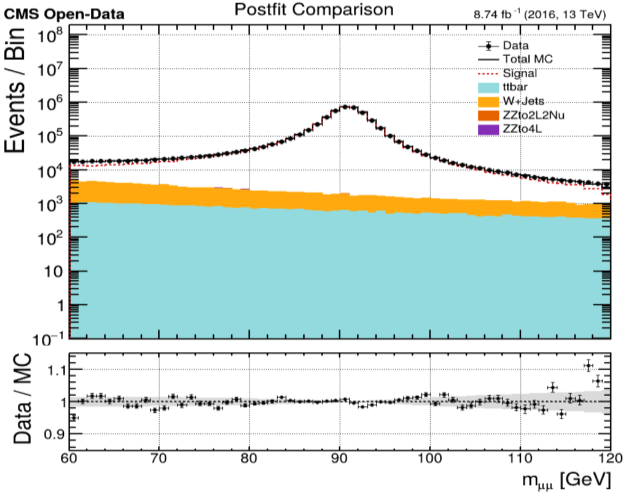
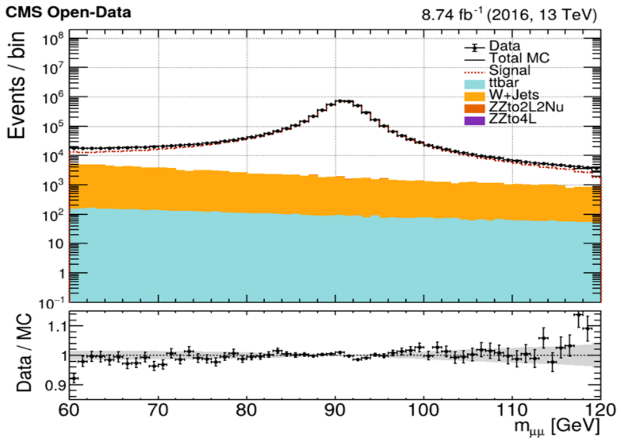
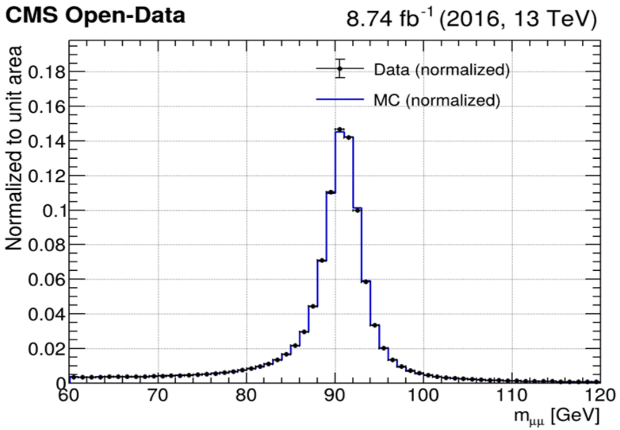
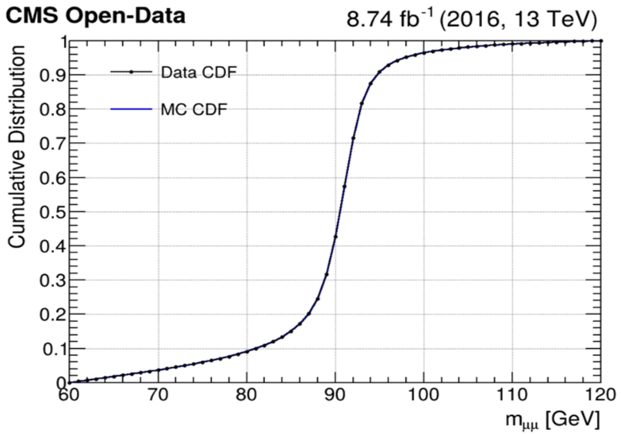





