Search for resonant pair production of scalar particles with ATLAS Run 2 and Run 3 data

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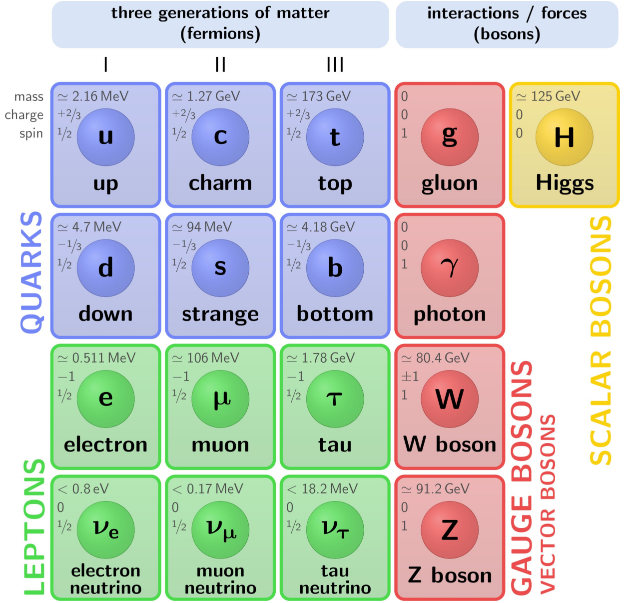
ATLAS EXPERIMENT

Probing the Higgs sector beyond the Standard Model

- Beyond the Standard Model (BSM) physics is needed to explain e.g. baryogenesis, neutrino masses and dark matter.
- Is the "SM Higgs" in fact part of something larger that we have not yet discovered?
- Many BSM models that include an **extended Higgs sector** predict additional new heavy scalars, X and S, **enabling decays of scalars to scalars, like $X \rightarrow HH$ or $X \rightarrow SH$.**
  - Examples include the Two-Higgs-Doublet Model (2HDM), the Next-to-Minimal Supersymmetric Standard Model (NMSSM), the Complex 2HDM (C2HDM), and the Two-Real-Scalar Model (TRSM).



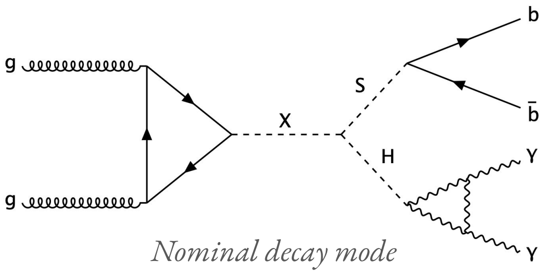
The elementary particles of the SM. Image: Wikipedia.

What are X and S?

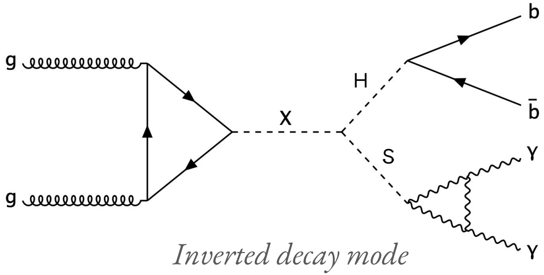
- Two scalar particles that would extend the Higgs sector of the SM.
- We do not know anything about them, but we assume here that $\mathbf{m_X > m_S + m_H}$, where m_H is the mass of the Higgs boson — this way **$X \rightarrow SH$ is kinematically allowed**.
- We introduce a simplified model with $X \rightarrow SH$ where m_S and m_X are allowed to vary. By including the scenario where $m_S = m_H$, we can also cover the scenario $X \rightarrow HH$.
- The decay modes of H assumed to be those of the SM Higgs boson.

