Search for a new resonance $X \rightarrow H(H/Y) \rightarrow \gamma\gamma bb$ in proton-proton collisions at $\sqrt{s} = 13$ TeV

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Outline

NOTE:

- *This work has been done for my PhD thesis at IISc, India (under CMS collaboration)*
- *Approved and public from CMS collaboration: CMS-PAS-HIG-21-011 (presented during ICHEP 2022)*

- Physics Motivation
- Analysis Strategy
- Results
- Summary

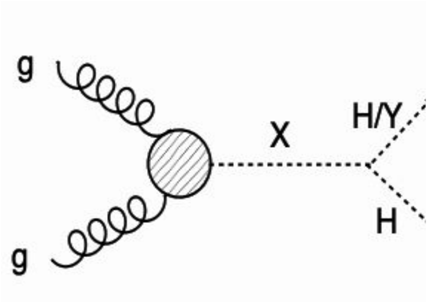
Physics Motivation

- **Search for resonant Higgs pair production at LHC**
    - Many BSM theories predict direct or indirect production of new resonances with enhanced cross-section ; direct coupling with SM-like or/and BSM Higgs boson
- **Analysis features:**
    - Model-independent approach with narrow-width approximation
    - Searches are motivated from:
      1) Warped extra dimension (WED) model (X→ HH)
      2) Next-to-minimal supersymmetric model (NMSSM) and Two-real-scalar-singlet model (TRSM) (X→ YH)
- **The full Run-2 analysis improves CMS 2016 results: 6-25%**
    - Use new object identification techniques
    - Efficient machine learning based background rejection
- **First time looking at NMSSM and TRSM motivated searches**

Physics Motivation

Warped extra dimension model

- Provide initial solution to SM hierarchy problems; predicts spin-0 and spin-2 particles
- Explore RS_bulk scenario: enhanced coupling to bosons and top quark
- New resonances have significant BR (~10%) to decay into Higgs boson pair (X→ HH)



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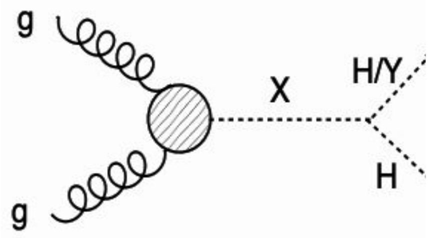
Next-to-minimal supersymmetric model

- Enriches Higgs sector with 7 Higgs bosons (lets label three NMSSM Higgs boson scalars as X, Y and H)
- dominant singlet component of Y suppresses its direct production at LHC; production via a heavy Higgs boson X → YH becomes important

Two-real-scalar-singlet model

- Extension of SM with two scalar singlet fields [Ref.]
- Three scalars⇒ one is identified as SM Higgs boson
- Gives same topology for Higgs-to-Higgs decay (X→YH)



Physics Motivation

Warped extra dimension model

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γγbb final state

- H→γγ handle with high purity and selection efficiency due to excellent ECAL response
- For H/Y→ bb handle b tagging rejects high multijet background contamination
- For X→ HH searches, it yields 0.26% BR

Next-to-minimal supersymmetric model

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Two-real-scalar-singlet model

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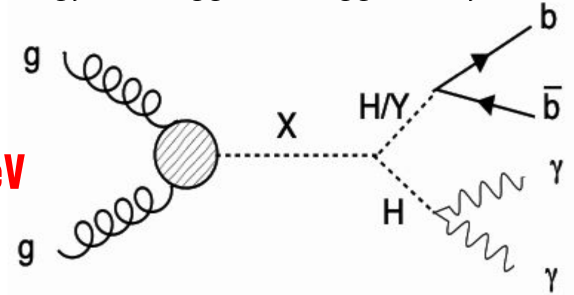
- Gives same topology for Higgs-to-Higgs decay (X→YH)

X mass upto 1 TeV
Y mass upto 800 GeV
$m_Y < m_X - m_H$



Analysis Strategy

Event selections

Online:
Event passing diphoton triggers

Offline:
selections on photons and jets from JHEP 03 (2021)

Analysis optimization methods

Non-resonant backgrounds:
MVA training
MVA categorization

Resonant backgrounds:
NN based ttHkiller

Statistical Analysis

Data driven Backgrounds:
2D envelope method
($m_{\gamma\gamma}$ X m_{jj}) fit in $\tilde{M}_X$ window

Signal:
$m_{\gamma\gamma}$:Sum of Gaussians
m_{jj}: Double Sided Crystal ball / Crystal ball + Gaussian

Event Selections

Trigger Selection (Standard H→ γγ triggers)

Photon selections

(Same as H→ γγ analysis)

- photon MVA ID > -0.9 (99% eff.)
- Electron veto (suppress Z→ ee)
- $p_T(\gamma 1)/M(\gamma\gamma) > 1/3$
- $p_T(\gamma 2)/M(\gamma\gamma) > 1/4$
- $100 < M(\gamma\gamma) < 180$ GeV

Jets selection

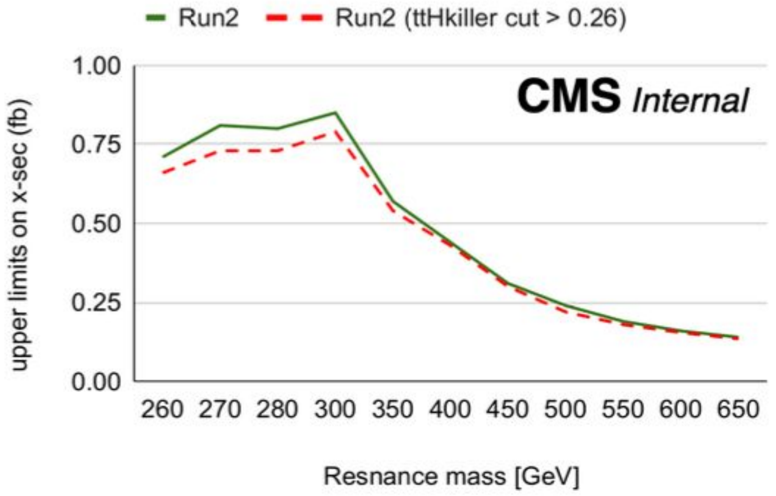
(similar to non-resonant HH→γγbb *JHEP 03 (2021)*)

- p_T (jets) > 25 GeV, $|\eta(\text{jets})| < 2.4(2.5)$ (2016(2017/18))
- Jet corrected with b jet energy regression (Ref.)
- Jet Id selection with efficiency > 99%
- $\Delta R(\text{jet},\gamma\text{'s}) > 0.4$
- $70 < M(jj) < 190$ (1200) GeV (WED (NMSSM))
- Jet pair with highest sum of DeepJet score

Resonant Background Rejection

Selection on ttHKiller discriminant

- Resonant background are single Higgs process which have similar diphoton distribution peaking around m_H
- Contamination is higher only for m_X < 600 GeV; ttH contribution dominates
  - Simply neglect for higher masses
- Apply a selection on **NN-based ttHkiller variable**
- Order of magnitude for sensitivity improvement with m_X < 600 GeV is up to 10%.



Non-resonant Background Rejection

BDT Classifier

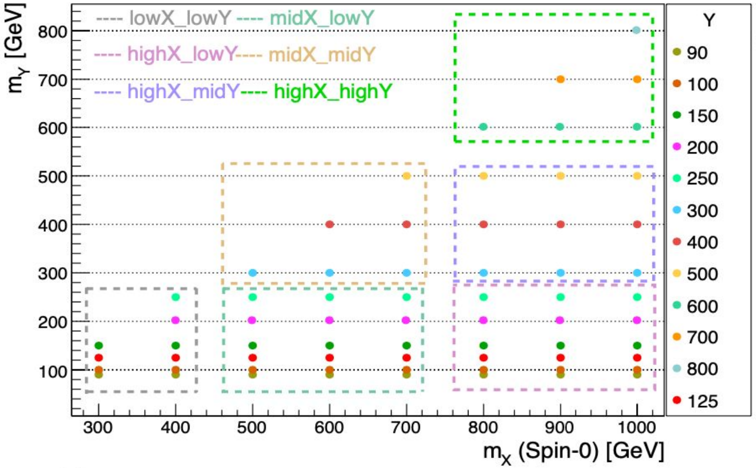
- Using XGBoost + Scikit-learn to train multiclass BDT classifier to discriminate signal from non-resonant backgrounds (in 6 different X-Y mass ranges in m_X:m_Y 2D plane)

  Signal: Resonant X → YH → bbγγ (Spin0)

  Non-resonant Background: SM multijet process with prompt photons⇒ γγ+Jets and γ+Jets

- Use three set of input variables

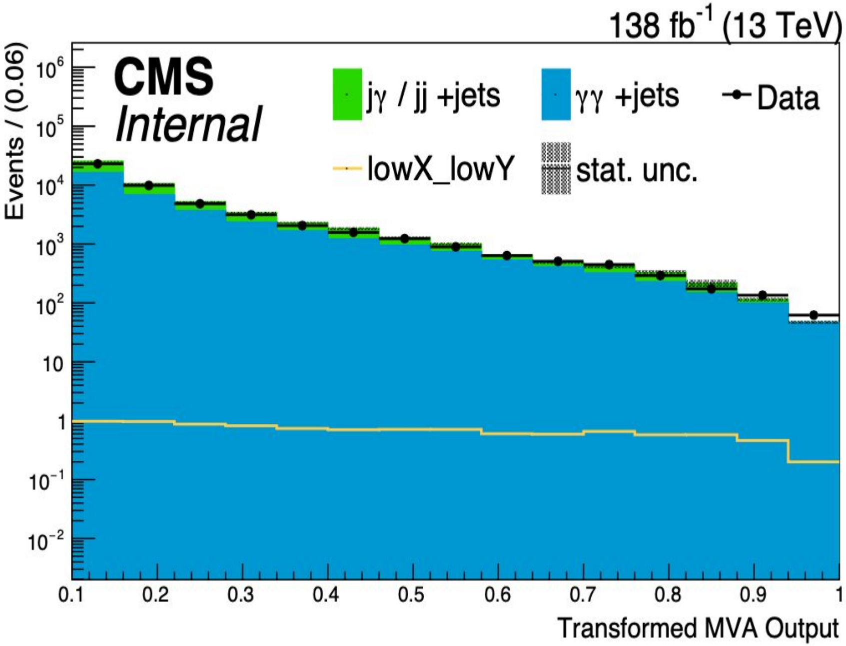
1) **Kinematic distributions which discriminate signal from background**
2) **Object identification variables to reject fake contribution**
3) **Energy resolution variables**