Post-fit Validation — Improved Data–MC Agreement







Kolmogorov-Smirnov Test Results

Analysis window: [60.0, 120.0] GeV

KS statistic D = 0.00133

Asymptotic p-value = 0.073074

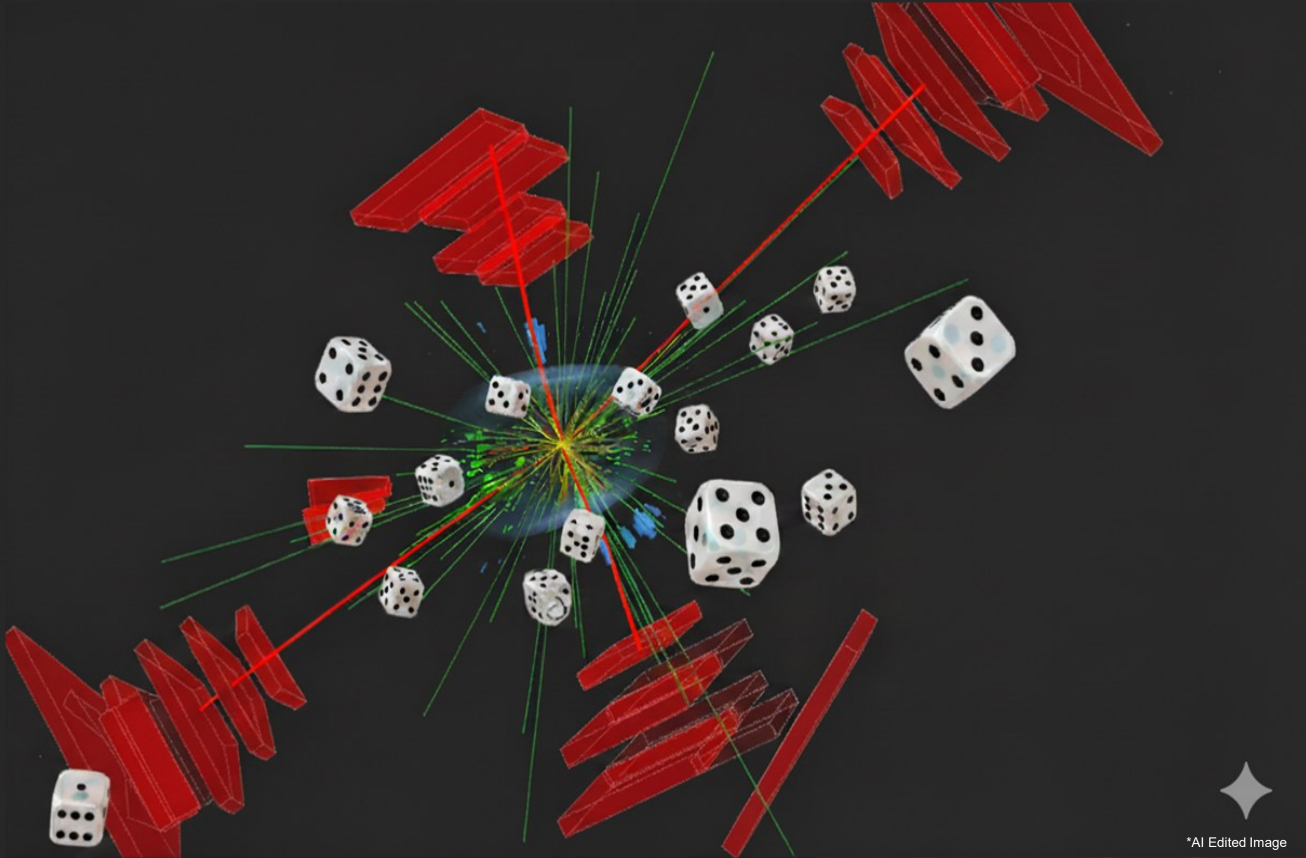
Signal strength: μ_{sig} = 0.9037

Background scales: β = [0.742, 0.757, 0.948, 0.950]

- Data–MC shape compatibility further improved (p-value from 0.048 → 0.073).
- Confirms that allowing background flexibility helps fine-tune modeling differences.
- μ_s remains stable → fit is statistically reliable.

With unconstrained backgrounds, Data and MC are statistically consistent and stable around $\mu_s \approx 0.90$.

Systematics Estimation



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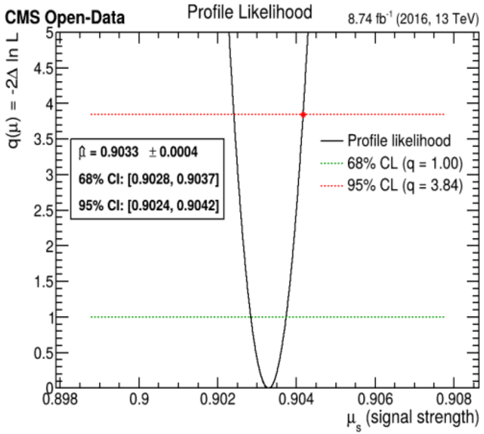
Shape Systematics (Morphing)

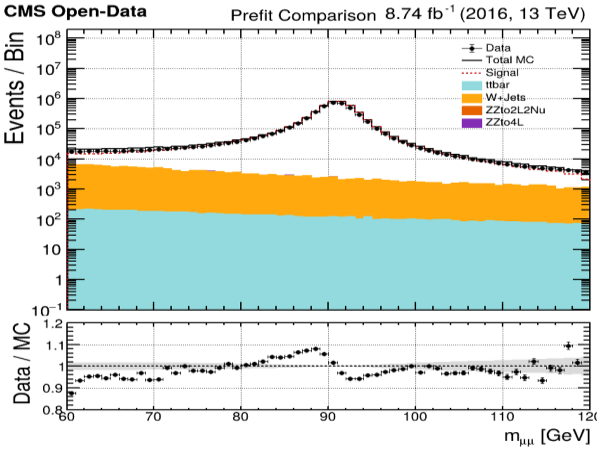
- **Goal: Quantify residual shape uncertainty in the signal using morphing** between the nominal and shifted templates.

- **Concept:** The **morphed shape** is built as a linear combination of nominal and shifted templates:
  - $\boldsymbol{h_{morphed} = \alpha \cdot h_{nominal} + (1 - \alpha) \cdot h_{alternate}}$
  - $\boldsymbol{\alpha = \frac{1}{2}[1 + \tanh(k\theta)]}$ controls the deformation strength.

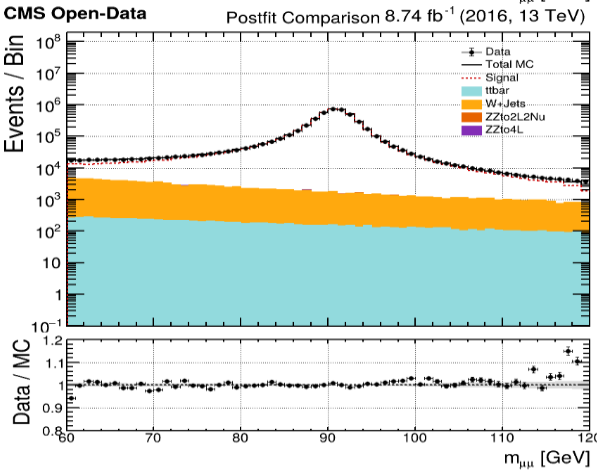
- It captures possible detector or modeling biases that shift or skew the signal shape.

Result : Applying a 12 % left shift aligns the Z peak and improves both fit and Data–MC consistency.

