Search for a resonance decaying to HH with WWγγ final state with CMS Run 2 data

CMS PAS B2G-24-010

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Introduction & Motivation

Why X → HH ?

Many BSM theories predict new resonances (X) decaying to HH pairs:

- Warped Extra Dimensions: spin-0 radion, spin-2 bulk graviton
- Extended Higgs sectors: heavy Higgs → HH

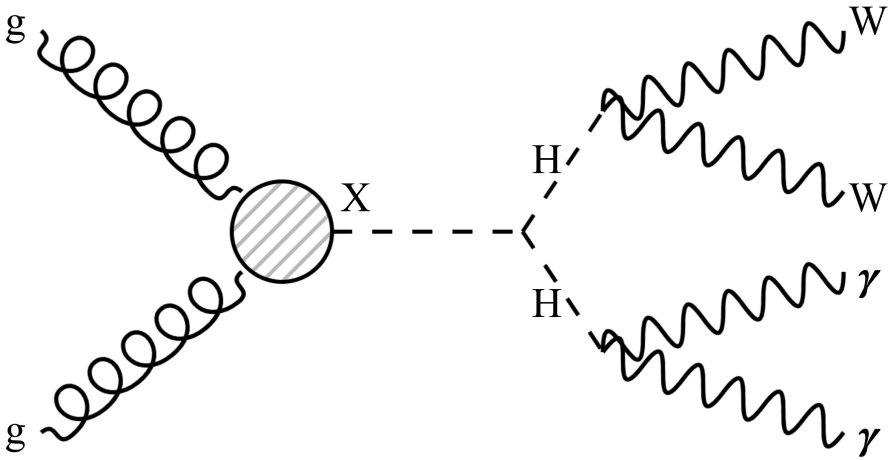
Why WWγγ final state ?

H→WW: second-largest Higgs branching fraction (~21%)

H→γγ: excellent mass resolution (~1–2%), high selection efficiency

This analysis: first CMS search for X → HH → WWγγ

- Dominant WW decay modes considered: fully-hadronic + semileptonic
- Mass range: 250 GeV – 3 TeV
- First LHC search in the boosted topology for this channel
- First LHC search with WW fully-hadronic decay mode in this channel



$gg \to X \to HH \to WW\gamma\gamma$

May induce substantial deviations of λ_3 and λ_4 from their SM predictions

Analysis Strategy Overview

Object Selection → $H \to \gamma\gamma$: modified EGamma photon ID for high-mass X
$H \to WW$: ParticleNet/ParT taggers; Hbb veto for orthogonality with $bb\gamma\gamma$

Event Categorization → 5 initial classes based on WW decay topology
Parameterized Neural Network (pNN) trained with mX as a feature
Bayesian optimization of category boundaries

Signal Modeling → Parametric fit to $m_{\gamma\gamma}$ with up to 5 Gaussians (from MC)

Background Modeling → Continuum: discrete profiling method on data sidebands
Resonant: single-Higgs modeled same as signal (from MC)

Limit Setting → Simultaneous binned ML fit across categories & years
CL_s asymptotic method with COMBINE

Dataset and MC samples

- Dataset: full Run 2 total lumi = 138 fb^{-1}
  - Diphoton triggers with leading γ p_T > 30 and subleading γ p_T > 18(22) GeV + loose calorimetric ID for 2016 (2017 and 2018) data-taking period
- Signal simulations:
  - Radion & graviton $X \rightarrow HH \rightarrow WW\gamma\gamma$, $bb\gamma\gamma$, $ZZ\gamma\gamma$, $\tau\tau\gamma\gamma$ at LO accuracy using MADGRAPH5_aMC@NLO
- Background simulations:
  - Single-Higgs (ggH, VBFH, VH, ttH): at NLO in QCD precision using MADGRAPH5 aMC@NLO
  - Non-resonant γ+Jet, $\gamma\gamma$+Jets: at LO with PYTHIA 8 and SHERPA v.2.2.1 separately, only used in the context of selection optimization and MVA classifier training
  - DY samples generated at NLO precision using MADGRAPH5 aMC@NLO, and used to derive correction factors for the energy scale, resolution, and photon selection efficiency
- PYTHIA 8 used for parton showering, hadronization, and the underlying event simulation of all signal and background samples

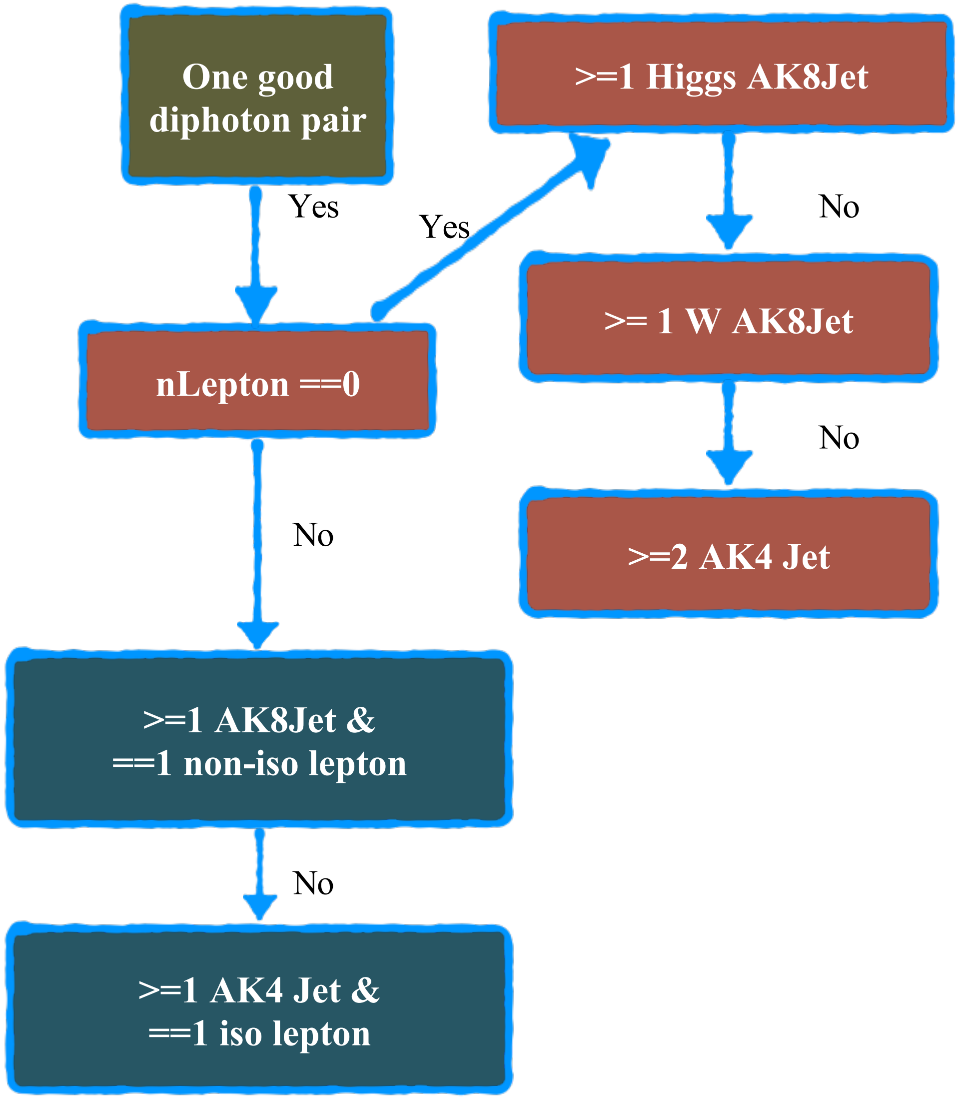
Object Selection

One good diphoton pair

$H \rightarrow \gamma\gamma$

- Photons: leading (subleading) $p_T > 35$ (25) GeV, $|\eta| < 2.5$, excluding barrel-endcap transition
- H/E, isolation cuts
- Modified EGamma photon ID to preserves efficiency for collimated photons from boosted $H \rightarrow \gamma\gamma$
- Leading γ: $p_T^{\gamma\gamma} / m_{\gamma\gamma} > 0.33$, sub-leading: > 0.25
- $100 < m_{\gamma\gamma} < 180$ GeV

Object Selection



- **Muon**
  - p_T > 10 GeV, | η | < 2.4
  - ΔR(μ,γ) > 0.4
  - $|d_{xy}|$ < 0.045 cm, $|d_z|$ < 0.2 cm
  - Isolated Muon: tight ID, I_μ < 0.15
  - Non-isolated Muon: highp_T ID, ΔR(μ,fatjet) < 0.8