BDT performance

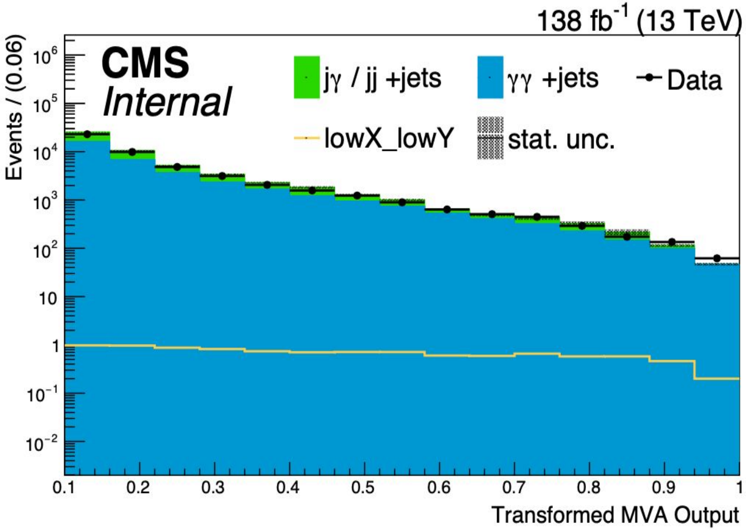
- Table shows the AUC from ROC
- As we tend to higher masses, training performance improves within same m_Y range$\Rightarrow$ performance gets improved as kinematics gets more discriminative

Mass Range	γγ+jets (AUC)	γ+jets(AUC)
lowX_lowY	0.9602	0.9744
midX_lowY	0.9896	0.9934
highX_lowY	0.9971	0.9981
midX_midY	0.9849	0.9930
highX_midY	0.9958	0.9978
highX_highY	0.9871	0.9956



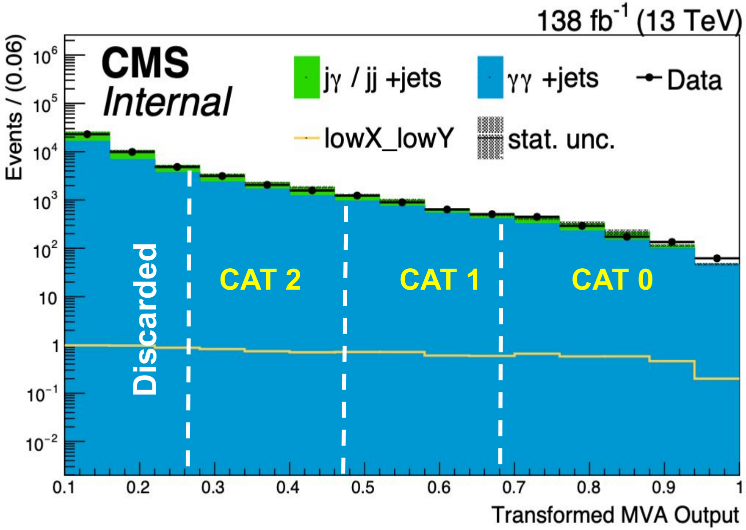
Event Classification

MVA Categorization



- Categorization using MC simulations samples
- For boundary optimization ROOT Minuit package is used with MIGRAD minimizer
    a. uses Punzi FOM ($S_{eff}/(1+\sqrt{B})$) as input function
- Constrain background statistics have robust background modeling

MVA Categorization



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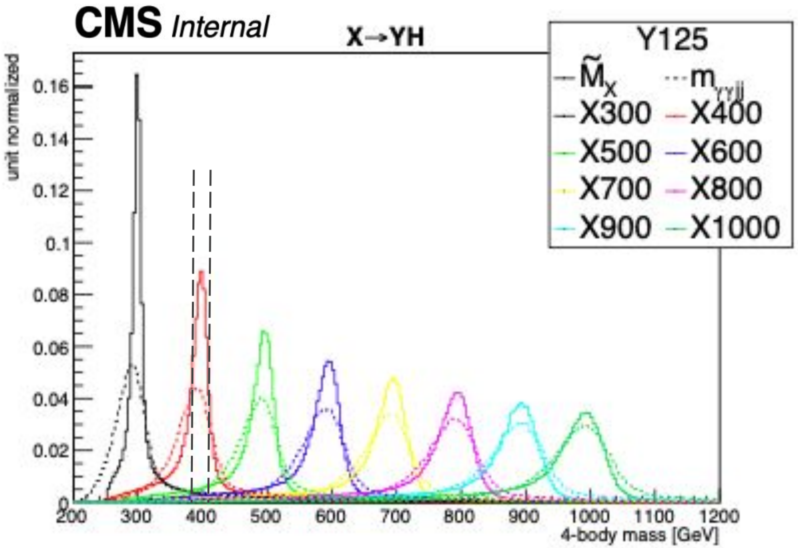
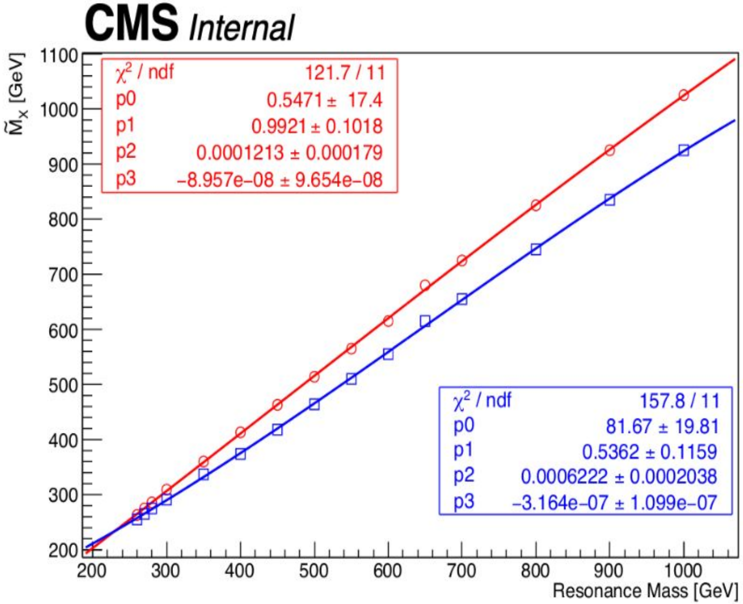
Optimized MVA categories

mass range & category	lowX_lowY	midX_lowY	highX_lowY	midX_midY	highX_midY	highX_highY
CAT2	[0.174, 0.329]	[0.213, 0.401]	[0.215, 0.304]	[0.180, 0.352]	[0.177, 0.239]	[0.129, 0.286]
CAT1	[0.329, 0.627]	[0.401, 0.550]	[0.304, 0.500]	[0.352, 0.600]	[0.239, 0.350]	[0.286, 0.400]
CAT0	[0.627, 1.000]	[0.550, 1.000]	[0.500, 1.000]	[0.600, 1.000]	[0.350, 1.000]	[0.400, 1.000]

$\tilde{M}_X$ Window Selection

- Selection on four-body mass $\tilde{\mathbf{M}}_X = (\mathbf{m}_{jj\gamma\gamma} - \mathbf{m}_{jj} - \mathbf{m}_{\gamma\gamma} + \mathbf{m}_H + \mathbf{m}_{Y,H})$
  - $\tilde{M}_X$ results better resolution (30-90%) w.r.t $m_{jj\gamma\gamma}$
- A Tight $\tilde{M}_X$ helps to enhance signal to background ratio
- It also helps to suppress single Higgs contribution (<1%)





Signal and Background Model

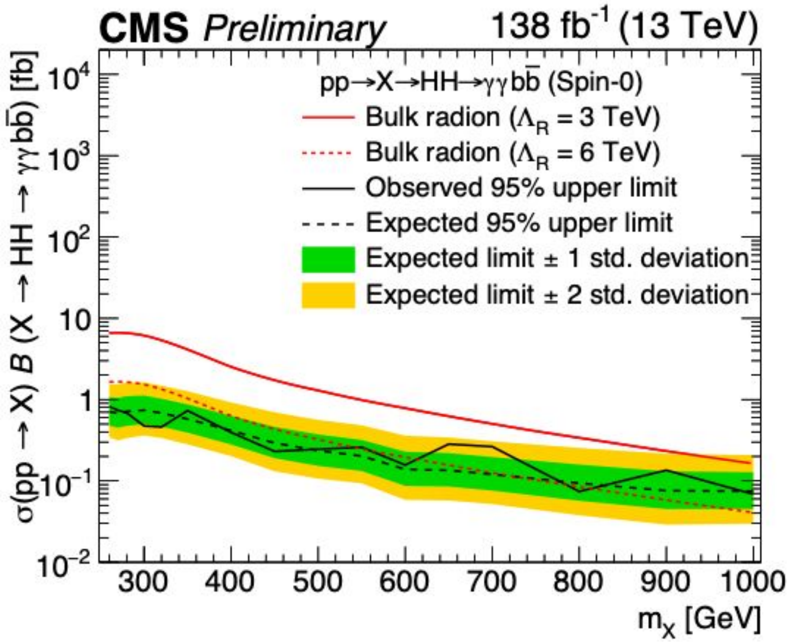
- **Signal**
  - **$m_{\gamma\gamma}$**: sum of gaussian functions is used (upto 5)
  - **m_{jj}**: DoubleCrystalBall (DCB) function or Sum of CB and Gaussian
- **Non-resonant background:**
  - Determine from data-driven method
  - 3 class functions : Exp., Bern. polynomial, Power Law
  - 2D envelope method (1Dx1D)
- **Resonant background:**
  - **$m_{\gamma\gamma}$**: Same as signal modeling
  - **m_{jj}**: Bernstein for bbH, ggH, VBFH; CB for VH; Gaussian for ttH
- **Validation with bias test**
- **Signal is extracted by 2D fit in $m_{\gamma\gamma}$:m_{jj} plane**