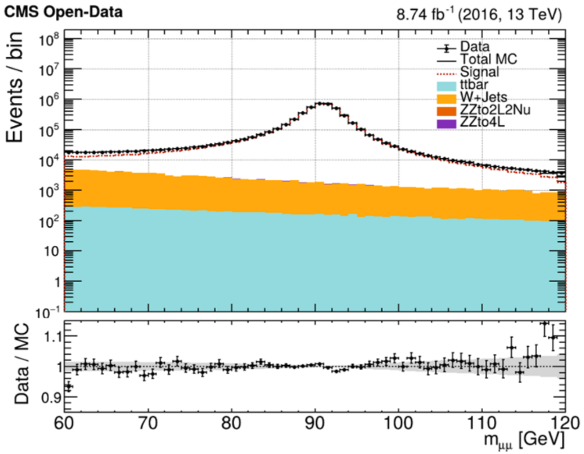


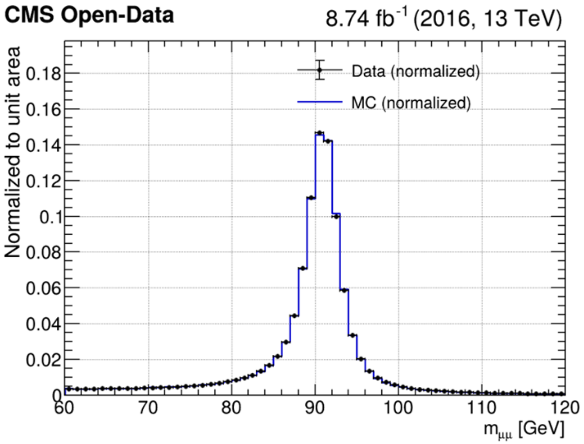


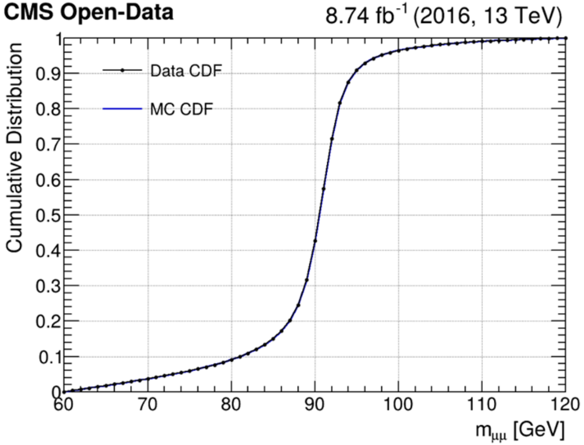

```
================================================================
Building RooFit model with RooWorkspace
================================================================

Applying shape systematics to: ['sig']
  - Creating morphed PDF for 'sig'

Model constructed with 4 rate constraints and 1 shape constraints

================================================================
Fitting
================================================================

Best-fit μ = 0.903262 ± 0.000448
β1 = 1.3035 ± 0.0982
β2 = 0.7035 ± 0.0073
β3 = 0.9450 ± 0.1011
β4 = 0.9402 ± 0.1010

================================================================
Verbose morphing summary per component
================================================================

--- Morphing summary (per component) ---

Component: sig
  Morphing: YES
  θ_sig = -0.3120 ± 0.0144  (Gaussian prior N(0,1))
  κ = 1.000
  tanh(κ·θ) = -0.302253  →  α = 0.5*(1 + -0.302253) = 0.348874
  Mix:       34.89% nominal  +  65.11% alternate
  pdf_morph = 0.349 · pdf_nom  +  0.651 · pdf_alt
  (alt template used: h_sig_alt)

Component: bkg1
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Component: bkg2
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Component: bkg3
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Component: bkg4
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate
```



Post-fit Validation — KS Test with Shape Morphing







Kolmogorov-Smirnov Test Results

Analysis window: [60.0, 120.0] GeV

KS statistic D = 0.00145
Asymptotic p-value = 0.038323

Signal strength: μ_{sig} = 0.9034
Background scales: β = [1.321, 0.704, 0.941, 0.956]

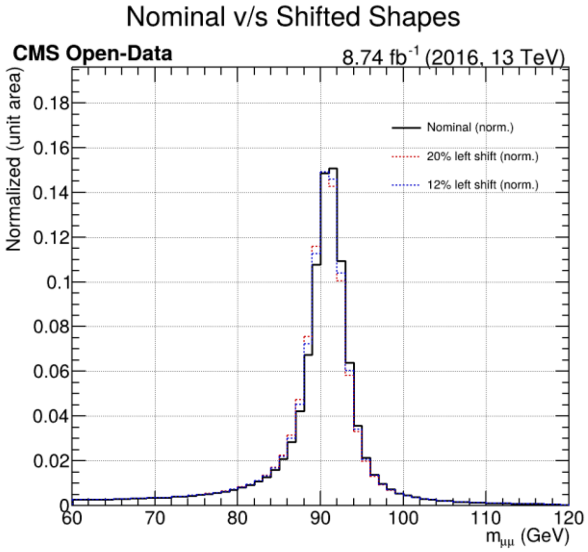
Toy MC
(N_{toys} =

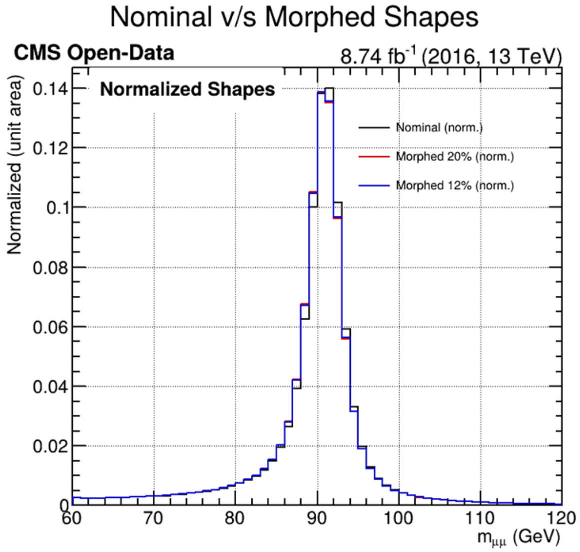
No morphing : D = 0.0187, p = 0
No morphing but shift applied: D = 0.00141, p = 0.046
With morphing: D = 0.00145, p = 0.038

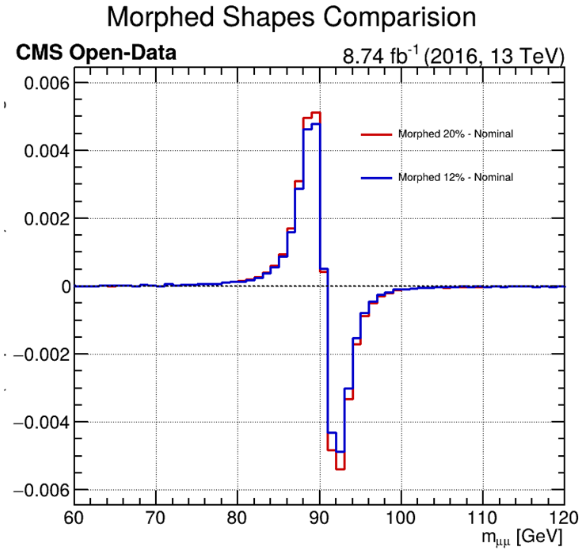
Slight improvement → residual shape mismatch absorbed.

Morphing captures small residual shape systematics, leading to marginally better Data–MC consistency without altering μ_s.

Visualizing Morphing







Nominal vs shifted templates show the Z-peak movement.