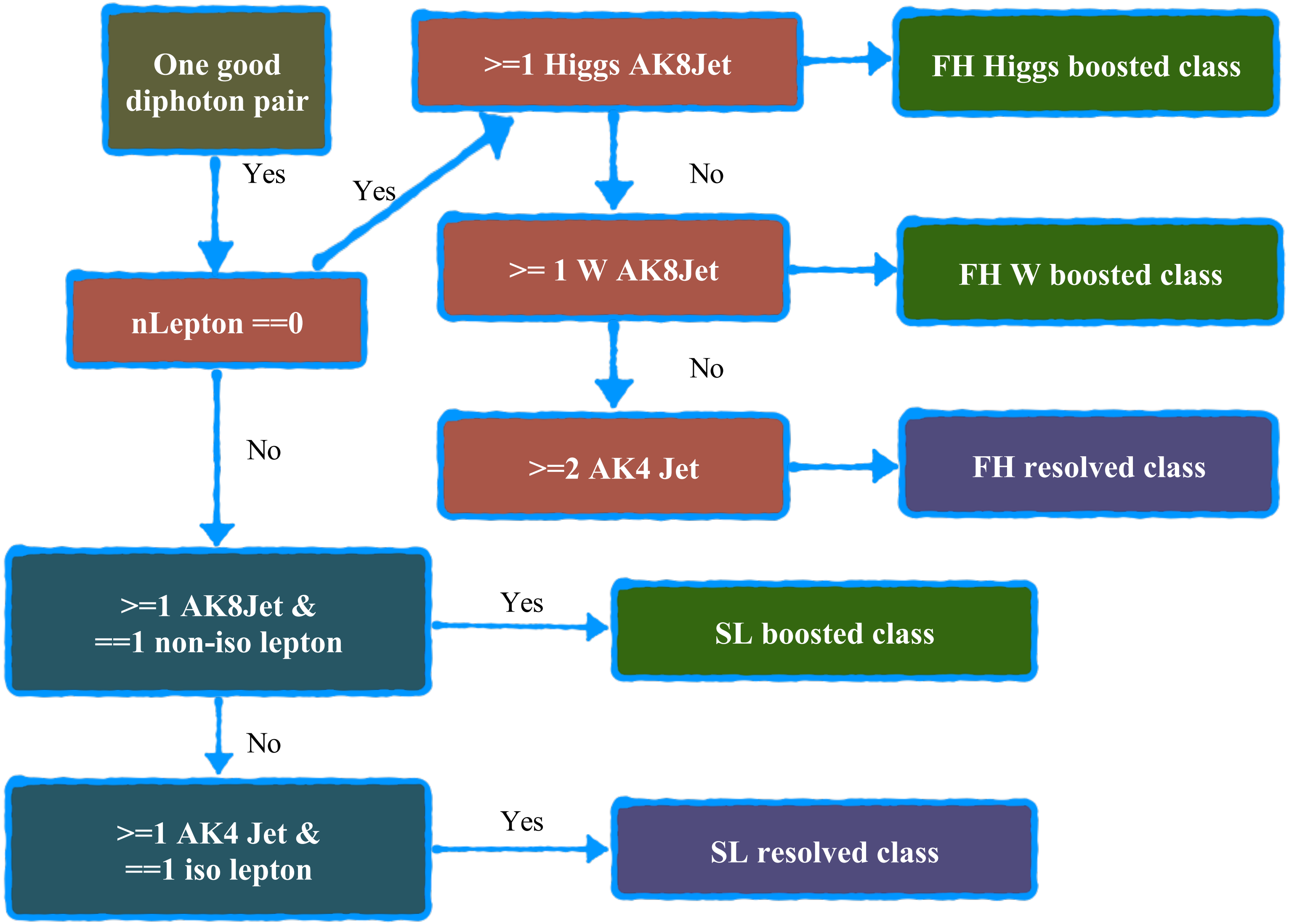
- **Electron**
  - p_T >15 GeV, | η | < 2.5 (< 1.4442 or > 1.566)
  - $|d_{xy}|$ < 0.045 cm, $|d_z|$ < 0.2 cm
  - ΔR(e,γ) > 0.4
  - Z veto: $|m_{e\gamma}$ - 91.187$|$ GeV > 5 GeV
  - Isolated Electron: mvaFall17V2Iso_WP80
  - Non-isolated Electron: mvaFall17V2noIso_WP90, ΔR(e,fatjet) < 0.8

- **AK4 Jet**
  - tight ID, tight PUID
  - p_T > 20 GeV, | η | < 2.4
  - ΔR(jet,γ) > 0.4, ΔR(jet,lep_{iso}) > 0.4

- **W AK8 Jet**
  - p_T > 100 GeV, | η | < 2.4
  - loose WP ParticleNet WvsQCD MD tagger

- **H AK8 Jet**
  - p_T > 100 GeV, | η | < 2.4
  - ParticleTransformer H_{WW} > 0.2

Event Selection



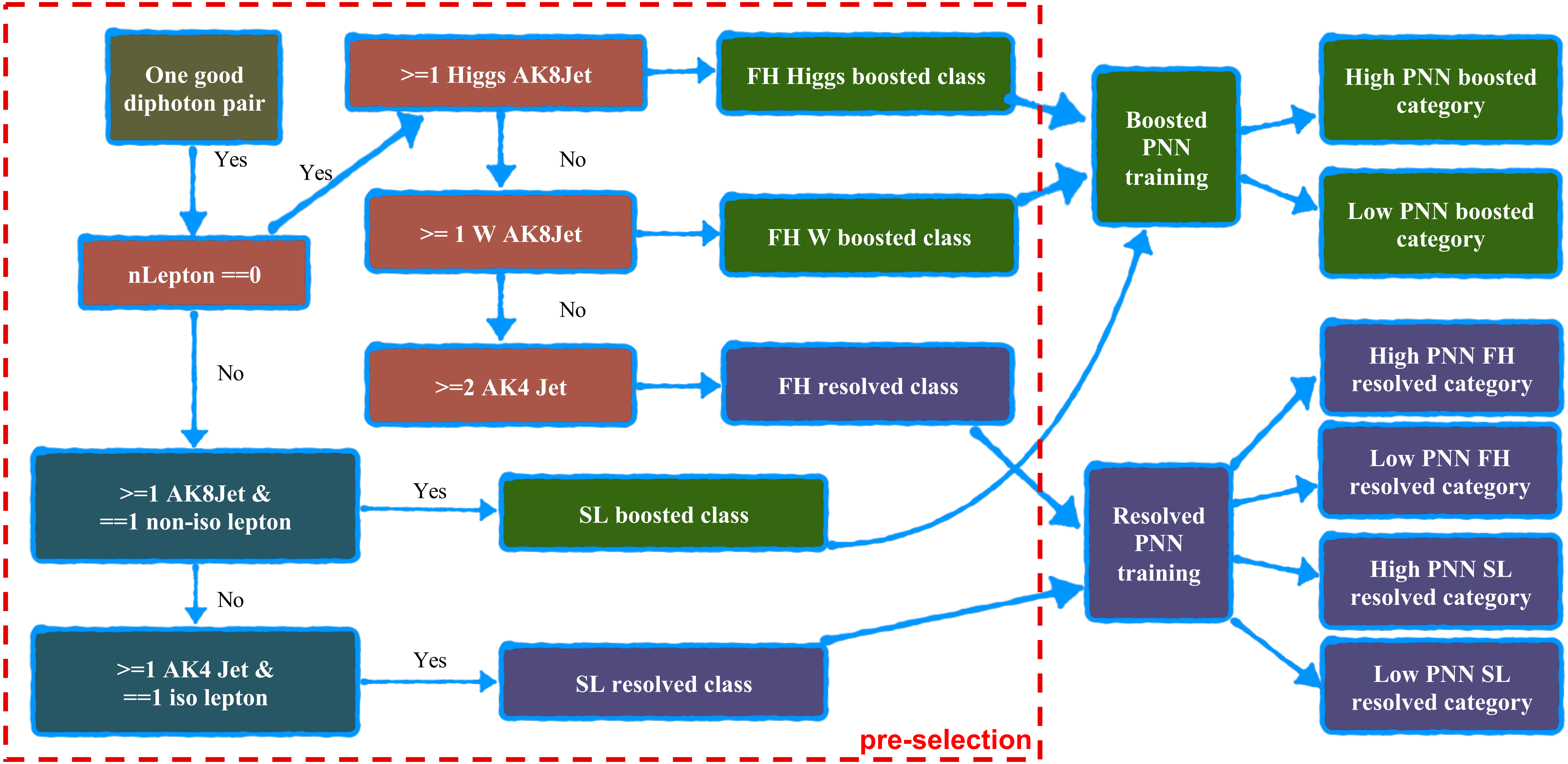
H → WW

- Fully-hadronic (FH): WW → qqqq → large-R jet (AK8, R=0.8)
  - Tagged with ParticleNet WvsQCD + ParT H→WW tagger
- Semileptonic (SL): WW → qqℓv
  - Exactly 1 lepton (e/μ), isolated or non-isolated
- H→bb veto: ParticleNet Hbb score < 0.9

  → Maintains orthogonality with bbγγ analysis; negligible impact on WWγγ
- H→WW tagger calibrated with Lund Jet Plane method

5 initial event classes: FH Higgs-like boosted | FH W-like boosted | SL W-like boosted | FH resolved | SL resolved