The bbγγ experimental final states

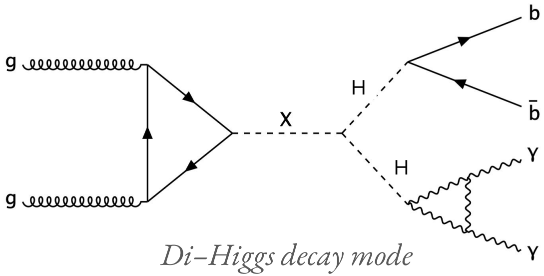
- The decay modes of S are model–dependent, and for this reason ATLAS and CMS explore various final states. Here, we focus on bbγγ final states.
- Two bbγγ final state has a relatively low SM background and in both scenarios we expect a narrow peak in the di–photon mass spectrum.
- We expect three peaks: in the $\mathbf{m_{\gamma\gamma}}$ **spectrum**, in the $\mathbf{m_{bb}}$ **spectrum**, and in the $\mathbf{m_{bb\gamma\gamma}}$ **spectrum** (corresponding to m_X).



Nominal decay mode
S→bb, H→γγ



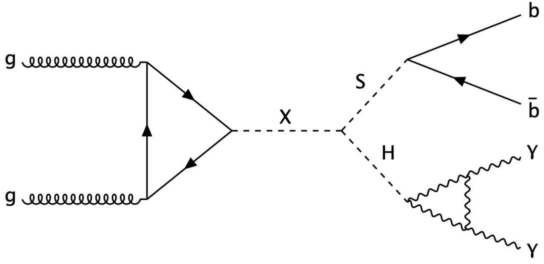
Inverted decay mode
S→γγ , H→bb

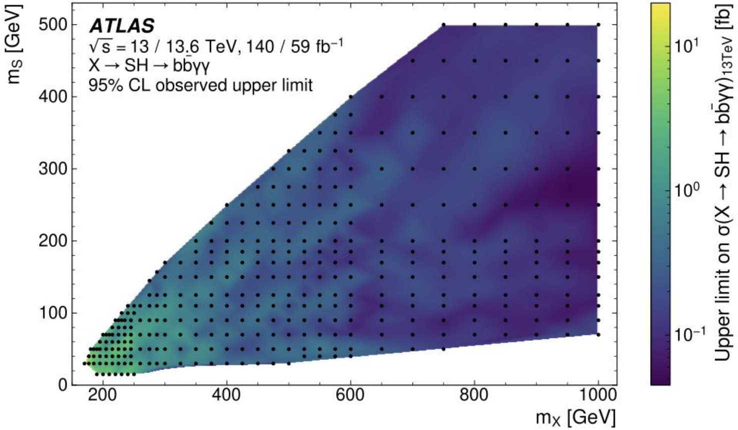


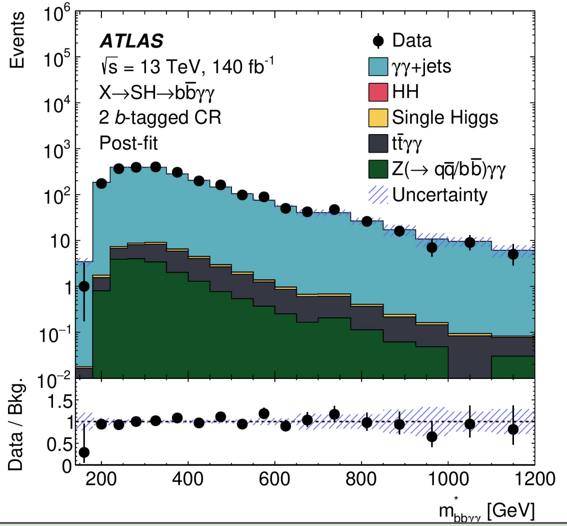
Di–Higgs decay mode
H→γγ , H→bb

Current research status – ATLAS search from 2025

- We performed a search for the nominal decay mode; X→S(bb)H(γγ), using **Run 2 + partial Run 3** data.
- Expected and observed 95% CL upper limits on cross section × branching ratio.
- No significant deviation from the SM expectation was observed.
- Introduced a parametrized neural network (PNN) in this analysis.