Morphed shapes interpolate smoothly between them.

Difference plots confirm that morphing introduces only minimal distortion, very less.

Morphing provides a smooth, data-driven way to incorporate shape uncertainties into the fit. It bridges between the nominal and shifted signal templates, allowing the fit to marginalize over realistic shape variations.

Final Signal-Strength Estimate

- The key message: **$\hat{\mu_s}$ ≈ 0.903 ± 0.001 is consistent across all configurations.**
- The Data–MC compatibility steadily improves, demonstrating that our modeling corrections genuinely fix the shape discrepancy.

Fit Configuration	**$\hat{\mu_s}$ ± Δμ**	**KS D**	**KS p-value**	**Comment / Observation**
Constrained Backgrounds (baseline)	0.9025 ± 0.0004	0.0716	≈ 0.00	Poor shape match, MC Z-peak slightly off
12 % Shifted Signal	0.9035 ± 0.0004	0.00141	0.048	Better alignment around Z-peak
Unconstrained Backgrounds (robustness)	0.9037 ± 0.0013	0.00133	0.073	Background flexibility improves fit
Morphing (shape systematics included)	0.9033 ± 0.0004	0.00145	0.038	Residual mismatch absorbed by morphing

Discussion & Takeaways

To wrap up :

- $Z \rightarrow \mu\mu$ serve as a good benchmark for validation of detector calibration and MC modelling
- The **KS test** offers a shape-level diagnostic, complementing likelihood-based fits.
- Step-wise modeling : from constraints → shift → morphing :: **systematically improves Data–MC agreement.**
- The final μ_s result is robust to statistical and systematic choices.
- And this same workflow extends naturally to **more complex analyses**, from precision measurements to new-physics searches.
- **In essence:** we've shown that careful statistical modelling — including both rate and shape systematics — can turn a simple benchmark process into a powerful validation tool for high-energy-physics analyses.
- **Combining shape tests and likelihood fits provides a complete, data-driven validation of Monte Carlo models — an essential step for precision and discovery analyses.**

My extra learnings:

- I learned to use *brilcalc* and *golden JSON* and *normtag* files to calculate the luminosity
- Learned about the *RooFit*, and *RooStat* etc fitting modules
- Leaned about the usage of Open-Data

Comments, Questions?

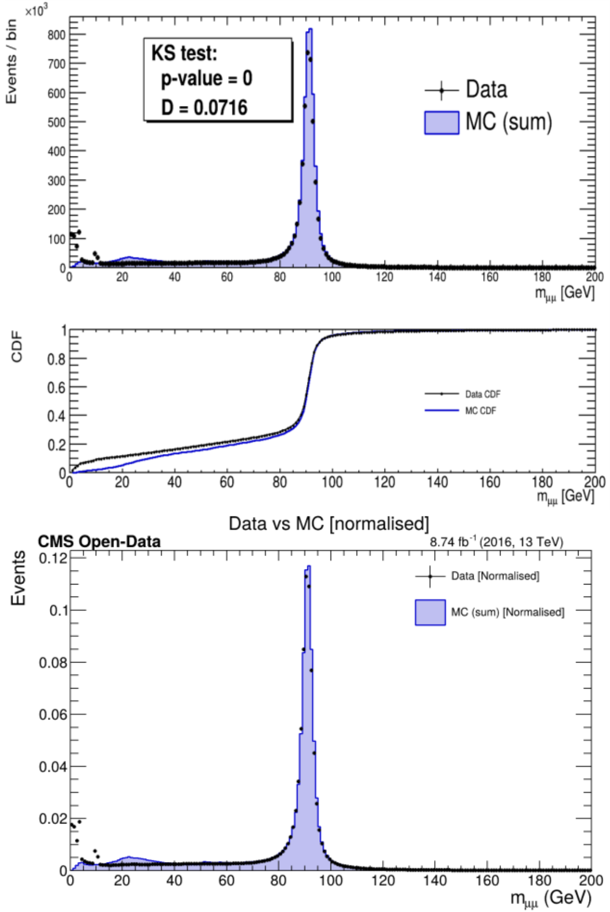
Thank you !!

Back-up

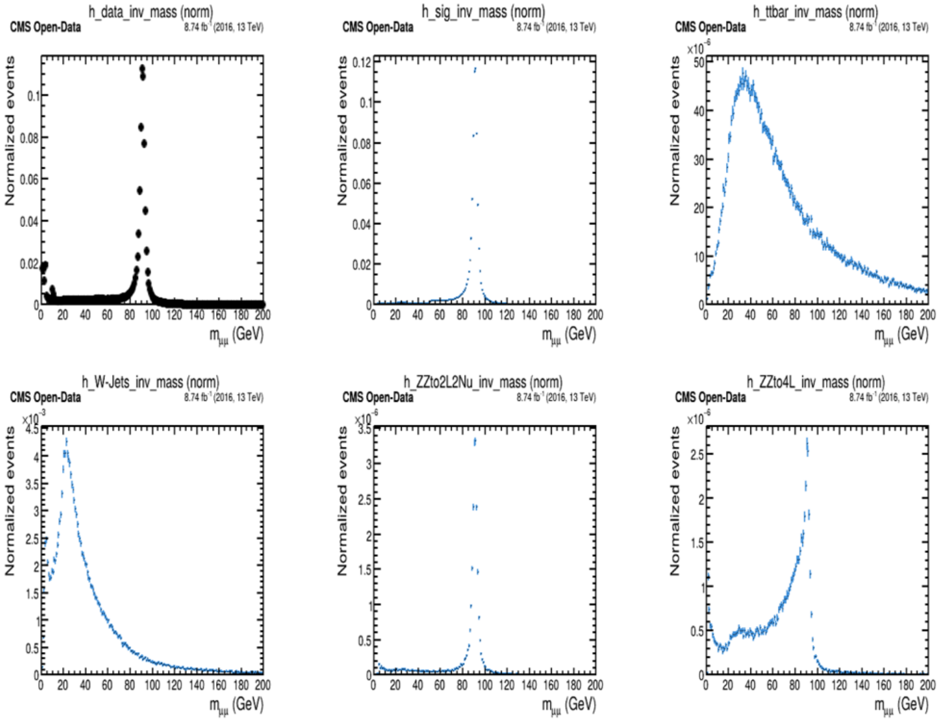
Data–MC Comparison: Kolmogorov–Smirnov (K-S) Test