Event Selection



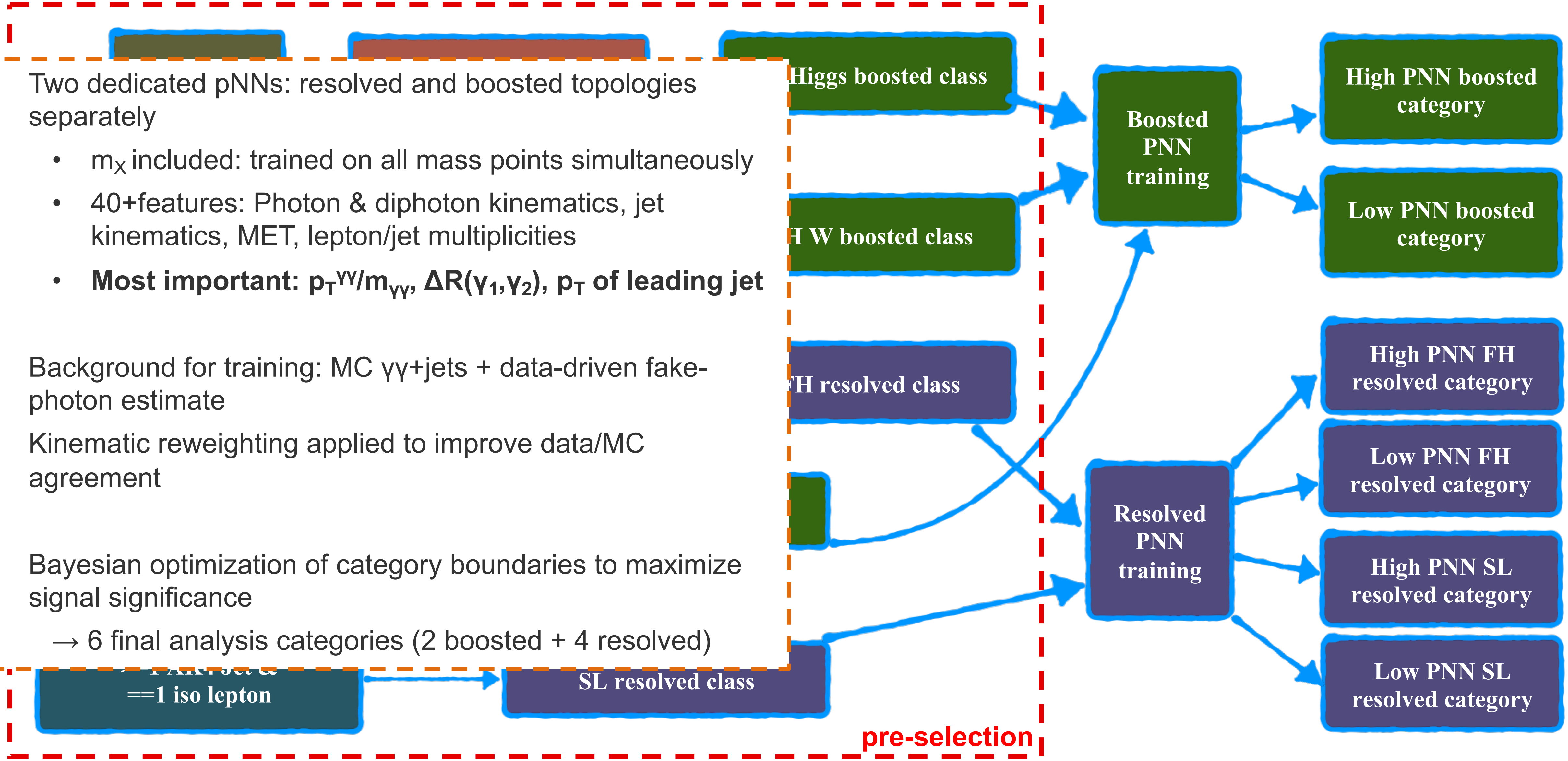
Event Categorization: Parameterized Neural Network

- Two dedicated pNNs: resolved and boosted topologies separately
  - m_X included: trained on all mass points simultaneously
  - 40+features: Photon & diphoton kinematics, jet kinematics, MET, lepton/jet multiplicities
  - **Most important: $p_T^{\gamma\gamma}/m_{\gamma\gamma}$, $\Delta R(\gamma_1,\gamma_2)$, p_T of leading jet**

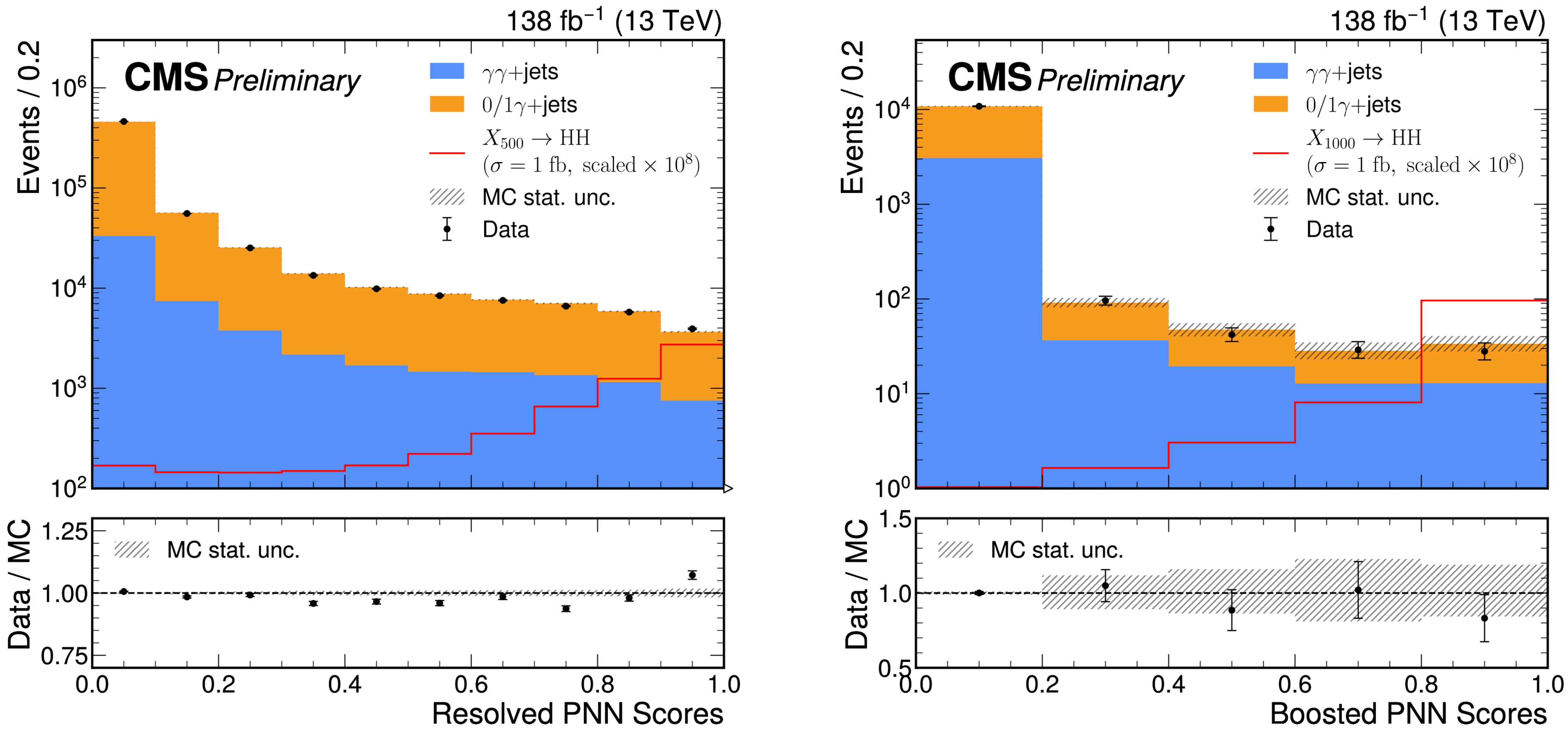
- Background for training: MC γγ+jets + data-driven fake-photon estimate
- Kinematic reweighting applied to improve data/MC agreement

- Bayesian optimization of category boundaries to maximize signal significance

  → 6 final analysis categories (2 boosted + 4 resolved)