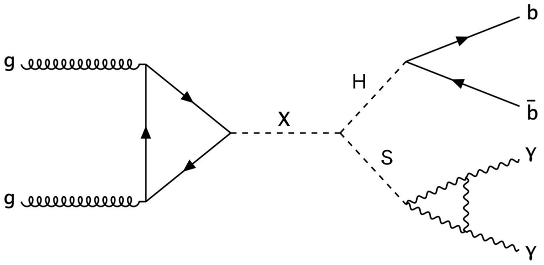


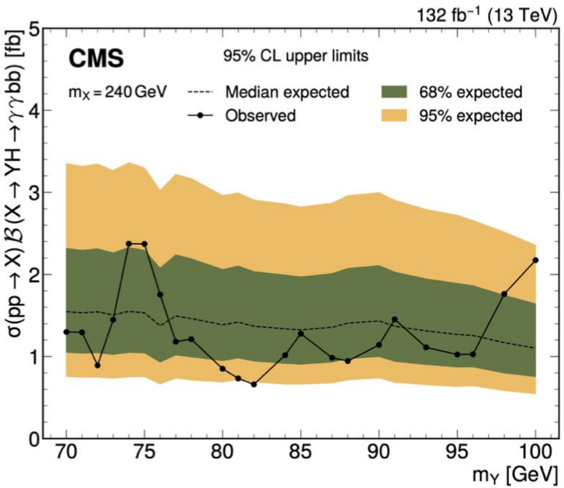


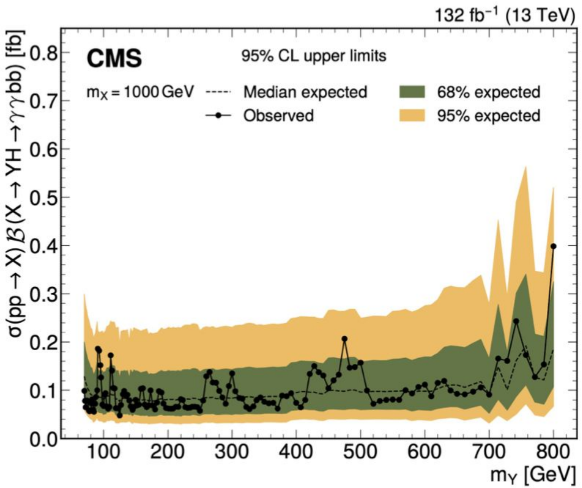
Plots from: arXiv 2510.02857

Current research status – CMS search from 2025

- CMS performed a search for the inverted decay mode; $X \rightarrow S(\gamma\gamma)H(bb)$, using **Run 2** data.
- Plots show expected and observed 95% CL upper limits on cross section × branching ratio for two m_X mass points.
- Slight excess for (m_X, m_S)=(300 GeV, 77 GeV)





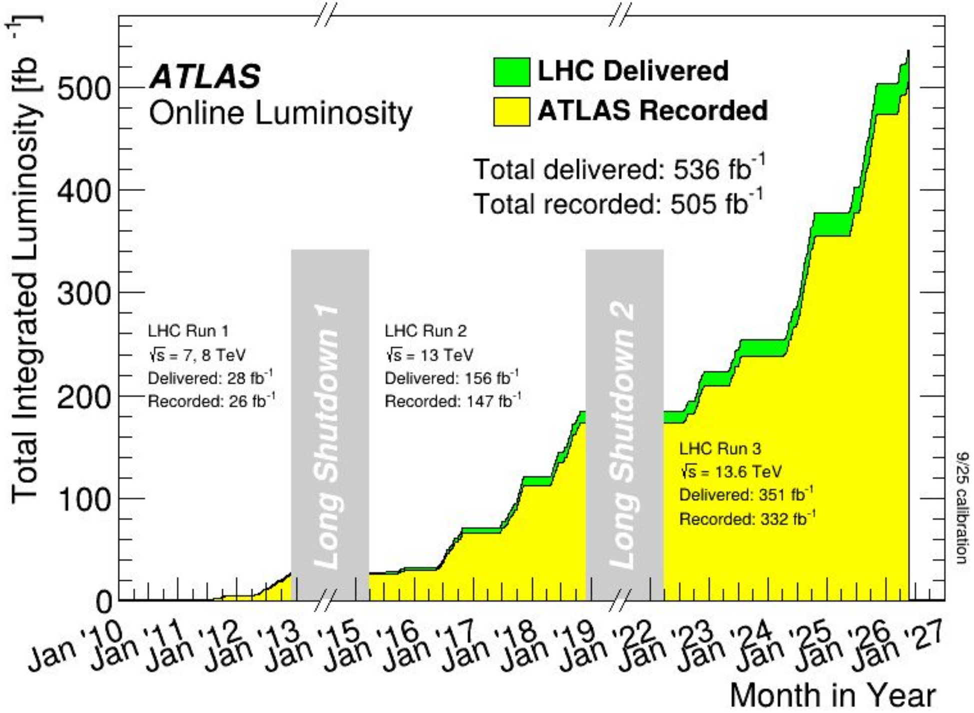


Plots from arXiv 2508.11494

New ATLAS full Run 2 + full Run 3 analysis

Run 3 just finished – we have access to more data than ever before; more than **2× the data** from the previous analysis, and more than **3× the data** from the CMS analysis.