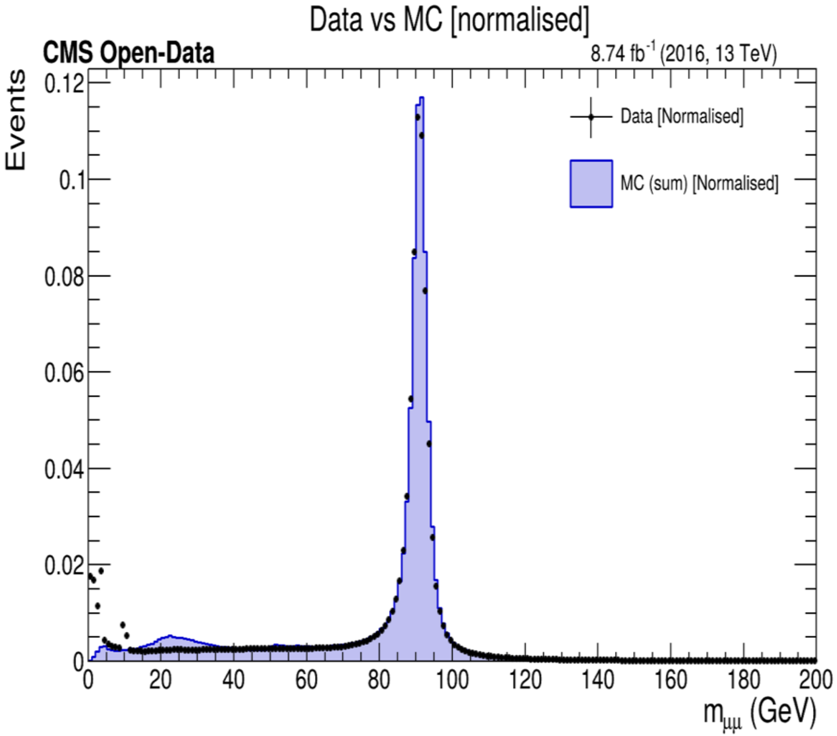
A **non-parametric statistical test** used to compare **two probability distributions** ⇒ Draws conclusion whether those **two PDFs** are drawn from the same underlying distribution or not.

- The test is based on **empirical cumulative distribution functions (ECDFs)**.
- For each PDF, the ECDF is given by : $\boldsymbol{F_n(x) = \frac{Number\ of\ data\ points \le x}{Total\ number\ of\ points: n}}$
- KS Test Statistics : $\boldsymbol{D = \sup_x [F_n(x) - F_m(x)] = \sup_x [F_{Data}(x) - F_{MC}(x)]}$ i.e, the largest vertical distance b/w 2 CDFs
- Effective sample size : $\boldsymbol{N_{eff} = \frac{nm}{n+m}}$, but our \`Data\` is unweighted but the \`MC\` is weighted (not integer sample size). So, $\mathbf{n_{MC}} = \frac{(\sum_j w_j)^2}{\sum_j w_j^2}$, then $\boldsymbol{n = n_{Data}}$ and $\boldsymbol{m = n_{MC}}$
- P-value [asymptotically ; large n] : $\boldsymbol{p \approx Q_{KS}(\lambda) = 2 \sum_{k=1}^{\infty} (-1)^{k-1} e^{-2k^2\lambda^2}}$ where $\boldsymbol{\lambda = \sqrt{N_{eff}}\, D}$
- So, if p=value is very low (→ 0), then samples drawn from different distributions OR, if p-value ≥ **0.05 (!!!),** then samples are consistent to each other.
- Non-parametric, so no assumption about the form of distribution
- Sensitive to difference in both **location (mean shift**) and **shape (skew)**
- **Used check Data-Monte Carlo agreement for generators and detector simulation validation**
- **Comparison between different unfolding methods.**