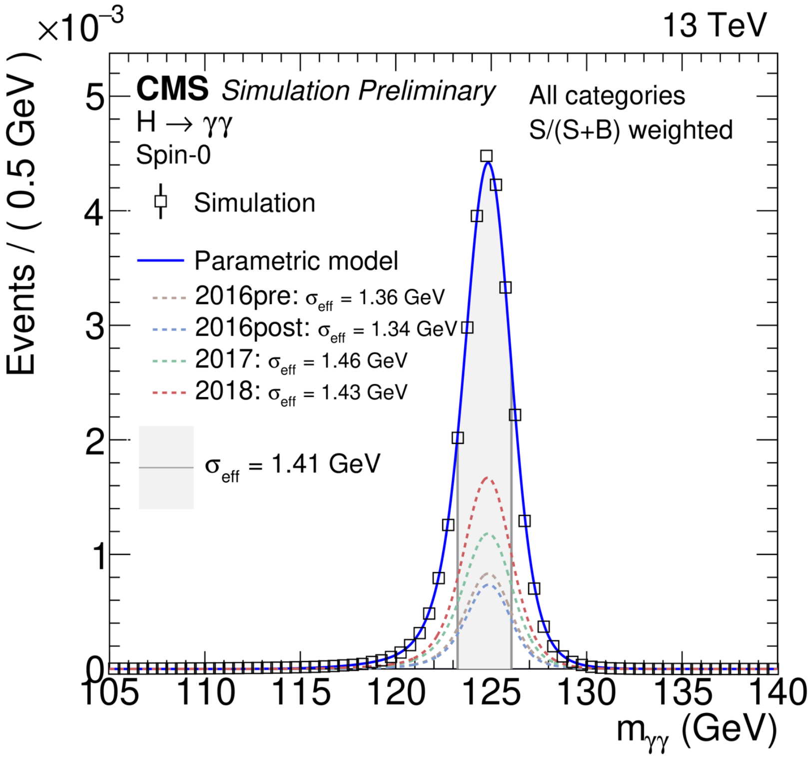
PNN Performance & Validation

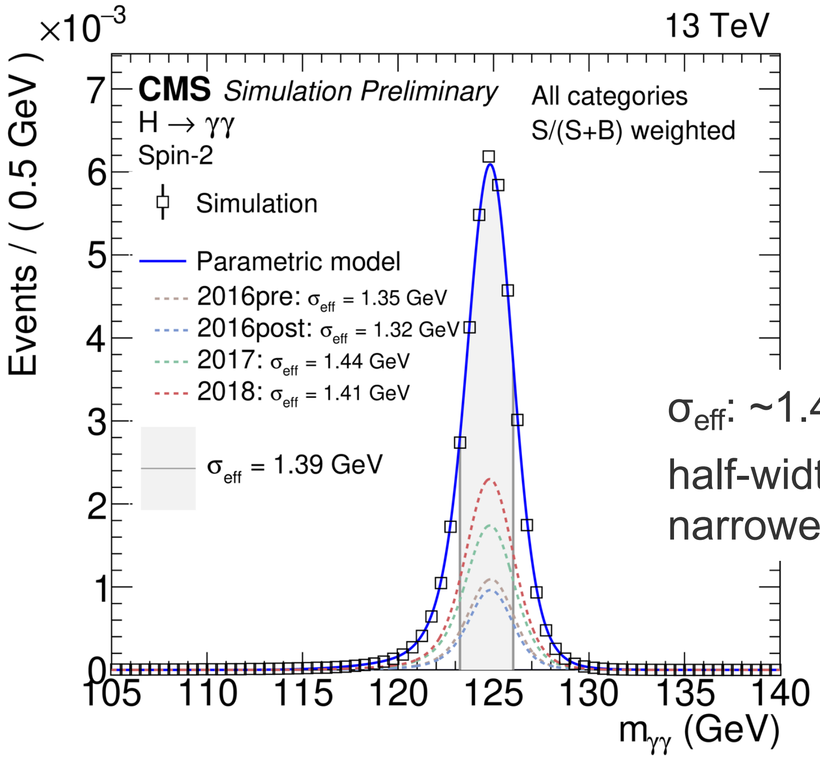


- PNN performance validated in the $m_{\gamma\gamma}$ sideband region
- Good data/MC agreement for all PNN input features
- No correlation between $m_{\gamma\gamma}$ and PNN inputs/outputs → no mass sculpting
- pNN validated against single-mass NNs: excellent interpolation ability

Signal Modeling

- Analytic fit to mγγ with sum of up to 5 Gaussians
- Fitted independently per category, per year (2016/2017/2018)
- F-test determines optimal number of Gaussians
- WWγγ signals + bbγγ, ZZγγ, ττγγ contributions included





σ_{eff}: ~1.4 GeV

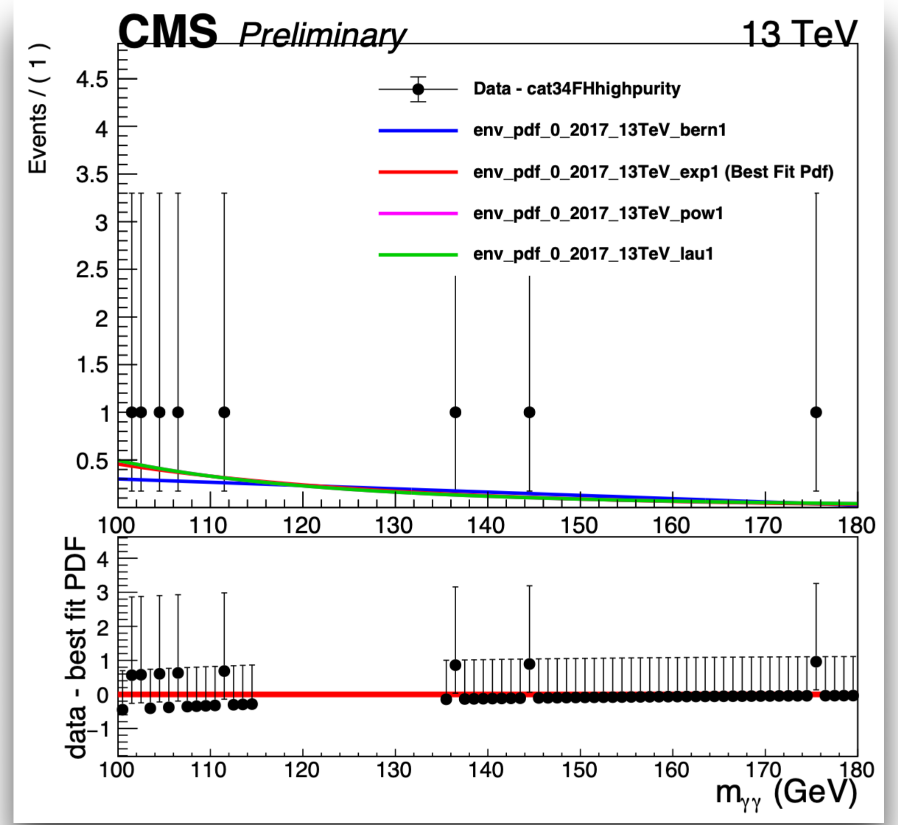
half-width of narrowest 68.3% interval

Spin-0 (Radion) and Spin-2 (Graviton), mX = 1 TeV, all categories combined

Background Modeling

Continuum background: fit to data sidebands

- Discrete profiling method (envelope method)
- Bernstein, Laurent, exponential, power law functions
- Signal region: 115 < $m_{\gamma\gamma}$ < 135 GeV (blinded during optimization)

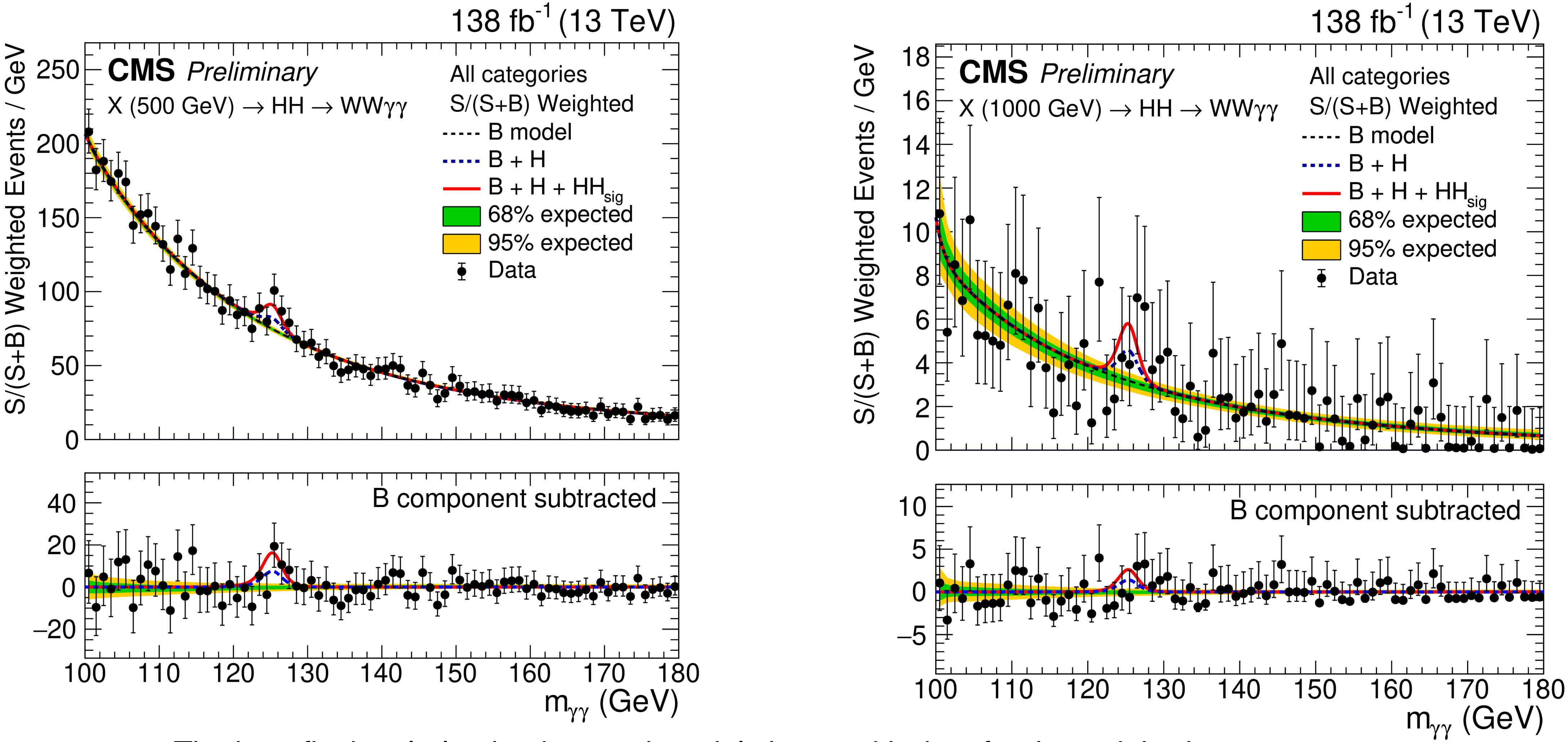


Resonant background: SM single-Higgs (ggH, VBF, VH, ttH)