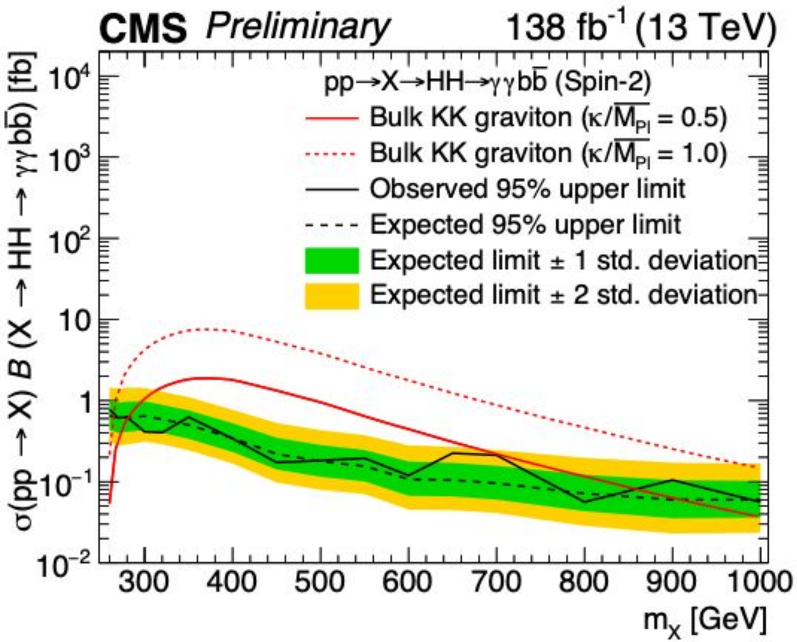
Results

- 95% CL upper limits on cross-section
- **γγbb channel is more sensitive for low resonance (m_X < 600 GeV) masses wrt other channels (CMS TWiki)**
- **Comparison between CMS and ATLAS public results for full Run 2 (X→HH only with m_X <= 1000 GeV)**

  - ATLAS observed (expected) limits
    ⇒ 1.6-0.12 fb (0.93-0.11 fb)
  - CMS observed (expected) limits
    ⇒ 0.82-0.07 fb (0.74-0.075 fb)
  - Expected results are upto 30% and observed results are upto 40% better wrt to ATLAS Run-2 results

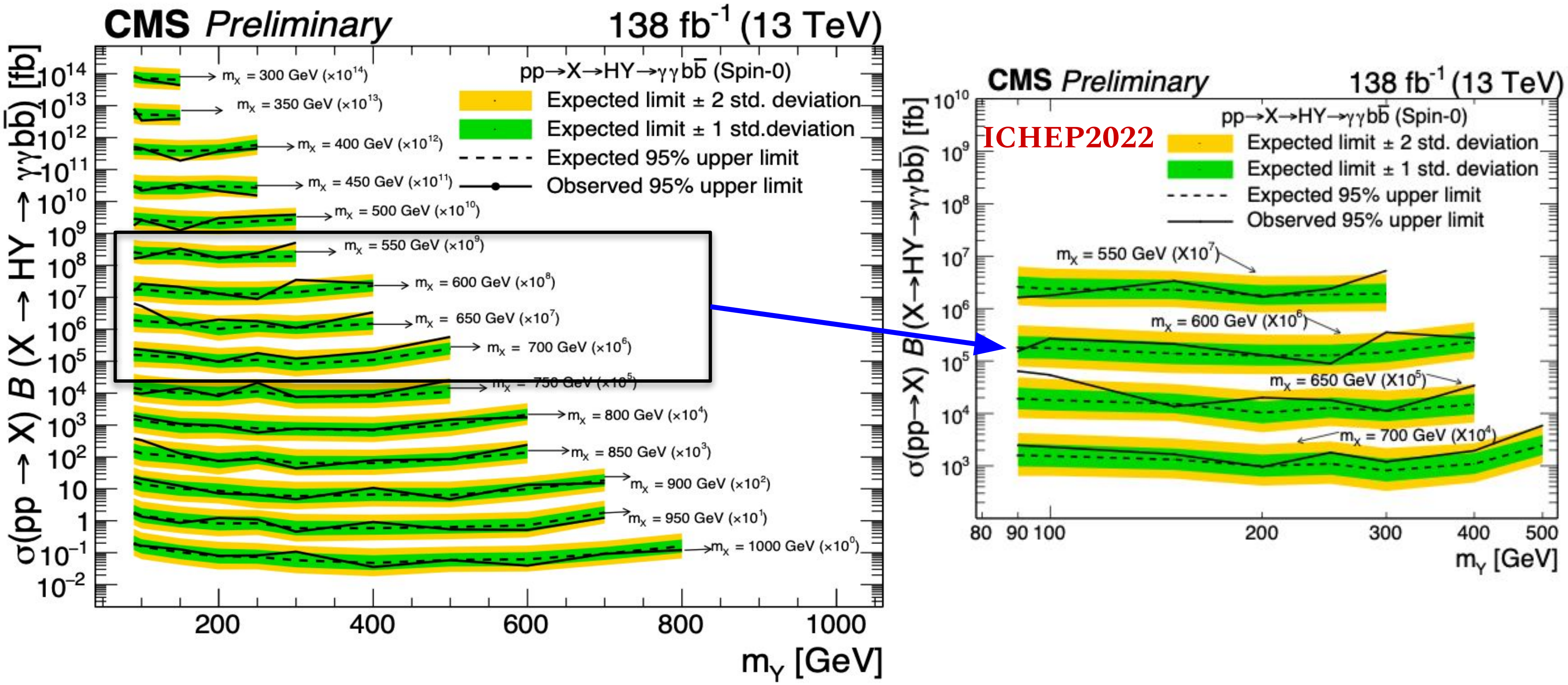
Results: X→HH





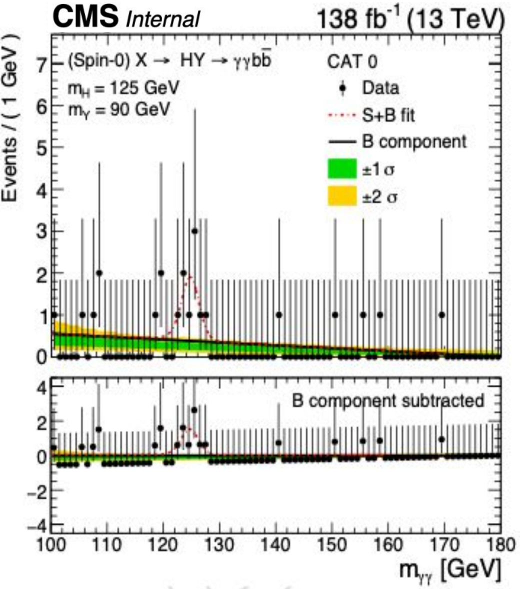
- **Left plot (spin-0):** For Λ_R= 3 TeV, excludes mass up to 1 TeV;
  For Λ_R= 6 TeV, excludes mass up to 600 GeV
- **Right plot (spin-2):** $\kappa/\overline{M}_{pl}$ = 0.5, excludes resonance mass upto 850 GeV

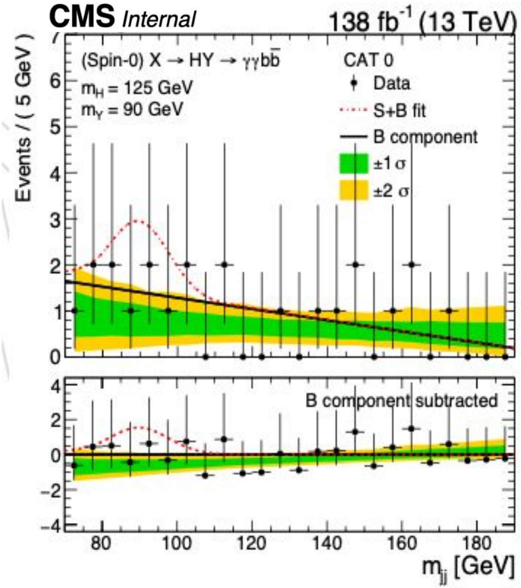
Results: X→HY

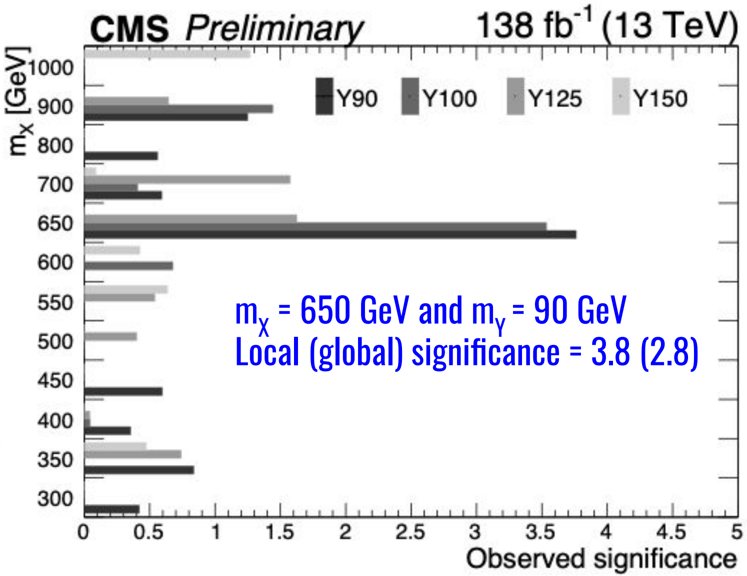


CMS Preliminary
138 fb^{-1} (13 TeV)
pp→X→HY→γγbb̄ (Spin-0)
Expected limit ± 2 std. deviation
Expected limit ± 1 std.deviation
Expected 95% upper limit
Observed 95% upper limit
m_X = 300 GeV (×10^{14})
m_X = 350 GeV (×10^{13})
m_X = 400 GeV (×10^{12})
m_X = 450 GeV (×10^{11})
m_X = 500 GeV (×10^{10})
m_X = 550 GeV (×10^{9})
m_X = 600 GeV (×10^{8})
m_X = 650 GeV (×10^{7})
m_X = 700 GeV (×10^{6})
m_X = 750 GeV (×10^{5})
m_X = 800 GeV (×10^{4})
m_X = 850 GeV (×10^{3})
m_X = 900 GeV (×10^{2})
m_X = 950 GeV (×10^{1})
m_X = 1000 GeV (×10^{0})
σ(pp → X) B (X → HY → γγbb̄) [fb]
m_Y [GeV]
CMS Preliminary
138 fb^{-1} (13 TeV)
ICHEP2022
pp→X→HY→γγbb̄ (Spin-0)
Expected limit ± 2 std. deviation
Expected limit ± 1 std. deviation
Expected 95% upper limit
Observed 95% upper limit
m_X = 550 GeV (X10^{7})
m_X = 600 GeV (X10^{6})
m_X = 650 GeV (X10^{5})
m_X = 700 GeV (X10^{4})
σ(pp→X) B(X→HY→γγbb̄) [fb]
m_Y [GeV]