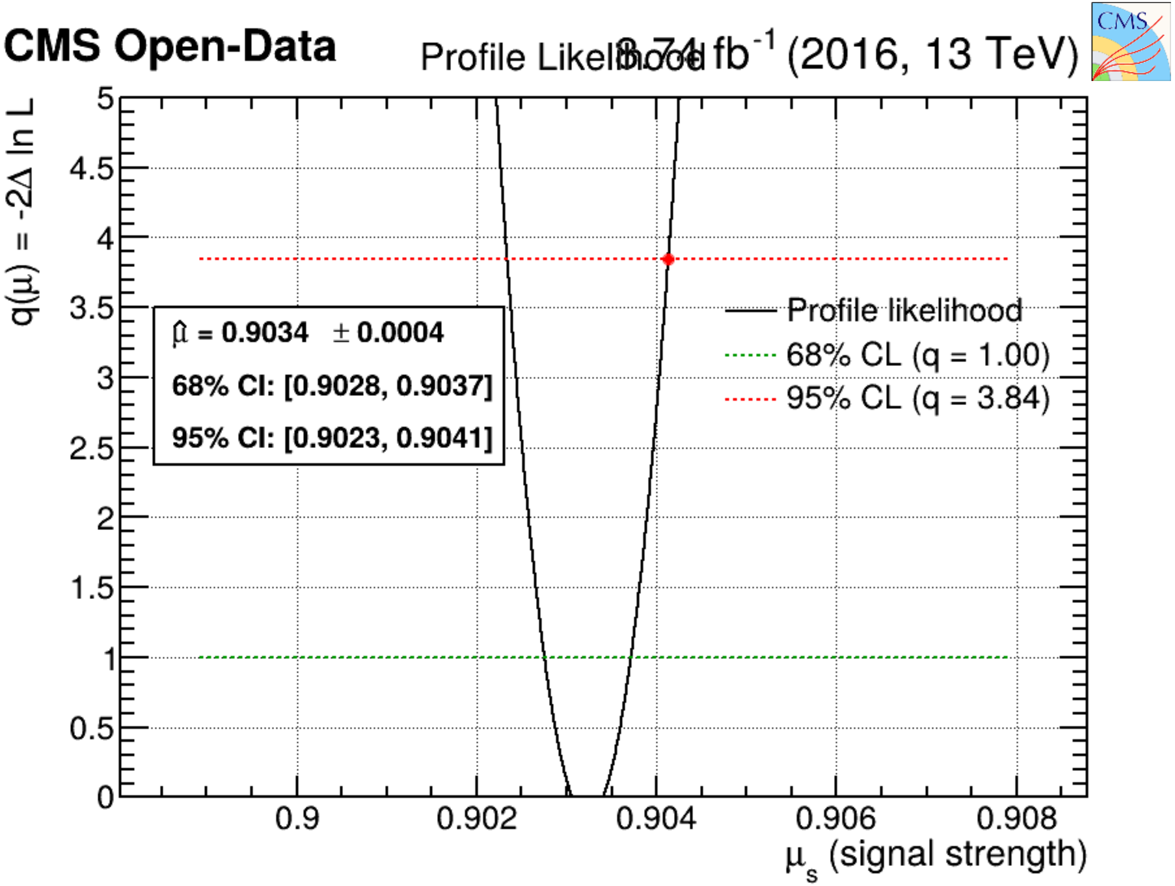


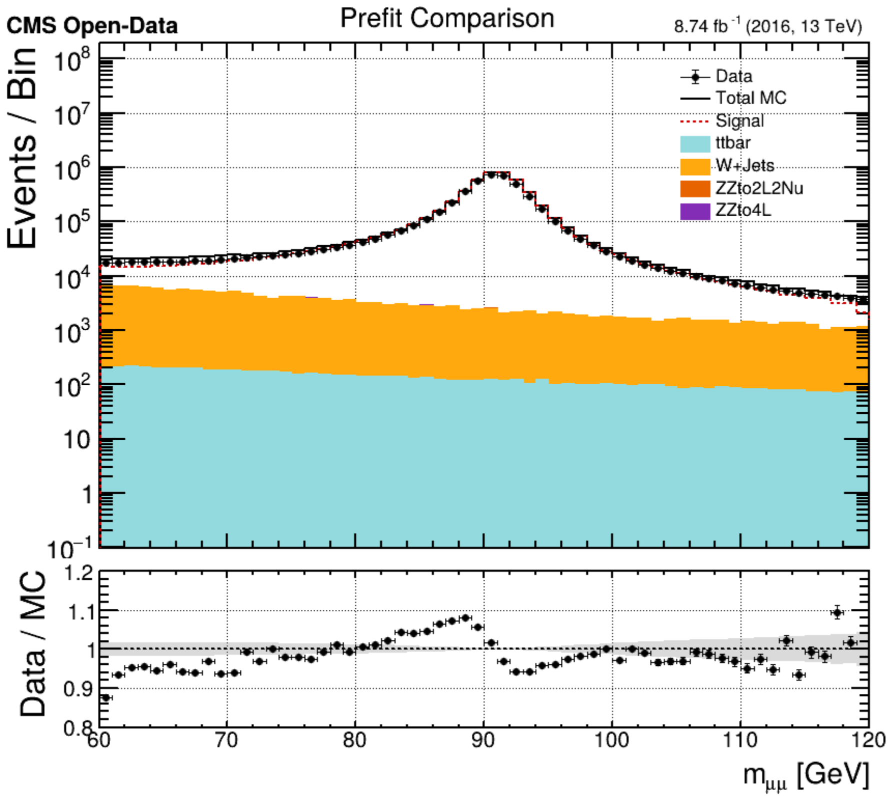
Shape Systematics 12% left shift


h_data_inv_mass (norm)
CMS Open-Data
8.74 fb⁻¹ (2016, 13 TeV)
Normalized events
m_μμ (GeV)
h_sig_inv_mass (norm)
h_ttbar_inv_mass (norm)
h_W-Jets_inv_mass (norm)
h_ZZto2L2Nu_inv_mass (norm)
h_ZZto4L_inv_mass (norm)