- Modeled same as signal (parametric fit from MC)
- Normalized to SM predictions

Signal + Background Fits

S/(S+B) weighted, all categories, $\pm 1\sigma_{eff}$ around m_H = 125 GeV



The best fit signal-plus-background model shown with data for the weighed sum of all analysis categories for two typical mass points (500 GeV and 1 TeV)

Systematic Uncertainties

Theoretical:

- $H \to \gamma\gamma$, $H \to WW/H \to bb/H \to ZZ$ branching fractions
- QCD scale & PDF (single Higgs only)
- PDF uncertainty < 3%

Experimental (normalization):

- Integrated luminosity: 1.2–2.5% per year
- Trigger efficiency: 0.1–3.5%
- Photon ID / preselection SFs
- Lepton reconstruction, ID, isolation
- Jet energy scale & resolution, b-tagging
- $H \to WW/H \to bb$ tagger efficiency SFs

Experimental (shape):

- Photon energy scale & smearing
- Material budget (FNUF/upstream)

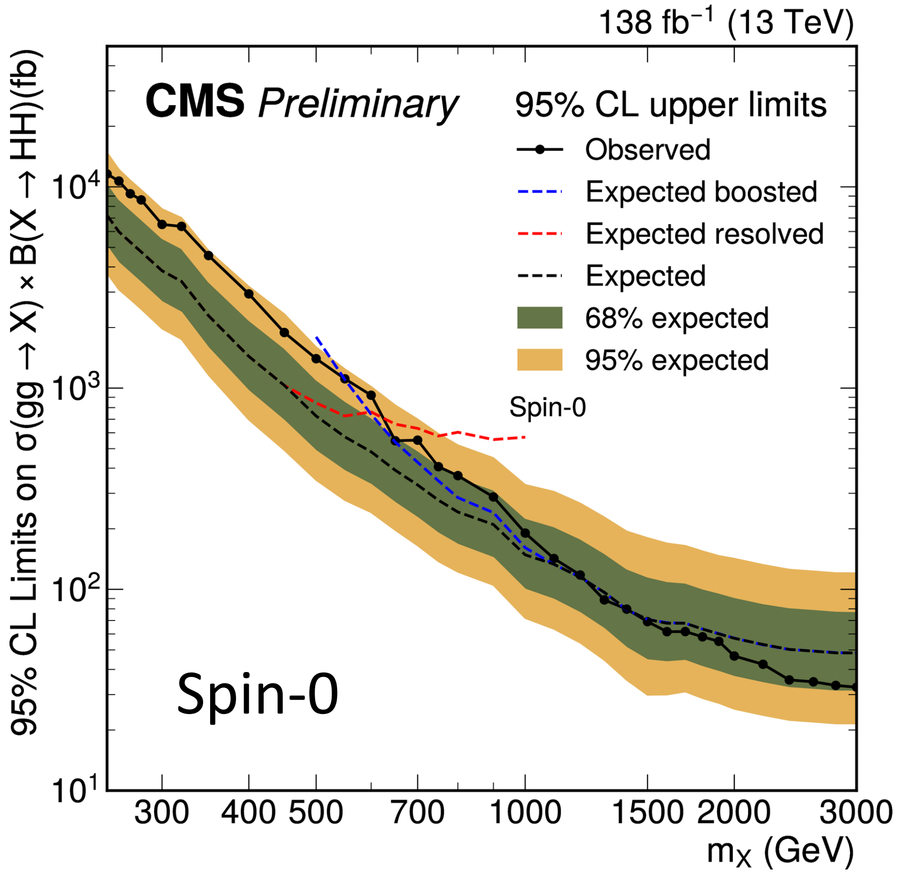
Most impactful systematics:

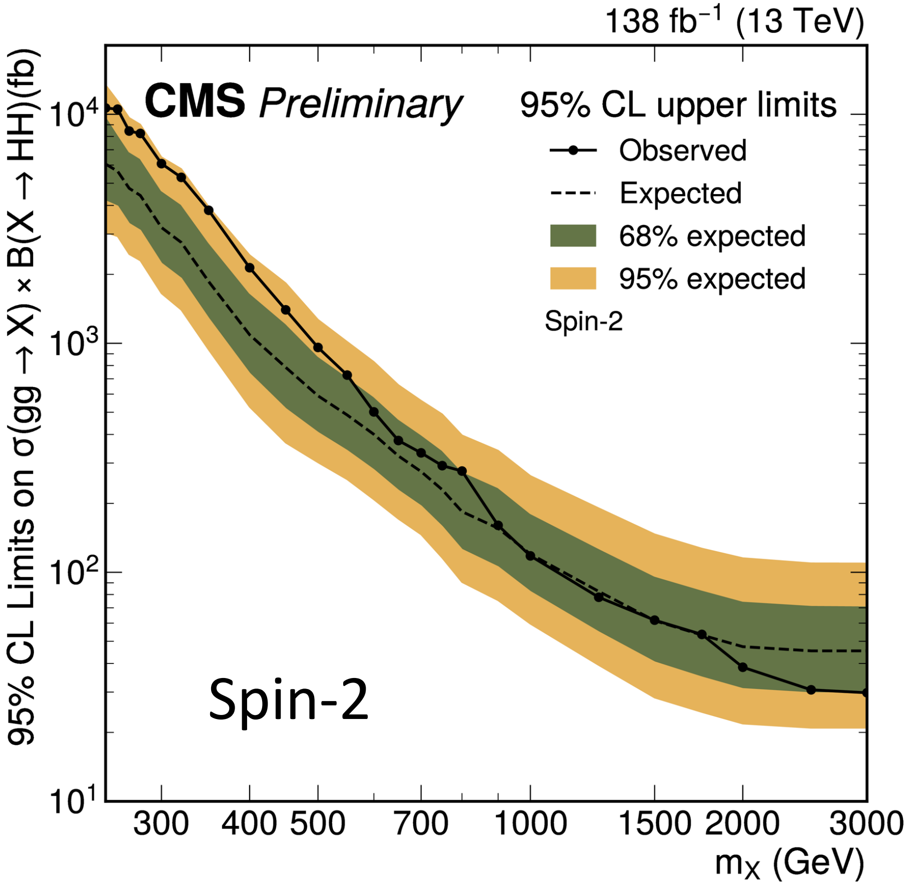
- $H \to WW$ tagger efficiency (up to 30%)
- Photon energy scale
- DeepJet b-tagging SFs
- Theoretical uncertainties

Statistically dominated across all mass points

Results: Upper Limits on σ(gg→X) × B(X→HH)

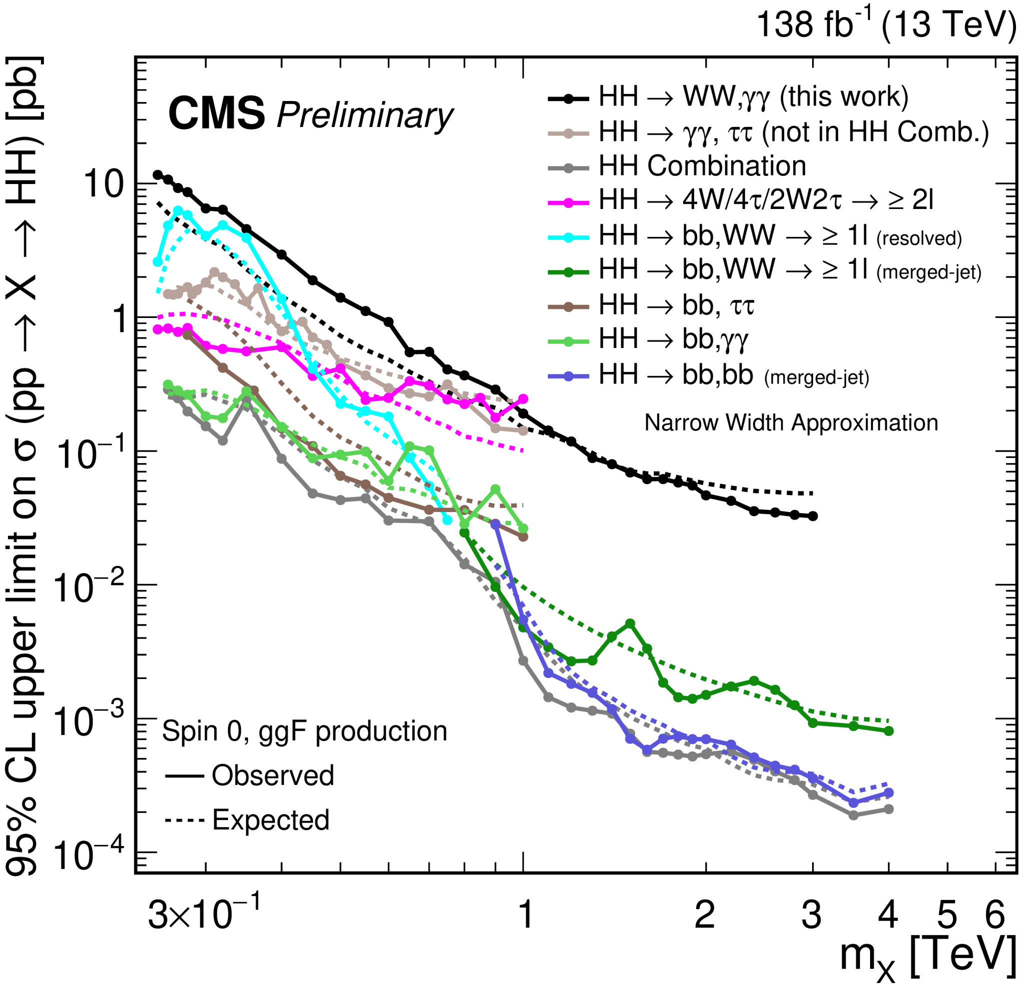
WWγγ channel, with residual bbγγ + ZZγγ + ττγγ contributions included