S + B fit and significance

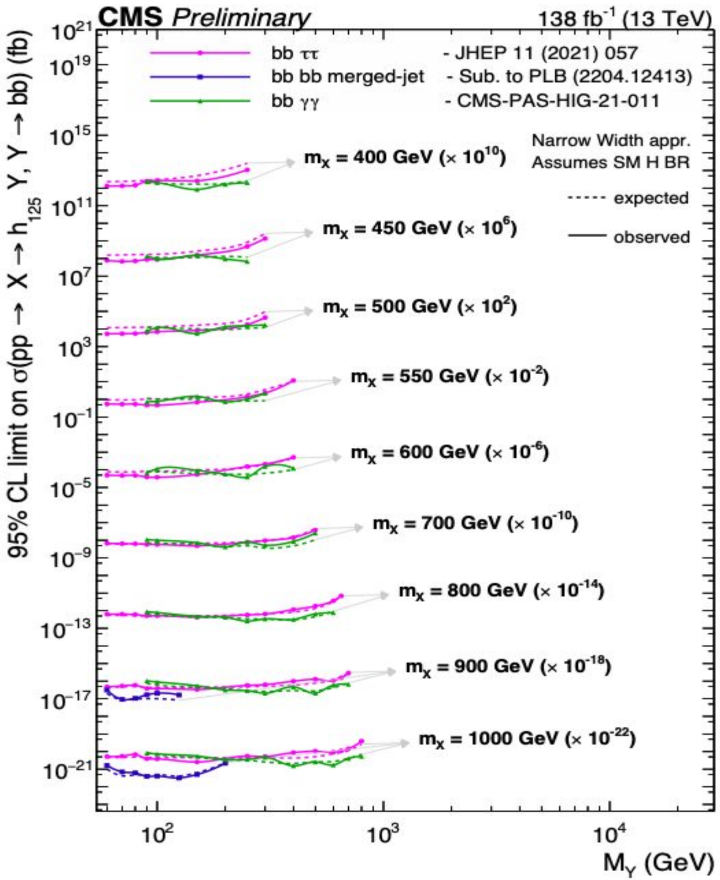






TWiki

More about “Excess”



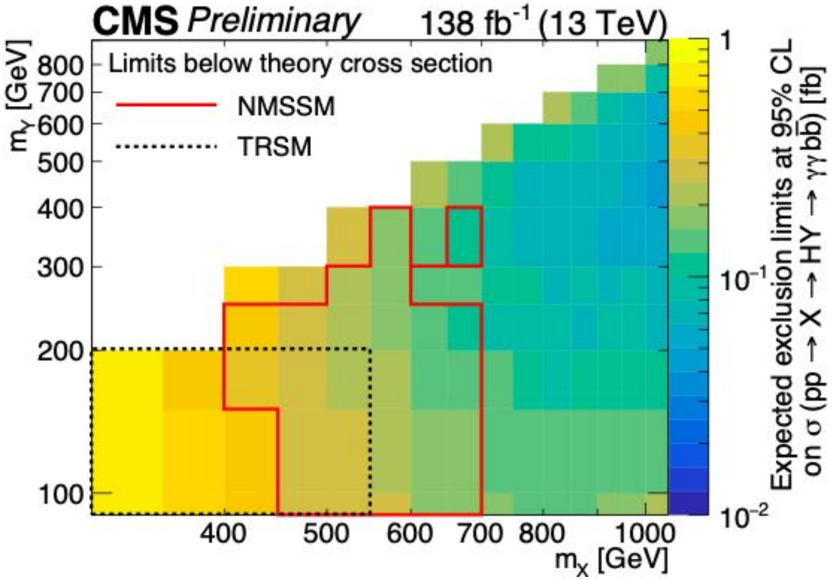
The reported excess coincides with:

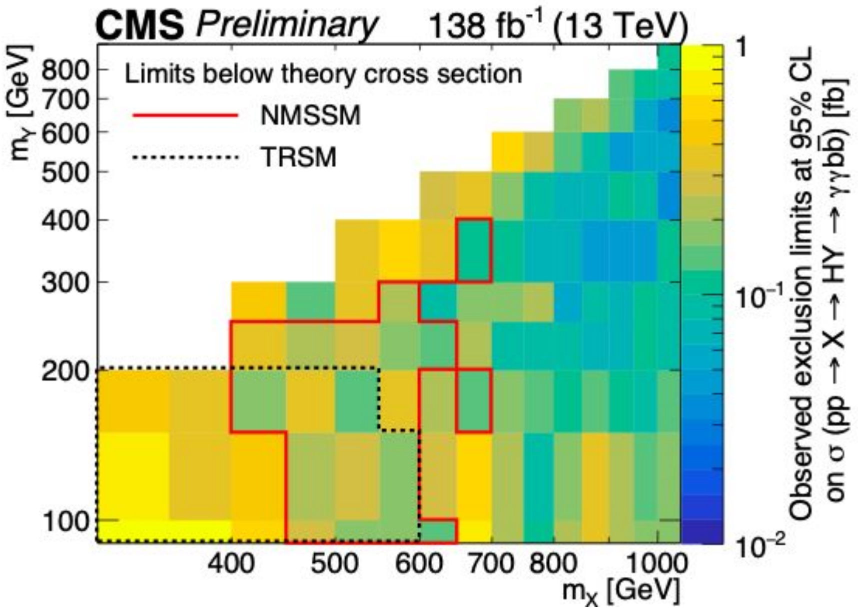
- Resonant WW searches (in fully leptonic final state) by CMS
  - Local (global) significance resonance mass 650 GeV = 3.8 (2.6)
- Additional BSM Higgs searches in ττ final states by CMS
  - Local (global) significance BSM Higgs mass 95 GeV = 2.6 (2.3)
- Low mass SM-like Higgs searches with γγ final state around 95 GeV by CMS
  - Local (global) significance 2.8 (1.3)
  - Full Run-2 results are ongoing

For X→YH, CMS compares ττbb, bbbb and γγbb:

- The excess reported in this analysis at m_X = 650 GeV, was only checked for γγbb
- Other channels still need to study this region

Results: X→ YH





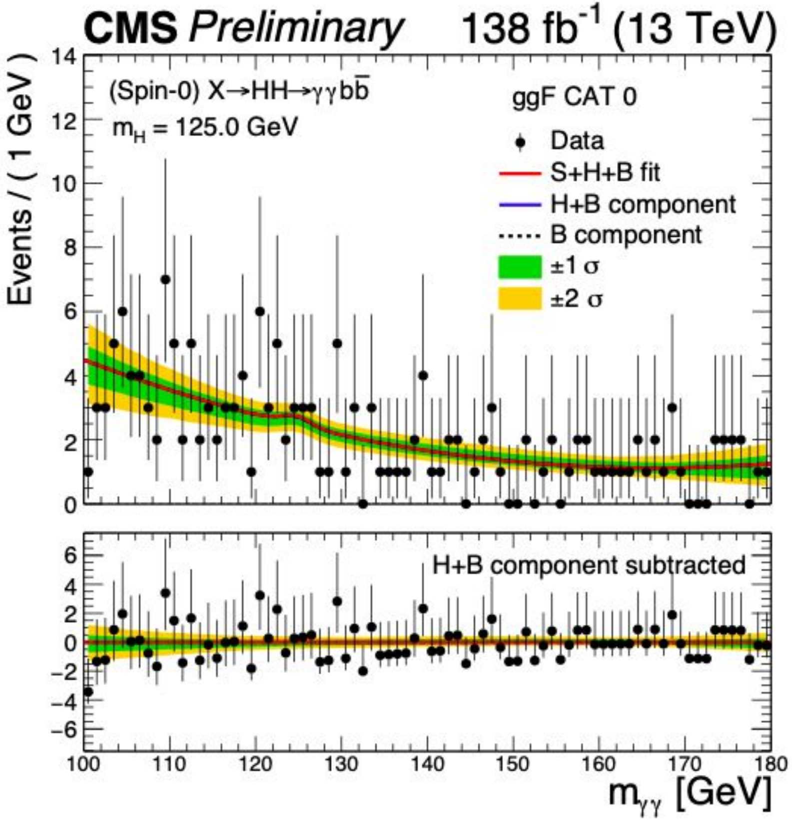
- **We make NMSSM and TRSM interpretations**
  - exclude region m_X=[400-600] GeV and m_Y = [90–300] GeV for NMSSM (TWiki)
  - exclude region m_X=[300-500] GeV and m_Y = [90–150] GeV for TRSM