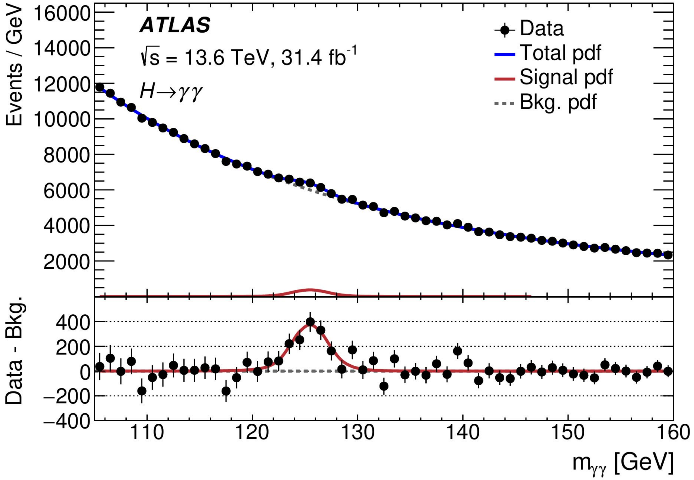
The analysis studying the inverted decay mode, X→S(γγ)H(bb), is in construction by ATLAS, as well as X→H(γγ)H(bb).



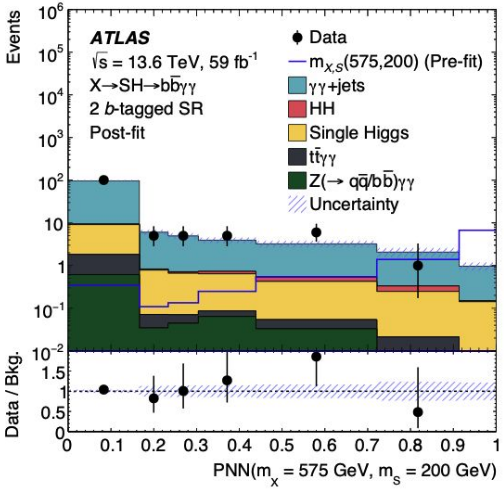
Plot showing the total integrated luminosity of LHC over time.
Image: ATLAS Collaboration/CERN.

Analysis strategies for the full Run 2 + full Run 3

Plot from: arXiv 2306.11379



Option 1: Use $m_{\gamma\gamma}$ as final discriminant. Same approach as in H→γγ. Relies on the ability to find analytical shape for $m_{\gamma\gamma}$ in the backgrounds.



Plot from: arXiv 2510.02857

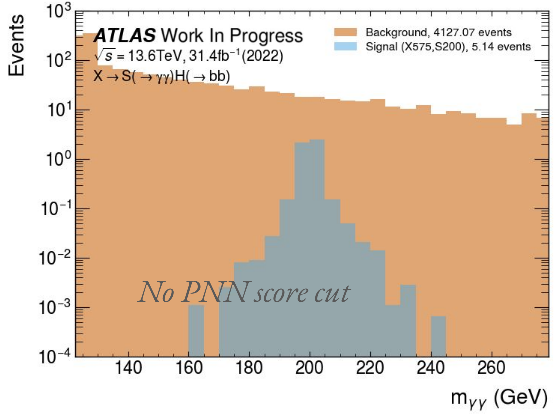
Option 2: Neural network (NN) approach. PNN assigns each event a signal–likeness score. Signal events cluster around score 1, background falls smoothly, so we fit the shape of this score distribution directly to test the signal hypothesis.