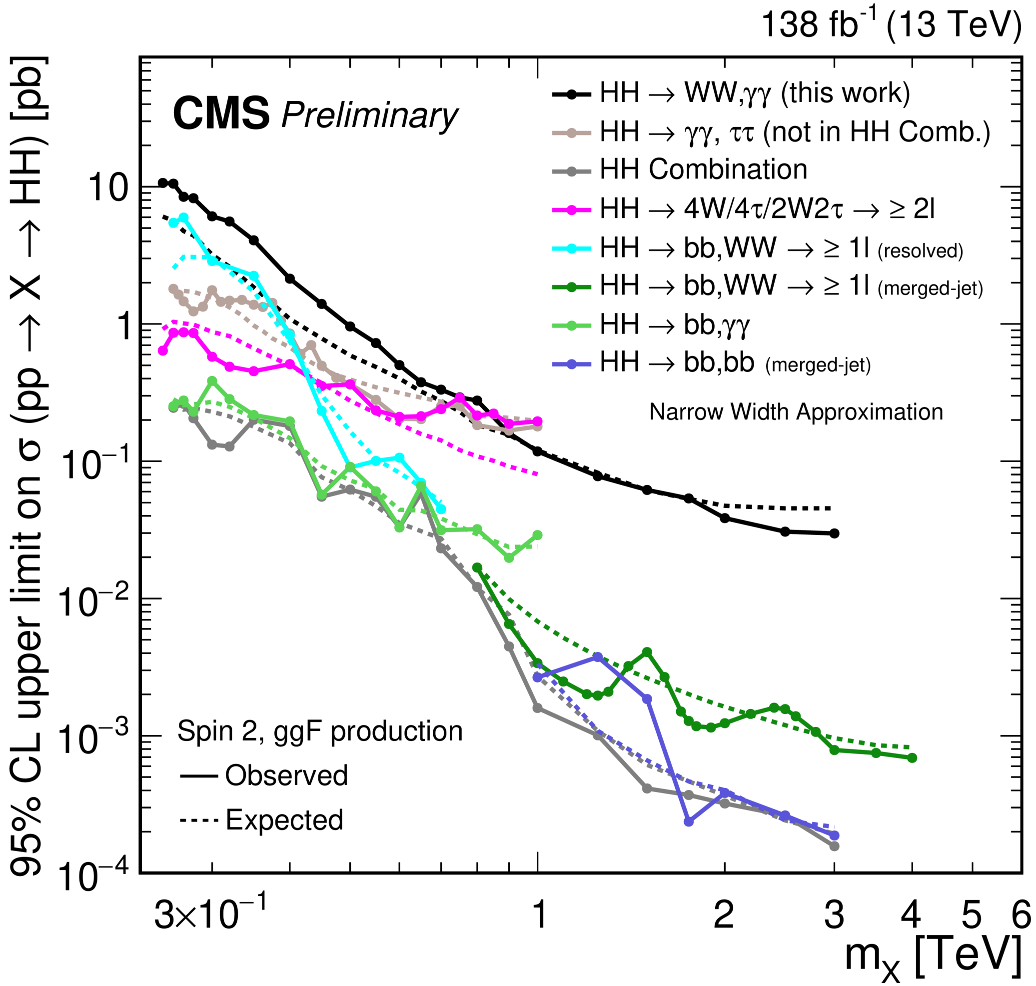




- Spin-0: Observed (expected) 95% CL limits: 32 fb – 11.6 pb (48 fb – 7.2 pb)
- Spin-2: Observed (expected) 95% CL limits: 30 fb – 10.7 pb (45 fb – 6.1 pb)
- Resolved category dominates at low mass; boosted at high mass
- Slightly tighter limits for spin-2 due to harder pT spectrum

Comparison with Other CMS HH Resonance Searches





The upper limits in this analysis are comparable with the ττγγ and multilepton final states in the intermediate resonance mass region, and with the resolved bbWW final state in the low-mass region.

Summary

- First CMS search for resonant HH production in the WWγγ final state using 138 fb^{-1} of 13 TeV pp collision data
- WW decay topologies (FH, SL, boosted, resolved) considered for the first time

- No significant excess over SM background expectations observed
- 95% CL upper limits set on $\sigma(gg \rightarrow X) \times B(X \rightarrow HH)$:
  - Spin-0: 32 fb (m_X=260 GeV) – 11.6 pb (m_X=3 TeV)
  - Spin-2: 30 fb (m_X=350 GeV) – 10.7 pb (m_X=3 TeV)
- Provides important constraints on BSM scenarios (WED, extended Higgs sectors)

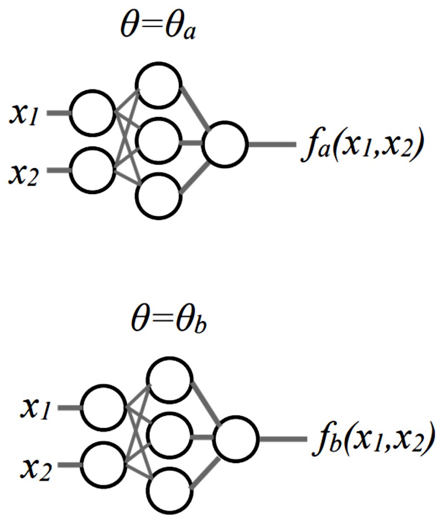
- Work ongoing to extend the analysis to X->YH->WWγγ
  - Expect dominant sensitivity in the scenarios when m_Y > 160 GeV with Y mainly decaying into WW

Thanks for your attention!

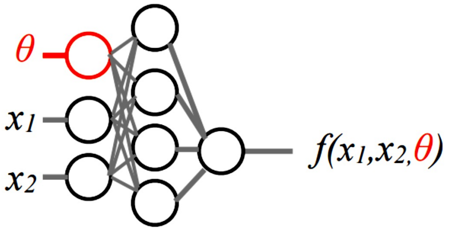
Backup

Parameterized Neural Network (pNN)

A neural network designed to adapt its predictions to a wide range of mass points.