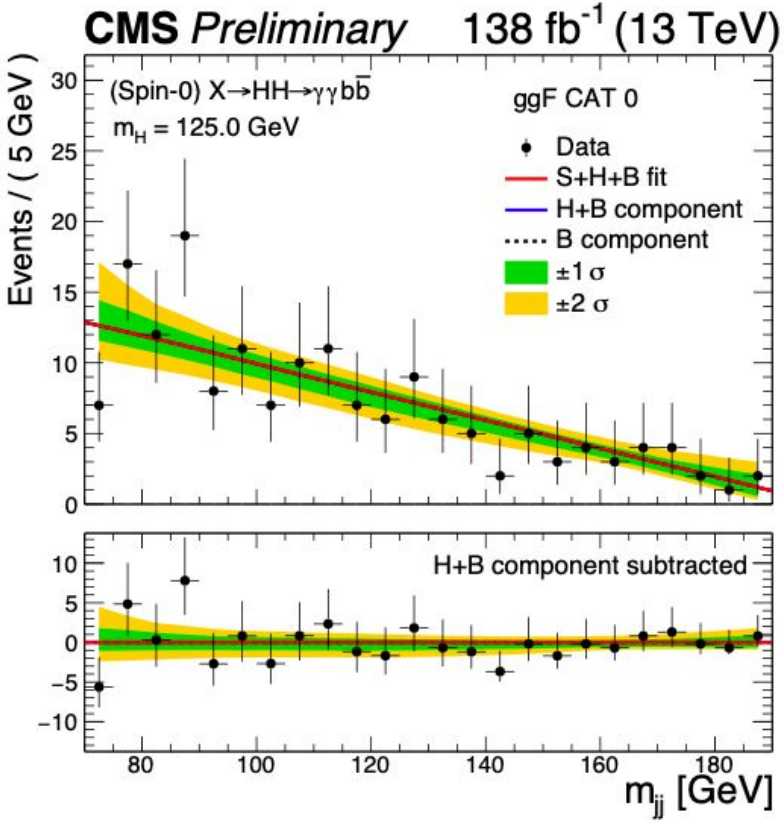
Summary

- Search for resonance X, decaying to two spin-0 bosons, in $\gamma\gamma bb$ final state is presented using CMS Run-2 data with $m_X <= 1$ TeV
- Explore symmetric X→ HH and asymmetric X→ HY (first time) decay modes with $m_Y <= 800$ GeV
- **Model independent results** are shown; **1-2% systematic impact**
  - Observe m_X = 650 GeV and m_Y = 90 GeV excess
  - An important cross check would be doing the same analysis for Y→ $\gamma\gamma$ and H→bb final state (A team from IP2I, Lyon is working on it)
- WED, NMSSM and TRSM interpretations are made which partially exclude allowed mass regions

Backup

S + B fit for X→HH





Systematic Uncertainty

Mostly standard $H \rightarrow \gamma\gamma$ systematics with jet systematics and theoretical systematics

- Preselection SF
- Triggers
- BR
- Luminosity
- PS / UE
- PDF and QCDscale
- Photons
- photon σ_E/E
- electron veto SF
- JEC and JER
- b-tagging SF
- HEM
- L1-prefiring

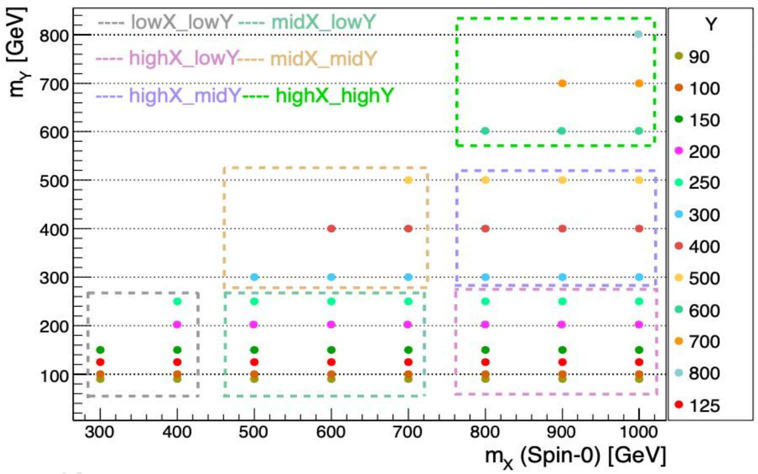
We check impact in all six mass ranges which modify limits 1-2%

Highest impact from QCD scale and b tagging systematics for all masses

- Other systematics contribution < 1%

BDT training strategy

- In order to make analysis strategy optimal for each (m_X,m_Y) point, we consider boost factor to divide (m_X,m_Y) into 6 mass bins
- **Boost Factor ~ m_X / (m_Y + m_H)** [Ref.](#) (backup)



LowX = [300,400] GeV **LowY = [90, 250] GeV**

MidX = [500, 700] GeV **MidY = [300, 500] GeV**

HighX = [800,1000] GeV **HighY = [600, 800] GeV**

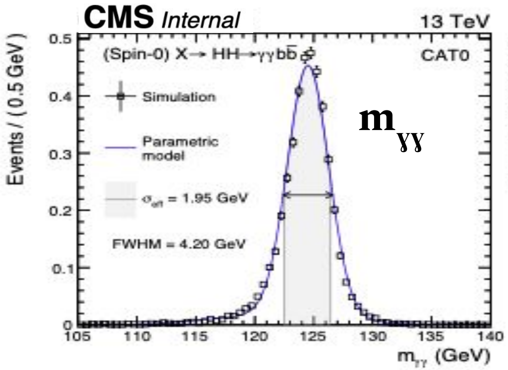
NOTE: training m_{jj} intervals are [70, 400] GeV, [150, 560] GeV and [300, 1000] GeV for LowY, MidY and HighY

- According to mass range definition signal events are mixed with same cross section
- Signal and Background events are normalised to unity separately
- **5-fold cross-validation and early-stopping feature is used to control overtraining.**

Signal Model

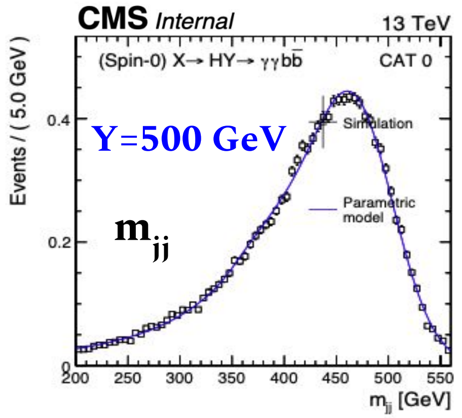
- $m_{\gamma\gamma}$:
  - sum of gaussian functions is used (upto 5)
  - number of gaussian function is decided from F-test
- m_{jj}:
  - DoubleCrystalBall (DCB) function or Sum of CB and Gaussian
  - Choose the best fit with best chi2
-

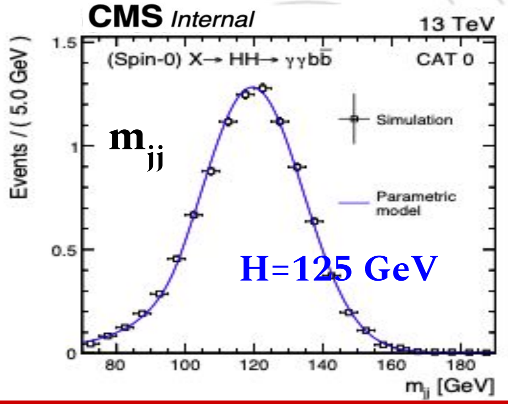
NOTE: m_{jj} plots are shown for all three bins

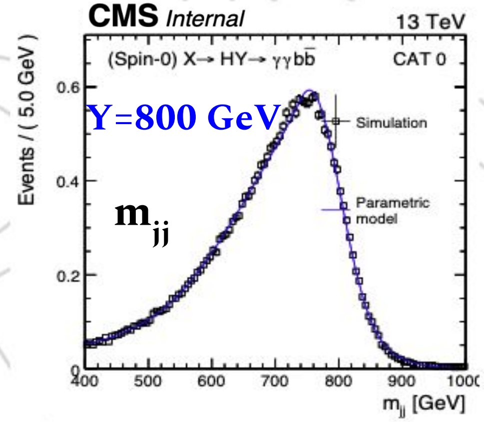


(a) Radion300

Figure 25: $M(\gamma\gamma)$ mod

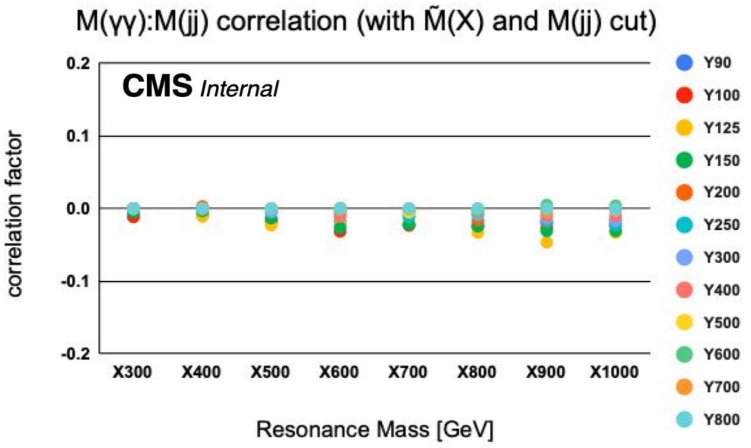


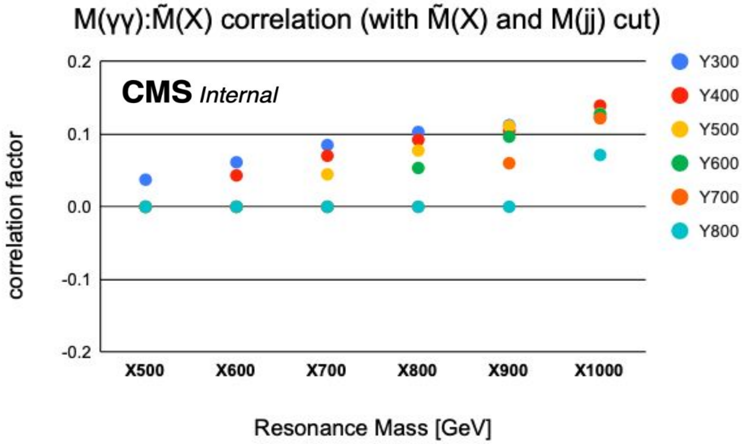




Signal Extraction Method

- Before using **$m_{\gamma\gamma}$: m_{jj}** signal 2D fit extraction method from HIG-19-018, we explore the possibility to use **$\tilde{M}_X$:$m_{\gamma\gamma}$** fit to use within analysis
- We compare **correlation** between pair of observables⇒ **higher for $\tilde{M}_X$:$m_{\gamma\gamma}$ fit**
- This leads us to go with **$m_{\gamma\gamma}$: m_{jj} 2D fit**