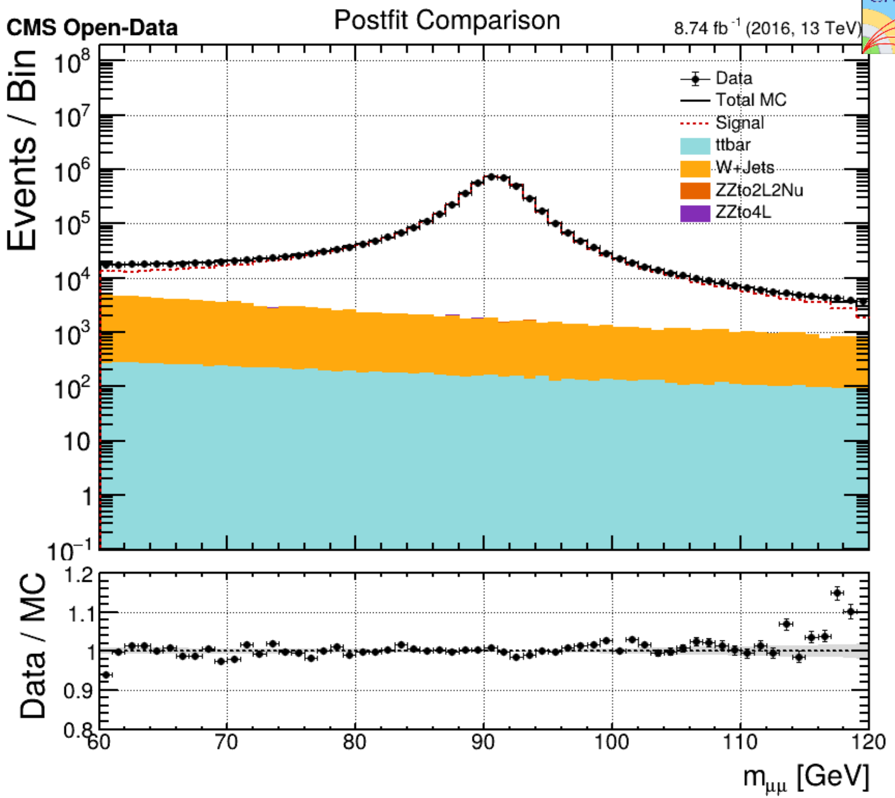

Data vs MC [normalised]
CMS Open-Data
8.74 fb⁻¹ (2016, 13 TeV)
Events
Data [Normalised]
MC (sum) [Normalised]
m_μμ (GeV)

```
================================================================
Preparing histograms in window [60.0, 120.0] GeV
================================================================
Signal:             5412870.60
Background 1:          7928.12
Background 2:        173500.67
Background 3:           155.67
Background 4:           304.84
Total MC:           5594759.90
Data:               5025648.00

================================================================
Building RooFit model with RooWorkspace
================================================================

Applying shape systematics to: ['sig']
  - Creating morphed PDF for 'sig'

Model constructed with 4 rate constraints and 1 shape constraints

================================================================
Fitting
================================================================

Best-fit μ = 0.903411 ± 0.000448
β1 = 1.3215 ± 0.0977
β2 = 0.7044 ± 0.0073
β3 = 0.9410 ± 0.1012
β4 = 0.9556 ± 0.1007

================================================================
Verbose morphing summary per component
================================================================

--- Morphing summary (per component) ---

Component: sig
  Morphing: YES
  θ_sig = -3.0852 ± 0.1308  (Gaussian prior N(0,1))
  κ = 1.000
  tanh(κ·θ) = -0.995828  →  α = 0.5*(1 + -0.995828) = 0.002086
  Mix:       0.21% nominal  +  99.79% alternate
  pdf_morph = 0.002 · pdf_nom  +  0.998 · pdf_alt
  (alt template used: h_sig_alt)

Component: bkg1
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Component: bkg2
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Component: bkg3
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Component: bkg4
  Morphing: NO
  Using:   100.0% nominal, 0.0% alternate

Yields (scale parameters):
  μ (signal strength) = 0.903411 ± 0.000448
  β1 = 1.3215 ± 0.0977  (10% Gaussian prior)
  β2 = 0.7044 ± 0.0073  (10% Gaussian prior)
  β3 = 0.9410 ± 0.1012  (10% Gaussian prior)
  β4 = 0.9556 ± 0.1007  (10% Gaussian prior)

Shape nuisance parameters:
  θ_sig = -3.0852 ± 0.1308

================================================================
Computing profile likelihood
================================================================

68% CI: [0.902757, 0.903718]
95% CI: [0.902342, 0.904132]
[postfit] bins with data>0 and MC==0: 140
 first few: [(61, 17463.0, 0.0), (62, 17634.0, 0.0), (63, 17934.0, 0.0), (64, 18029.0, 0.0), (65, 18099.0, 0.0)]

================================================================
```





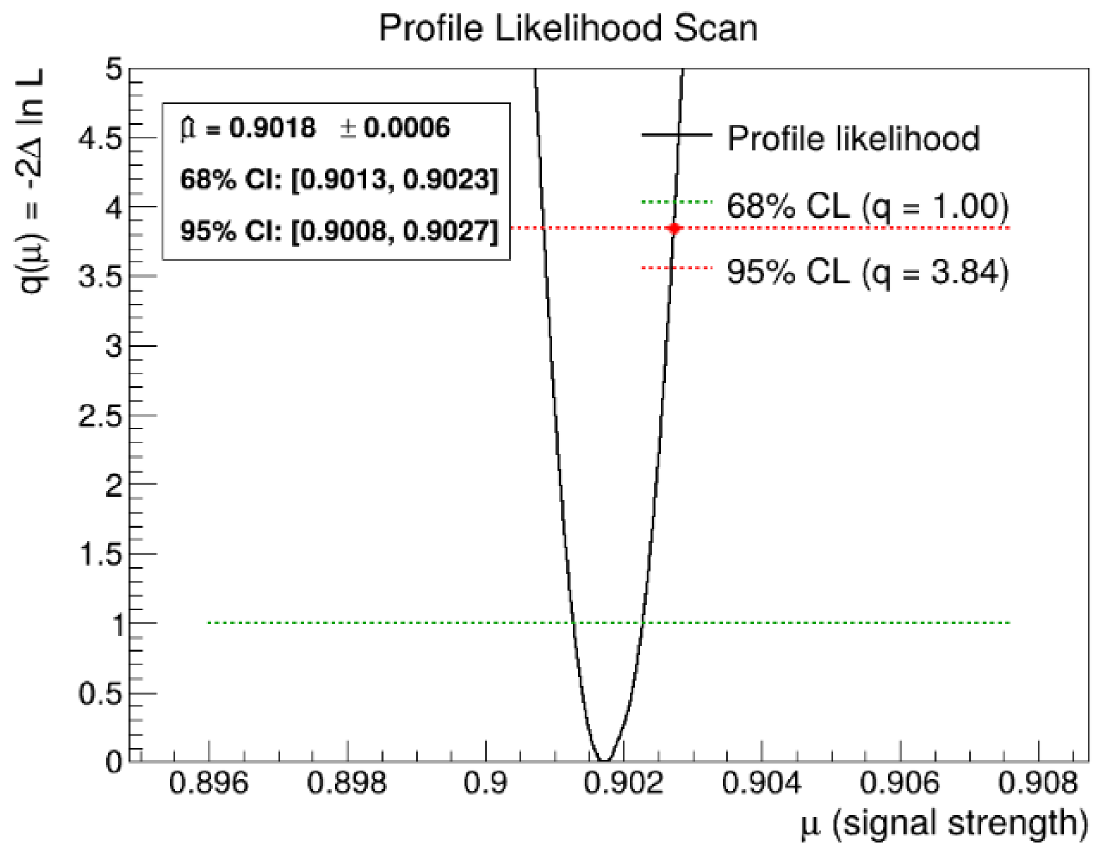
CMS Open-Data
Prefit Comparison
8.74 fb^{-1} (2016, 13 TeV)
Events / Bin
Data
Total MC
Signal
ttbar
W+Jets
ZZto2L2Nu
ZZto4L
Data / MC
$m_{\mu\mu}$ [GeV]