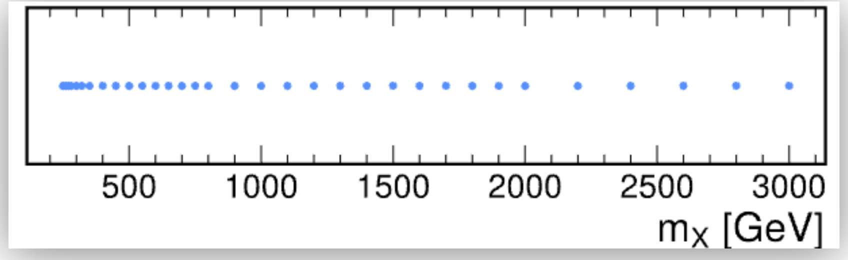


2 NNs trained on different single mass points



1 pNN trained with signal mass as one input parameter

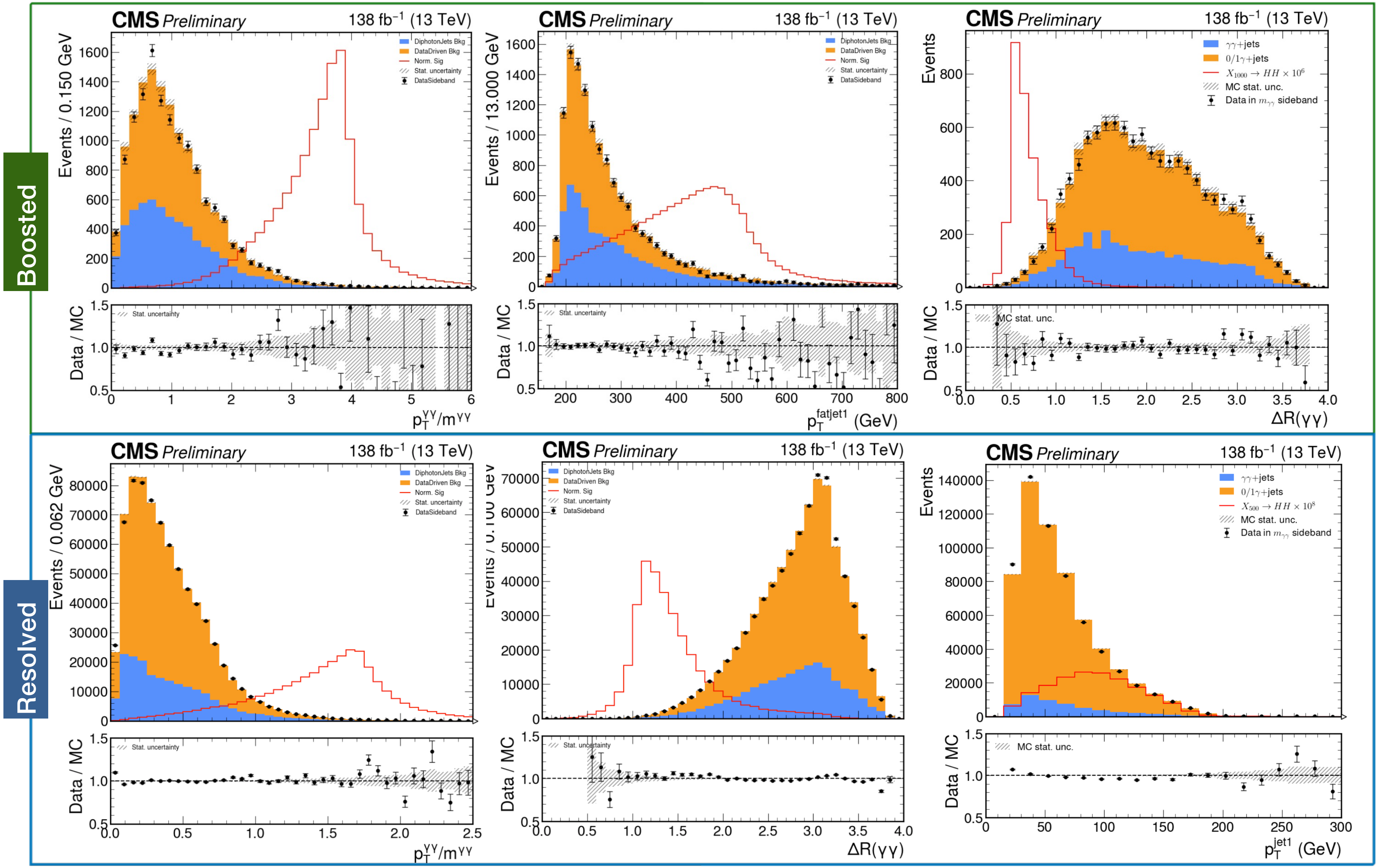
[Parameterized neural networks for high-energy physics]



Mass points generated for the X → HH Radion samples

1. Include mX as one training feature.
2. Train on all signal MC simultaneously, assigning each event its corresponding mX value.
3. Keep the class balance
   - Duplicate background events for each mass point with corresponding mX values, ensuring mX cannot discriminate signal from background.
   - Normalize signal datasets to have equal total weights across all mX values.
   - Normalize signal and background datasets to have equal total weights collectively.

Training feature distributions



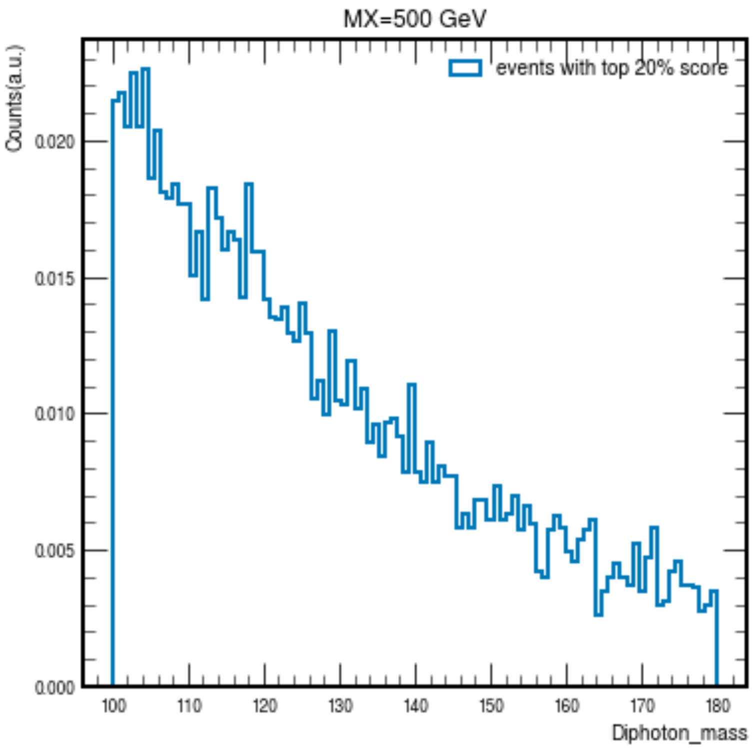
Good Data/MC agreement for all variables.

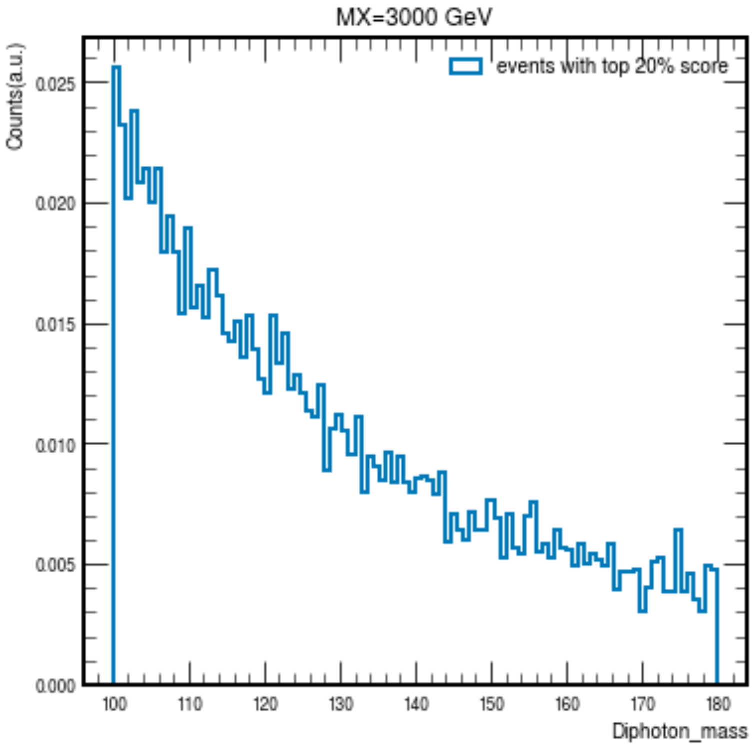
Correlation check: pNN vs $m_{\gamma\gamma}$

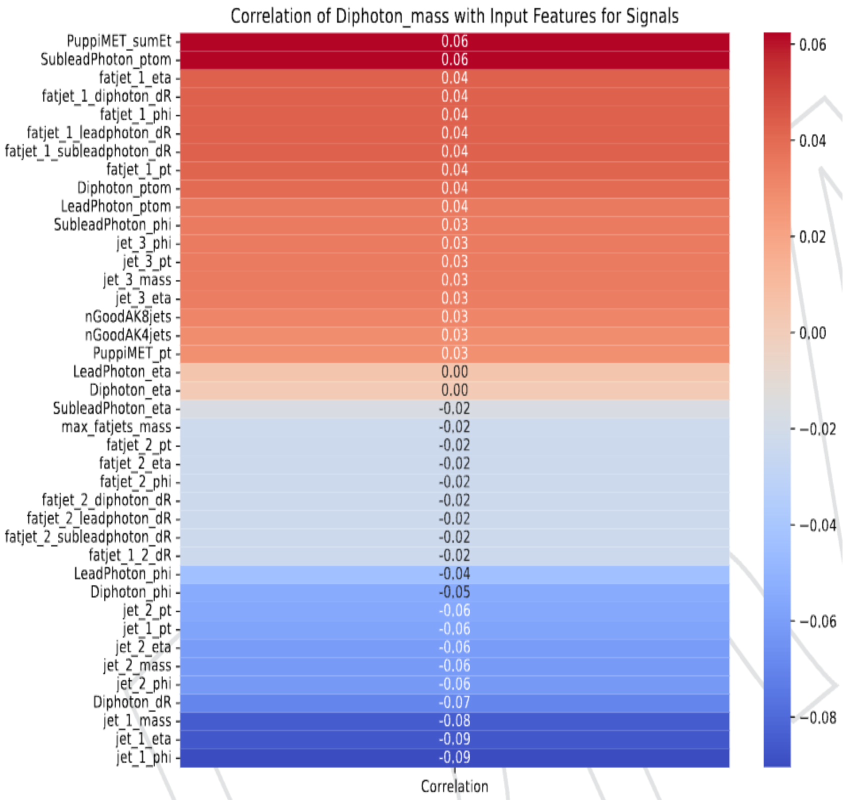
Correlations between $m_{\gamma\gamma}$ and input variables, pNN outputs are carefully checked