Testing Option 1 (traditional method) in X→S(yy)H(bb)

- Preselection (two photons, two b–jets)
- Apply cut on mass–point aware NN to maximally exploit all kinematic information, a so called parametrized neural network (PNN).
- Use $m_{\gamma\gamma}$ as final discriminant to test signal hypothesis.

80+ variables in different categories.

Evaluate the viability to apply the trad–itional method by looking at the $m_{\gamma\gamma}$ spectrum after cutting on the PNN.



Working on finding the *sweet spot*;
how many training variables, and which, are optimal?

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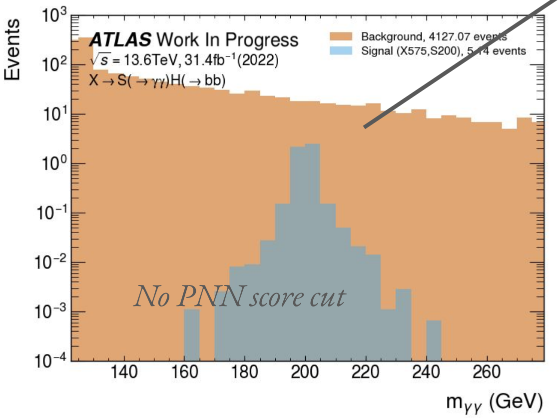