Correlation factor = Cov(M1, M2)/ std(M1)/std(M2)

- **Apart from this, for low resonance masses the turn-on in data $\tilde{M}_X$ distribution is issue to use $\tilde{M}_X$:$m_{\gamma\gamma}$ fit** (**plot is in backup**)

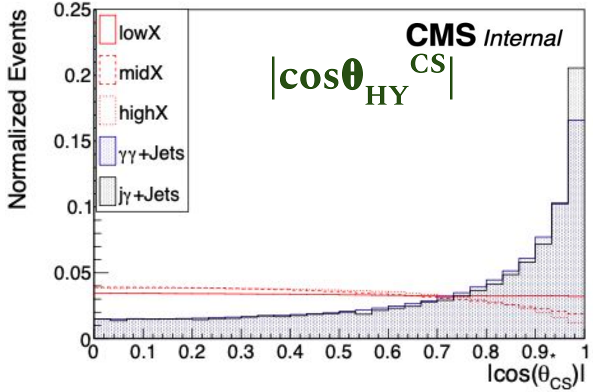
Comparison of the resonant analyses ATLAS vs CMS

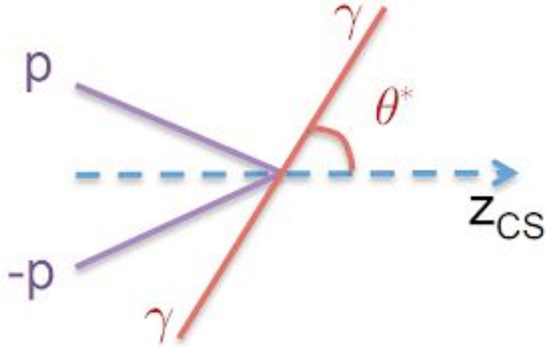
- Similar performance of ɣ reco+ID and b jet ID
- Similar analyses preselections

	ATLAS	CMS
Interpretations	• Spin-0 X→ HH→ bbɣɣ	• Spin0/2 X→ HH→ bbɣɣ • NMSSM X→ YH → bbɣɣ
ttH rejections	• ele and muon veto and < 6 jets	• ttH vs HH→ bbɣɣ DNN
MVA approach	• BDT to reject ttɣɣ & ɣ(ɣ)+jets • BDT to reject single H	• BDT to reject ɣ(ɣ)+jets
BDT training	• Inclusive to all m_X points • Signal m_X reweighted to match continuum bkg shape	• Separate in six mass region defined by boost factor $m_X/(m_X + m_Y)$
Categories	• 1 BDT-based category	• 3 BDT-based category
Signal extraction	• 1D $m_{\gamma\gamma}$ fit	• 2D $m_{\gamma\gamma}$:m_{jj} fit

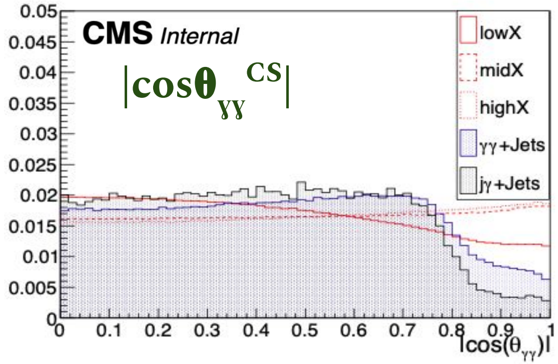
BDT classifier input variables

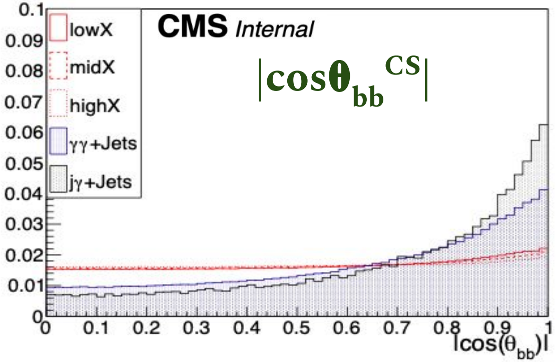
1) **Discriminative signal and background kinematic distributions:**
   a) Helicity angles, $|\cos\theta_{HY}{}^{CS}|$, $|\cos\theta_{bb}{}^{CS}|$, $|\cos\theta_{\gamma\gamma}{}^{CS}|$ where CS refer to Collins-Soper frame
   b) First two minimal angular distance between selected photons and jets ($\Delta R(\gamma,jet)$)
   c) $p_T(jj)/m_{jj\gamma\gamma}$ and $p_T(\gamma\gamma)/m_{jj\gamma\gamma}$
   d) Leading and subleading photons $p_T(\gamma)/m_{\gamma\gamma}$ and jets $p_T(j)/m_{jj}$





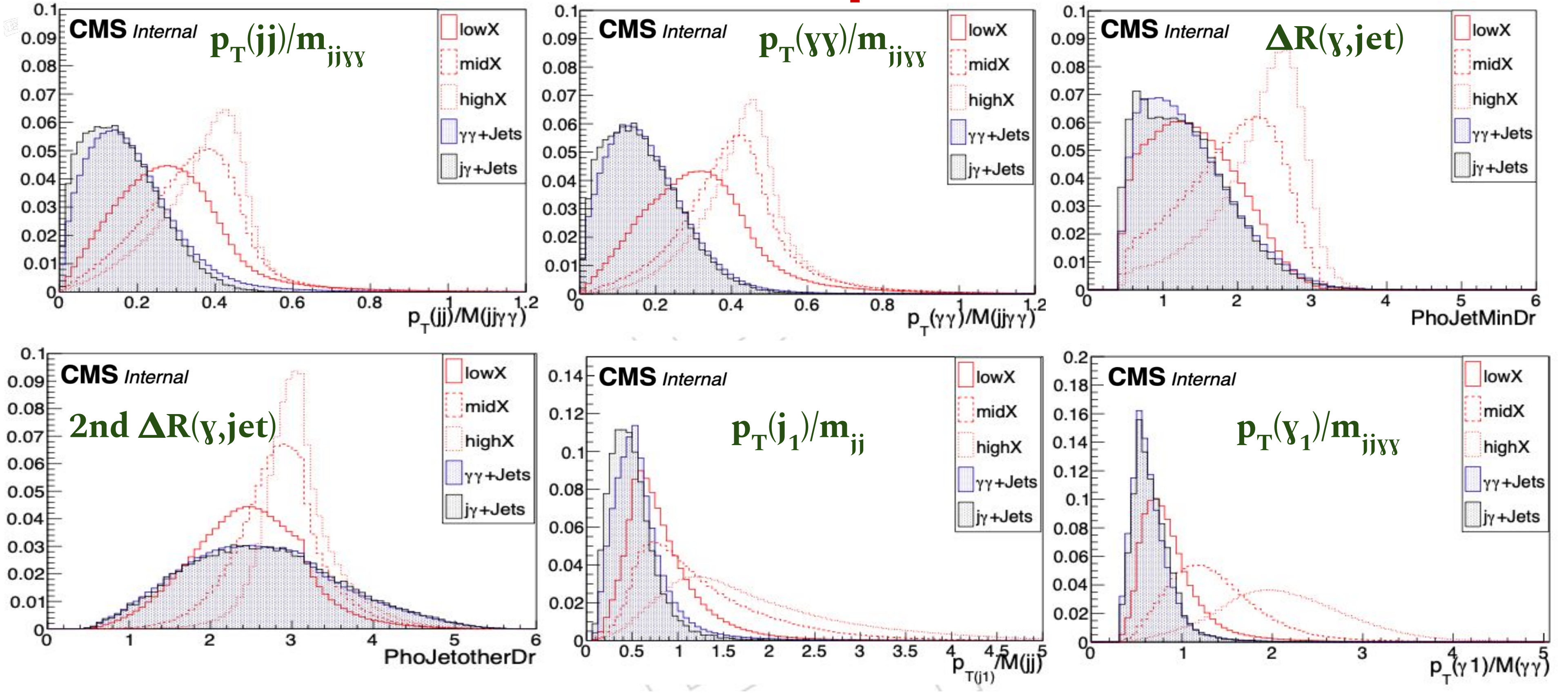
Collins-Soper Frame





NOTE: Red histograms represent the signal for three different m_X

BDT classifier input variables



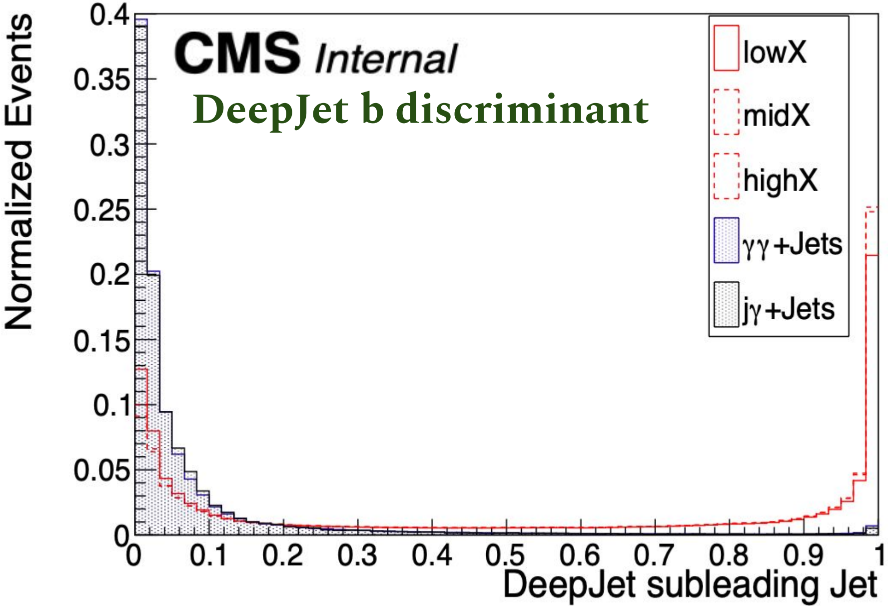
NOTE: Red histograms represent the signal for three different m_X