- Mass sculpting check
- Linear correlation check

No correlation observed



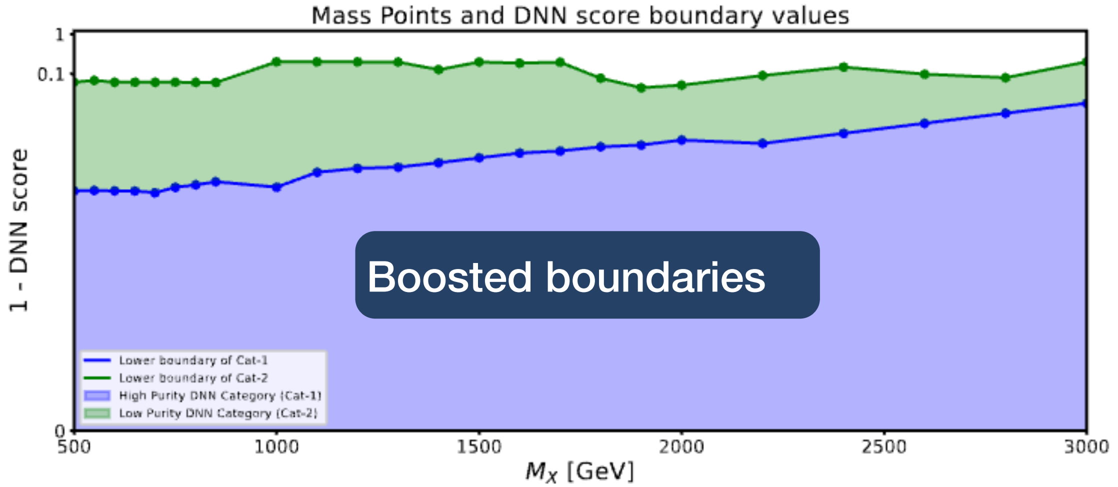


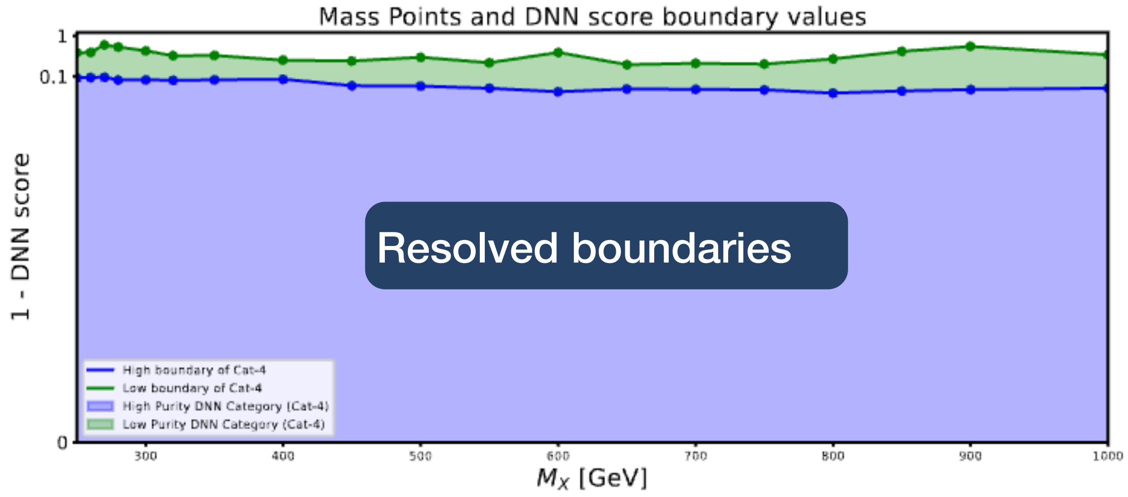


pNN Categorization

Employed Bayesian algorithm ([link]) to categorize boosted and resolved classes based on PNN score mass point by mass point

- Widely used for ML hyper parameters tuning (eg. CMS H→γγ group [[link]]).
- Bayesian method for boundary optimization:
  - Get the **maximum significance** boundaries of each signal mass point.
  - Optimize the boundary values (*b_i* parameter) for each category *i*, run 1000 rounds.
- Optimized pNN boundaries for all mass points：
  - Boosted: 2 categories
  - Resolved: 4 categories





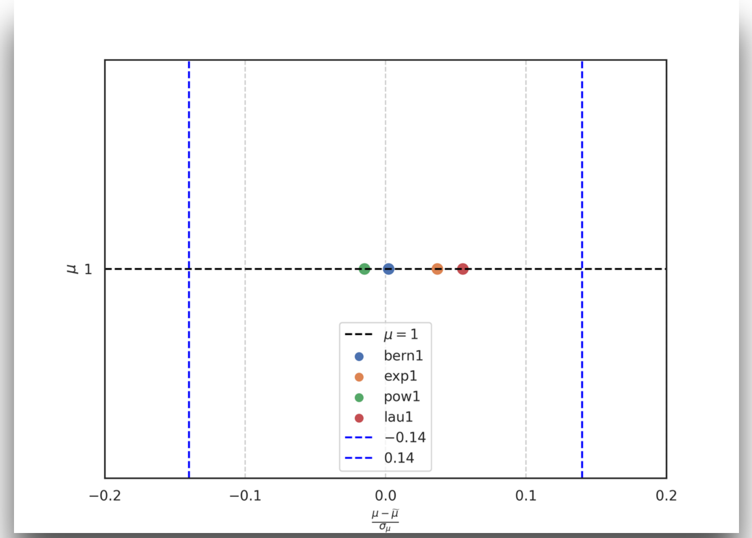
Bias study

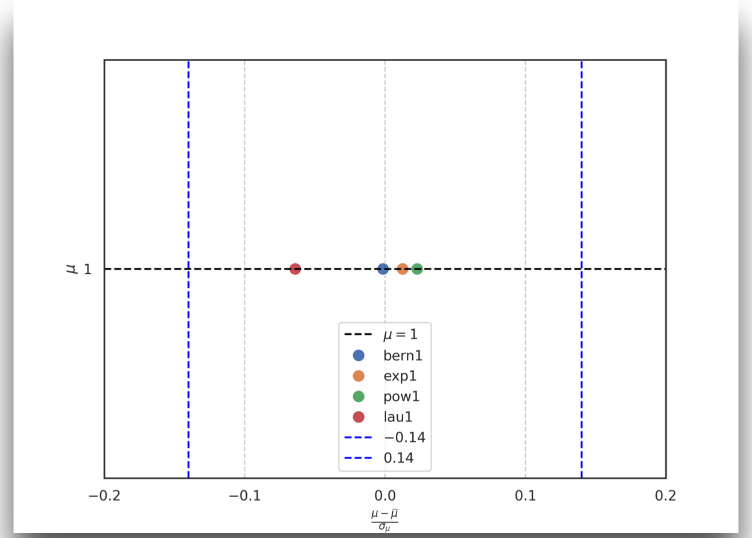
- Bias: mean of the pull distribution

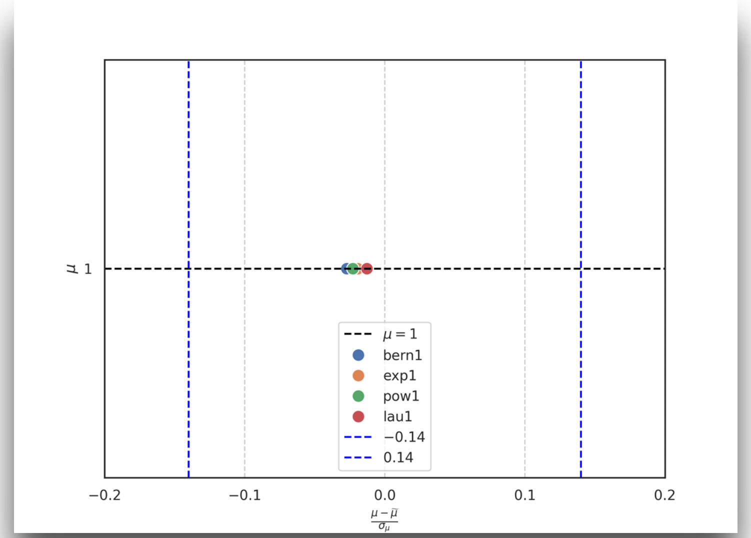
  r_{truth}: Inject signal strength = 1

  pull value: $P = \frac{(r_{truth} - r_{fit})}{\sigma_{fit}}$

  – Throw 1000 toy datasets with choice of alternative background functions, fit back with envelop method.
  – 0.14 as the threshold: a bias below this value would change the total uncertainty by less than 1% : $\sqrt{1^2 + 0.14^2}$
- Similar studies done for all mass points.
- No bias observed with all background modelling in all categories.







Comparison with ATLAS & Key Achievements

ATLAS published $X \to HH \to WW\gamma\gamma$ with 36.1 fb^{-1} (2015–2016 data):

Eur. Phys. J. C 78 (2018) 1007

- Only Semi Leptonic resolved final state considered

This analysis with similar 2016-only dataset shows >30% improvement

→ Benefit from ML-based categorization (pNN), modified photon ID, and inclusion of FH + boosted topologies

Key achievements of this CMS analysis:

✓ First CMS search for $X \to HH \to WW\gamma\gamma$

✓ First LHC search in boosted topology for this channel

✓ First LHC search with fully-hadronic WW decays