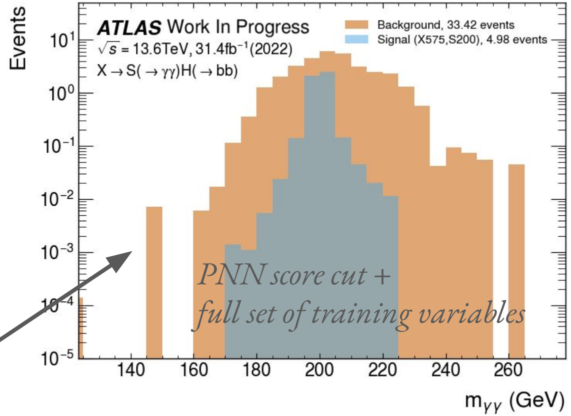

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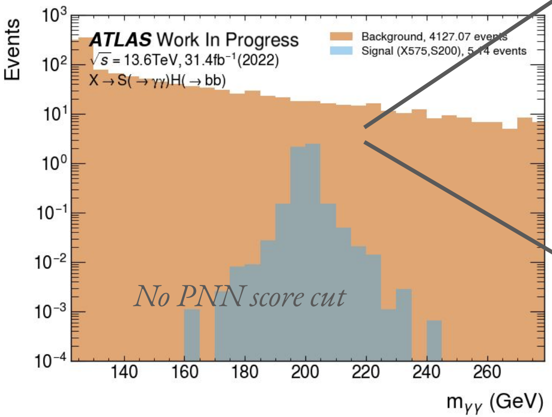
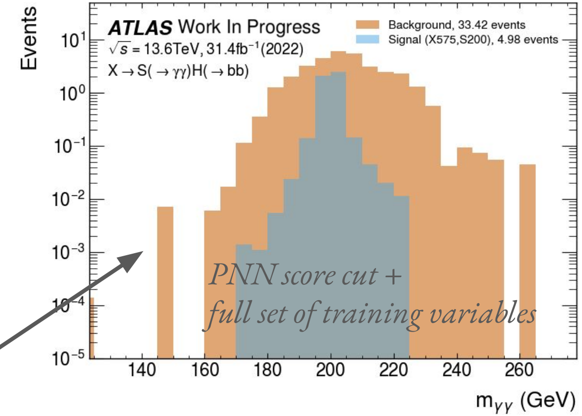
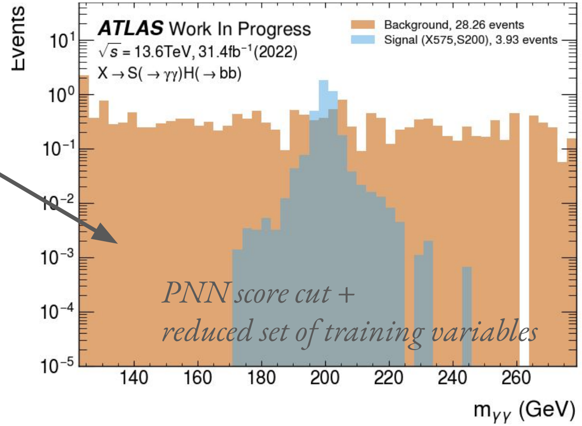
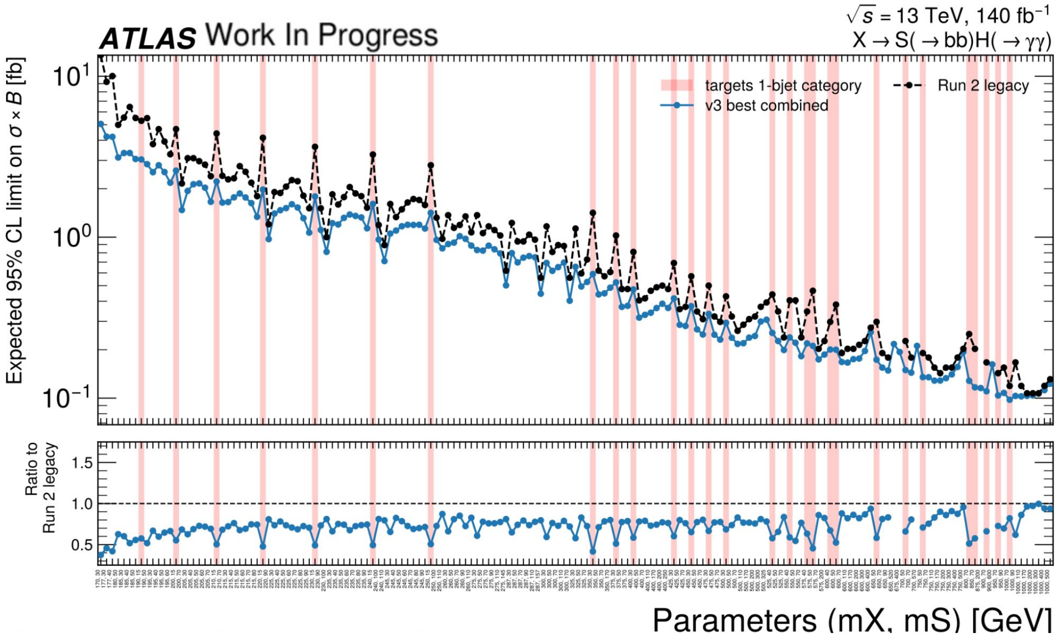






Testing Option 2 (NN approach) in X→S(bb)H(yy)

- Preselection (two photons, two b jets)
- Use PNN score as final discriminant to test signal hypothesis.
- Can potentially make use of all kine–matic information.
- Identified set of variables that opti–mizes the limits on cross section × branching ratio.
- Up to 60% better than legacy limits with Run 2 results.



Conclusions and outlook

- We recently performed search using Run 2 and partial Run 3 data – X→S(bb)H(yy).
- Now expanding by studying S(yy)H(bb), S(bb)H(yy) and H(bb)H(yy) channels, using **full Run 2 and full Run 3** data.
- Studying which set of PNN training variables optimise the results.
- What is next?
    - Decide which final discriminant to use; either $m_{\gamma\gamma}$ or the PNN score (Option 1 or Option 2).
    - Compare our current limits (obtained in the nominal channel) with the unbinned fit limits and see which strategy is the best.

Thank you for listening!