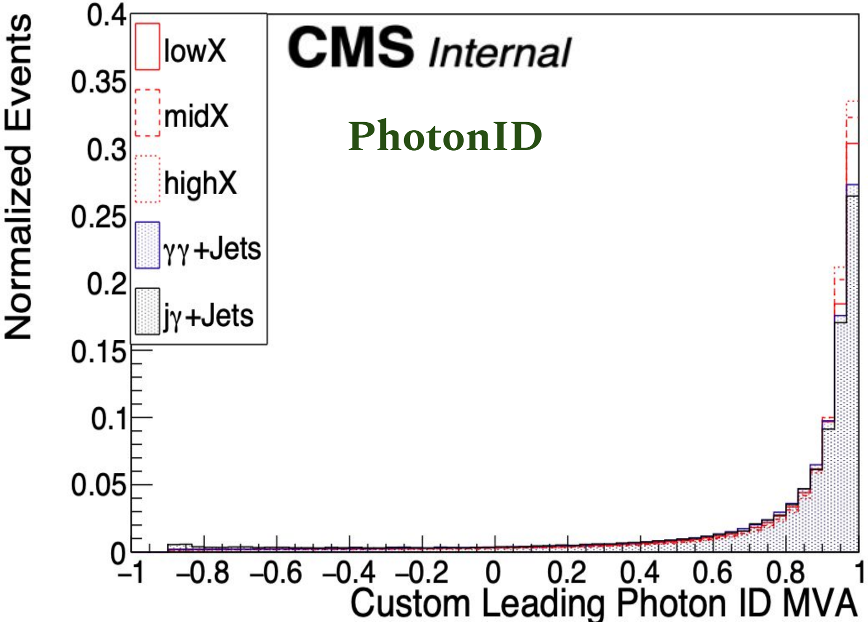
BDT classifier input variables

2) Object identification variables to reject fake contribution

a) Leading and subleading photonID MVA

b) Leading and subleading DeepJet b tagger score of jets



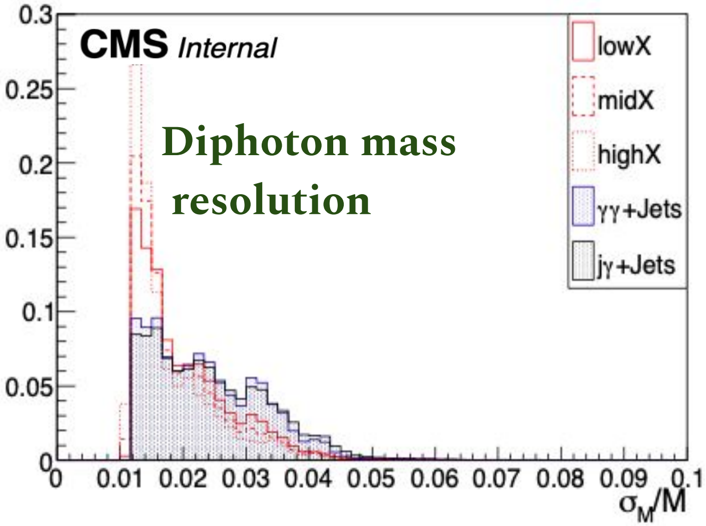


NOTE: Red histograms represent the signal for three different m_X

BDT classifier input variables

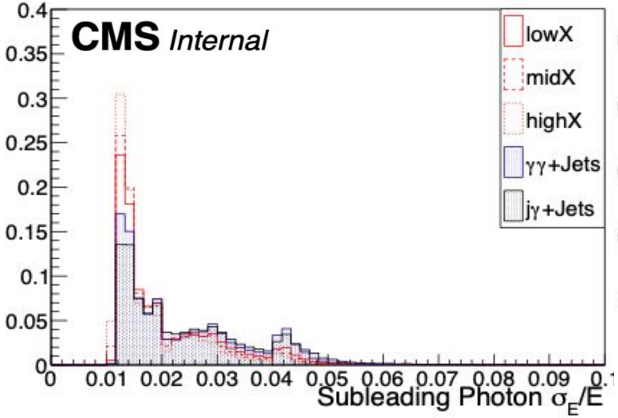
3) energy resolution variables

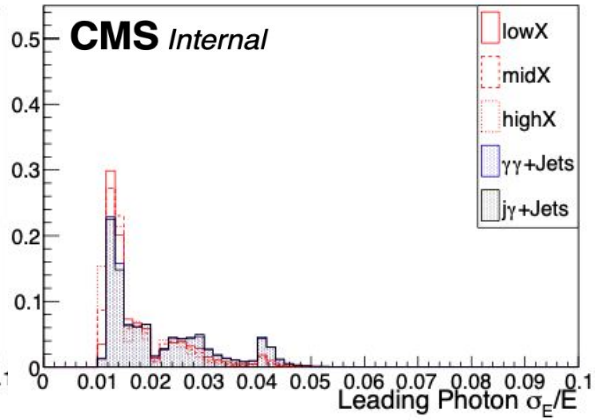
a) Leading and subleading photon energy resolution
b) Mass resolution of selected photon pair
c) Leading and subleading jet energy resolution
d) Dijet mass resolution



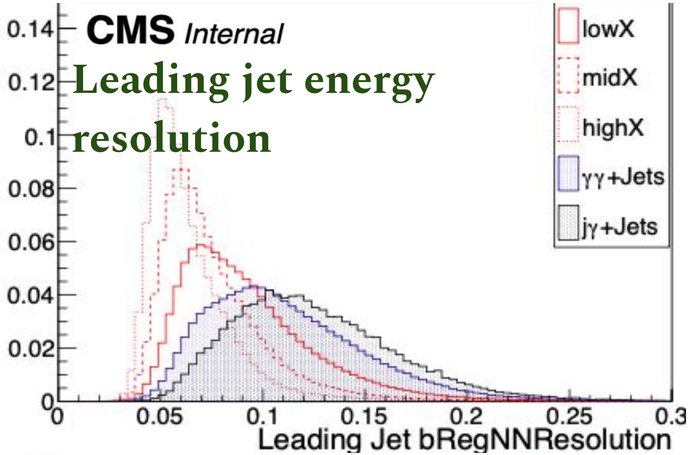
Diphoton mass resolution

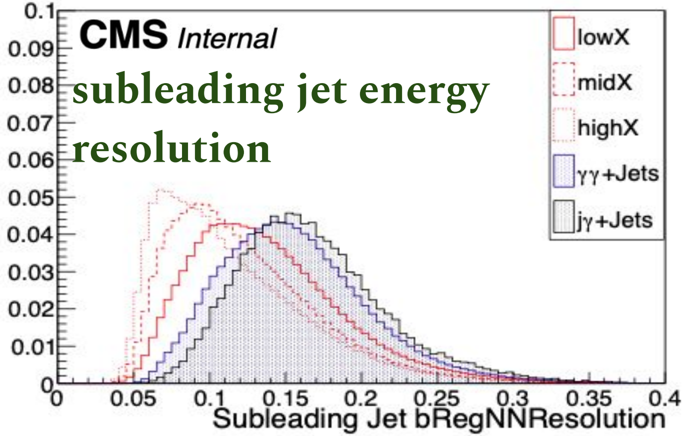
Leading and subleading photon energy resolution