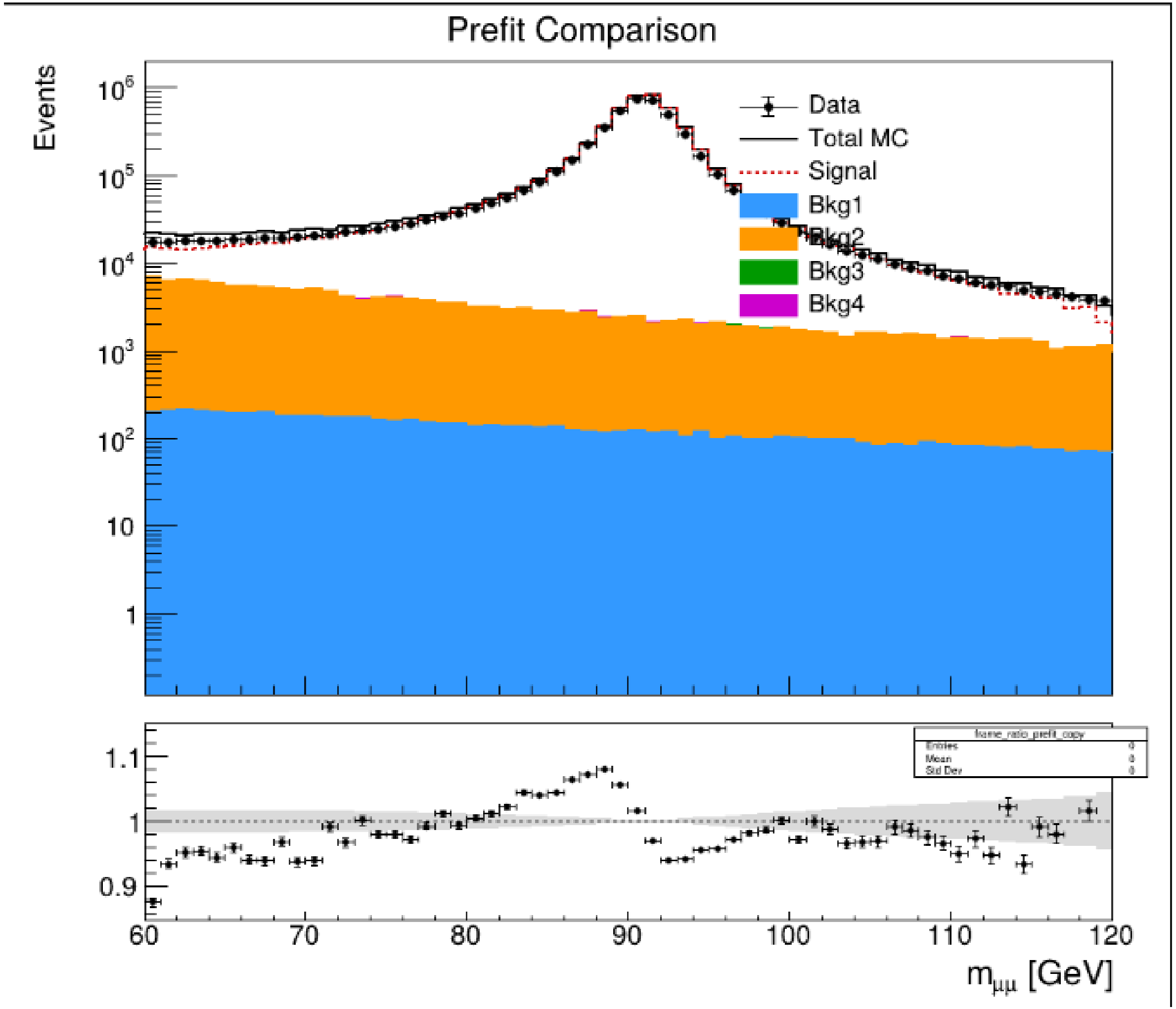


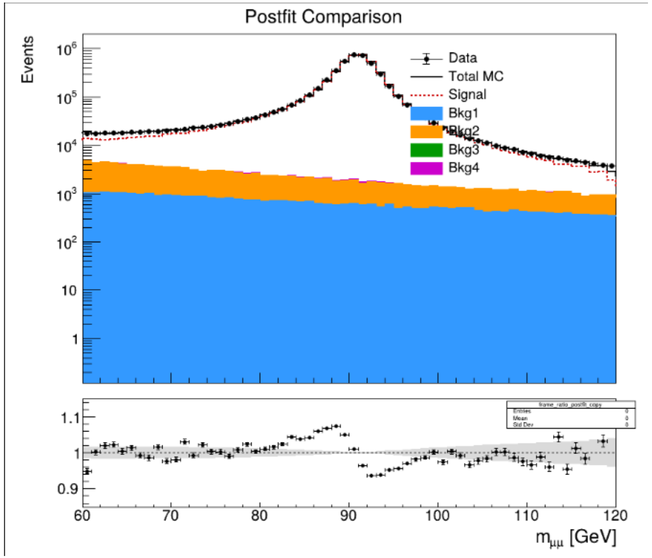
CMS Open-Data
Postfit Comparison
8.74 fb^{-1} (2016, 13 TeV)
Events / Bin
Data
Total MC
Signal
ttbar
W+Jets
ZZto2L2Nu
ZZto4L
Data / MC
$m_{\mu\mu}$ [GeV]

beta_k without any shift

```
===========================================================
Preparing histograms in window [60.0, 120.0] GeV
===========================================================
Signal:              5412870.60
Background 1:           7928.12
Background 2:         173500.67
Background 3:            155.67
Background 4:            304.84
Total MC:            5594759.90
Data:                5025648.00

===========================================================
Building RooFit model (generalized background constraints)
===========================================================
Constraint: bkg1 is FREE (no Gaussian).
Constraint: bkg2 is FREE (no Gaussian).
Constraint: bkg3 is FREE (no Gaussian).
Constraint: bkg4 is FREE (no Gaussian).

===========================================================
Fitting (μ profiled; selected backgrounds free)
===========================================================

Best-fit μ = 0.901779 ± 0.000579
β1 = 5.0000 ± 0.0592  [FREE]
β2 = 0.5723 ± 0.0083  [FREE]
β3 = 3.5535 ± 2.9430  [FREE]
β4 = 5.0000 ± 0.2167  [FREE]

===========================================================
Computing profile likelihood
===========================================================

68% CI: [0.901273, 0.902276]
95% CI: [0.900845, 0.902726]

===========================================================
Done! Four plots created:
  1. Profile likelihood scan
  2. RooFit postfit
  3. Prefit comparison with ratio
  4. Postfit comparison with ratio
===========================================================
```




Prefit Comparison
Events
Data
Total MC
Signal
Bkg1
Bkg2
Bkg3
Bkg4
frame_ratio_prefit_copy
Entries 0
Mean 0
Std Dev 0
$m_{\mu\mu}$ [GeV]


Postfit Comparison
Events
Data
Total MC
Signal
Bkg1
Bkg2
Bkg3
Bkg4
$m_{\mu\mu}$ [GeV]

```
[KSTestTool] Canvas saved to cKS_postfit.png
Info in <TCanvas::Print>: png file cKS_postfit.png has been created
```