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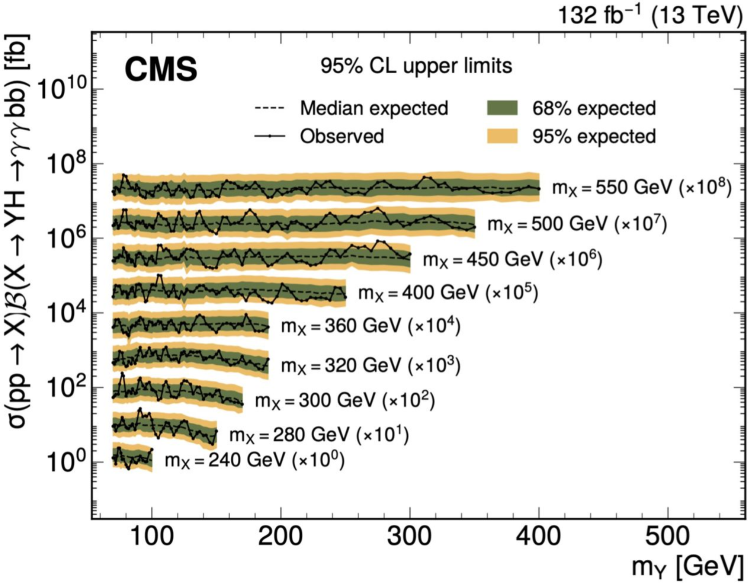
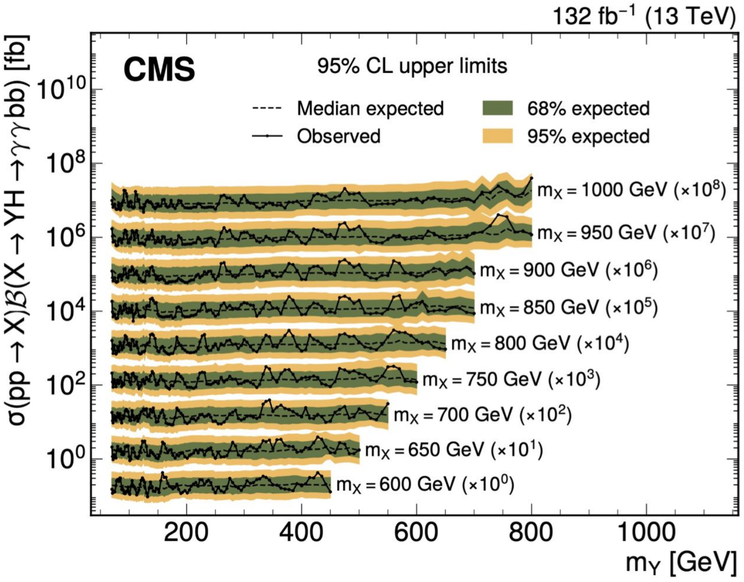
Backup slides

X→S(γγ)H(bb): previous results by CMS (arXiv 2508.11494)





PNN variables — full set

*Variables in **boldface** used by CMS in [their PNN training]*

Mass variables
mbb, **mb1**, myy, mbbyy, mbbyy_mod_inverted

b-jet kinematics
HbbCandidate_Jet1_pt, px_b1, px_b2, py_b1, py_b2, pz_b1, pz_b2, HbbCandidate_Jet1_E, HbbCandidate_Jet2_E, HbbCandidate_Jet2_pt, eta_b1, eta_b2, phi_b1, phi_b2, HbbCandidate_Jet1_eta, HbbCandidate_Jet2_eta

bb system
pT_bb, **dR_bb**, px_bb, py_bb, pz_bb, E_bb, cos_dPhi_bb, eta_bb, phi_bb

Candidates for removal
mb1, mbbyy (keep mbbyy_mod_inverted), redundant variables

Photon kinematics
Photon1_ptOvermyy, **Photon2_ptOvermyy**, px_y1, px_y2, py_y1, py_y2, pz_y1, Photon1_E, Photon1_pt, Photon2_E, Photon2_pt, eta_y1, Photon2_eta, Photon1_phi, Photon2_phi

yy system
pT_yy_over_myy, **dR_yy**, **delta_eta_yy**, px_yy, py_yy, pT_yy, pz_yy, E_yy, cos_dPhi_yy, eta_yy, phi_yy

bbyy system
dR_y1b1, **dR_y1b2**, **dR_y2b1**, **dR_y2b2**, **dR_y1bb**, **dR_y2bb**, **dR_yyb1**, **dR_yyb2**, **dR_bbyy**, **delta_eta_yybb**, **delta_eta_yyb1**, **delta_eta_y1b2**, **delta_phi_yybb**, **delta_phi_yyb1**, **delta_phi_yyb2**, cos_dPhi_bbyy, cos_dPhi_bbyy_bb, cos_dPhi_bbyy_yy, E_bbyy, px_bbyy, py_bbyy, pz_bbyy, pT_bbyy, phi_bbyy, dR_bbyy_bb, dR_bbyy_yy, eta_bbyy

Note: all variables with dimension were scaled to TeV scale to facilitate better PNN training.