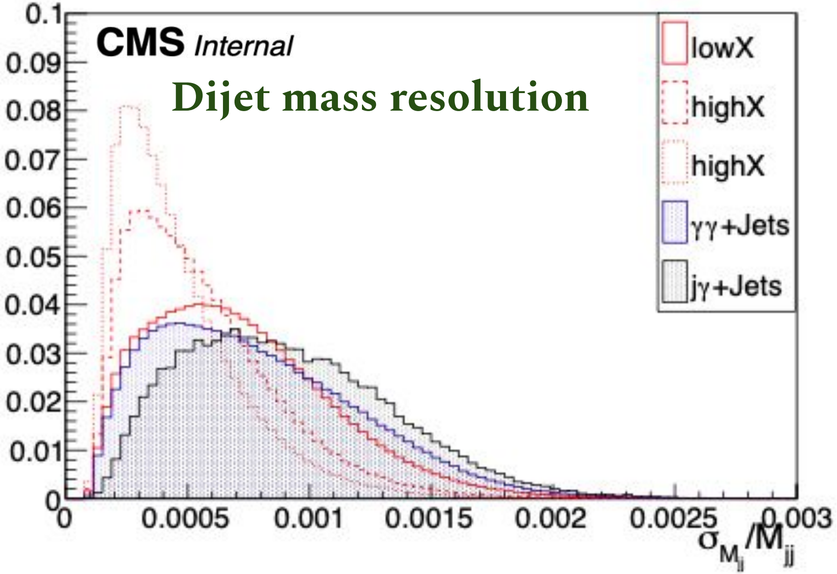




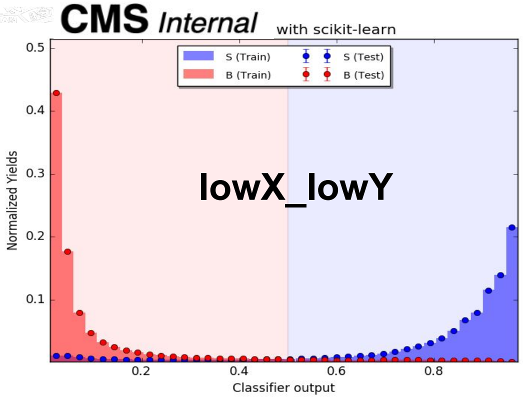
BDT classifier input variables

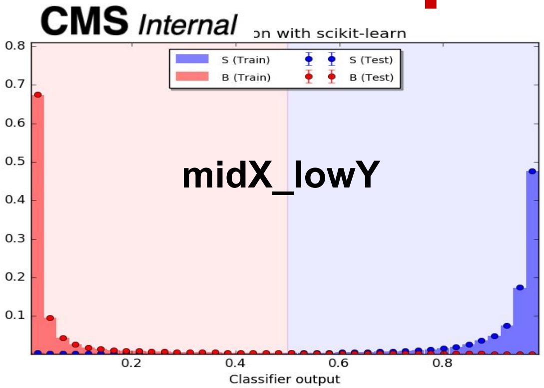


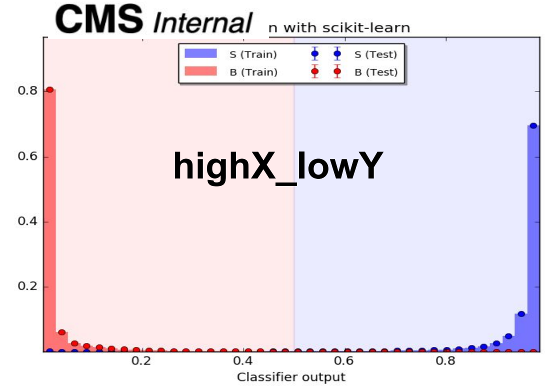


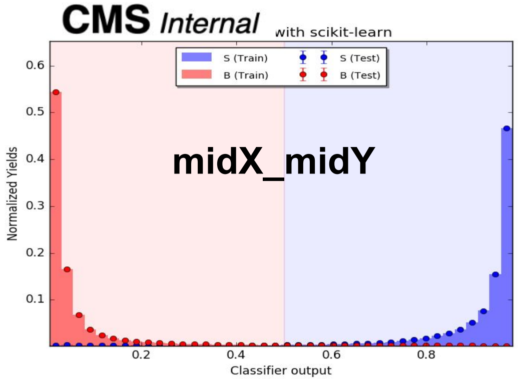


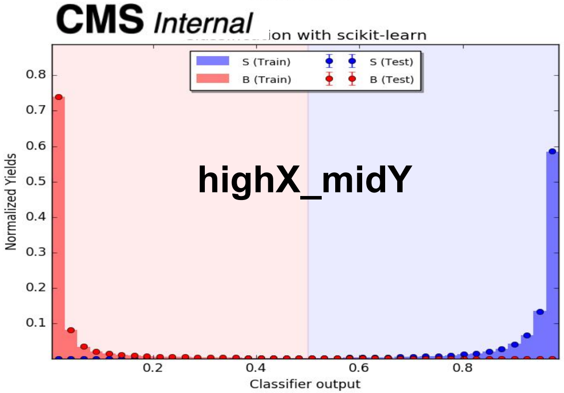
MVA Output

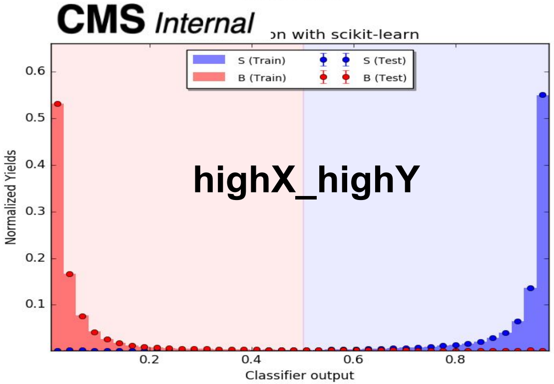

CMS Internal
with scikit-learn
S (Train)
B (Train)
S (Test)
B (Test)
lowX_lowY
Normalized Yields
Classifier output


CMS Internal
on with scikit-learn
S (Train)
B (Train)
S (Test)
B (Test)
midX_lowY
Classifier output


CMS Internal
n with scikit-learn
S (Train)
B (Train)
S (Test)
B (Test)
highX_lowY
Classifier output


CMS Internal
with scikit-learn
S (Train)
B (Train)
S (Test)
B (Test)
midX_midY
Normalized Yields
Classifier output

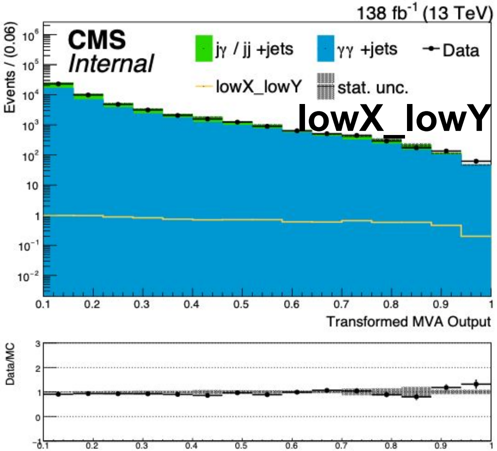

CMS Internal
ion with scikit-learn
S (Train)
B (Train)
S (Test)
B (Test)
highX_midY
Normalized Yields
Classifier output

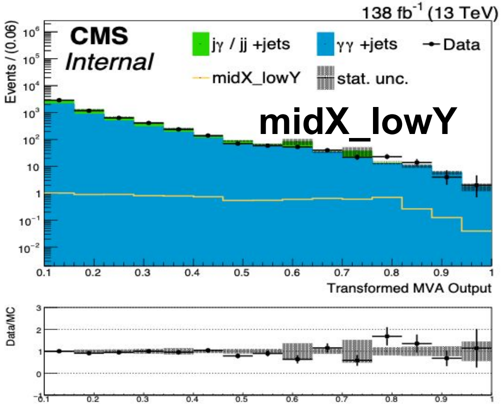

CMS Internal
on with scikit-learn
S (Train)
B (Train)
S (Test)
B (Test)
highX_highY
Normalized Yields
Classifier output

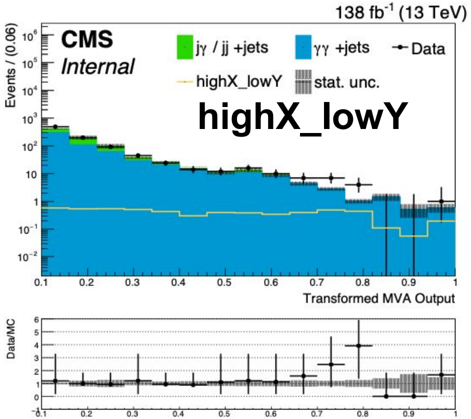
Input variables

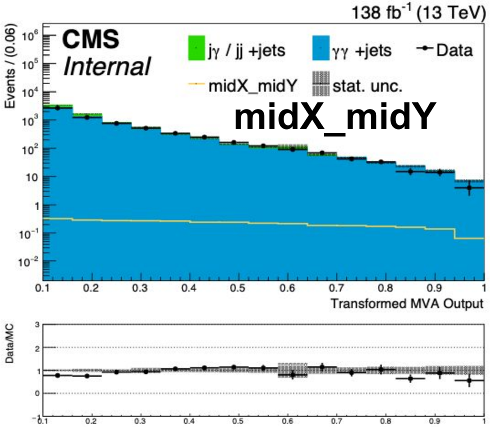
- f0= $\cos\theta^{*}_{HH}$
- f1= $\cos\theta^{*}_{bb}$
- f2= $\cos\theta^{*}_{gg}$
- f3= Min (ΔR (γ, j))
- f4 = other Min (ΔR (γ, j))
- f5= leadingPhotonId_MVA
- f6= subleadingPhotonId_MVA
- f7= leadingJet_DeepJet
- f8= subleadingJet_DeaepJet
- f9= leadingPhoton $\sigma(E)$ / E
- f10= subleadingPhoton $\sigma(E)$ / E
- f11= $\sigma(M\gamma\gamma)$ / $M\gamma\gamma$
- f12= $p_T(\gamma\gamma)$ / $Mjj\gamma\gamma$
- f13= $p_T(jj)$ / $Mjj\gamma\gamma$
- f14= leadingJet b-reg resolution estimator
- f15= subleadingJet b-reg resolution estimator
- f16= $\sigma(Mjj)$ / Mjj
- f17= leadingPhoton(pT/M$\gamma\gamma$)
- f18= subleadingPhoton(pT/M$\gamma\gamma$)
- f19= leadingJet(pT/Mjj)
- f20= subleadingJet(pT/Mjj)
- f21= rho

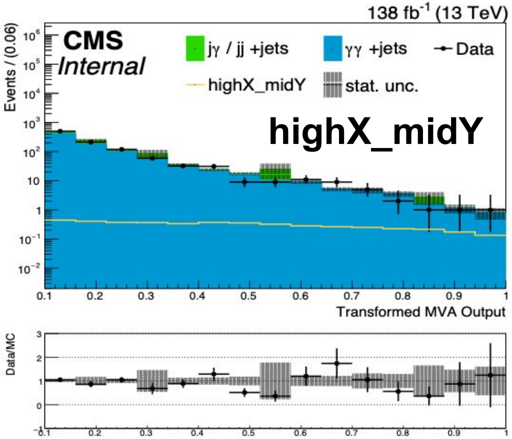
DATA-MC comparison

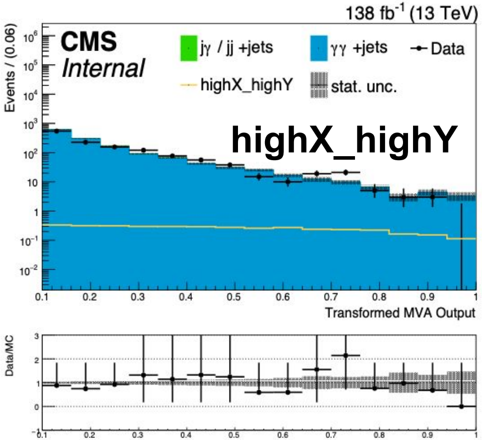












One BDT training for full Run-2