New Physics Search with Parameterized NN

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Search for new physics using ML

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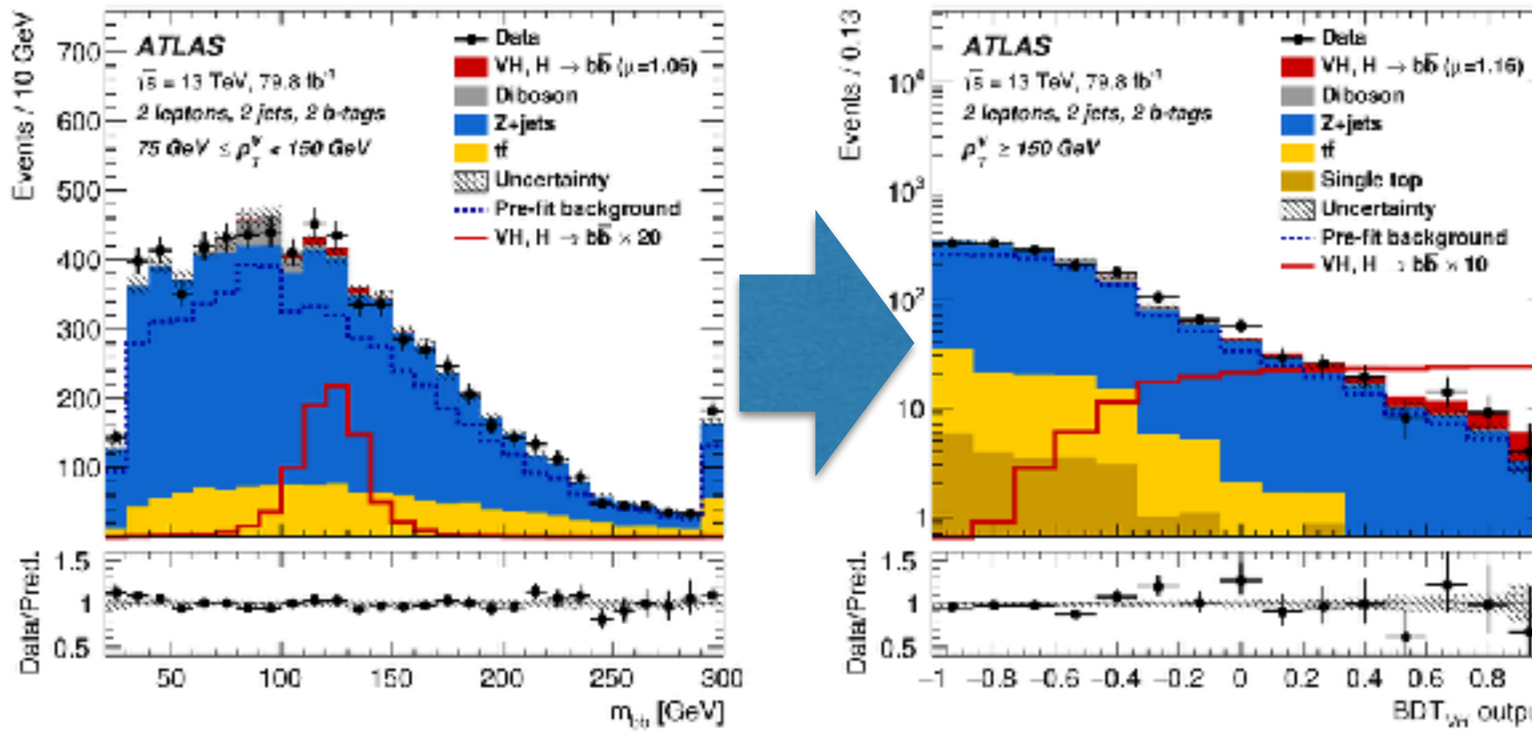
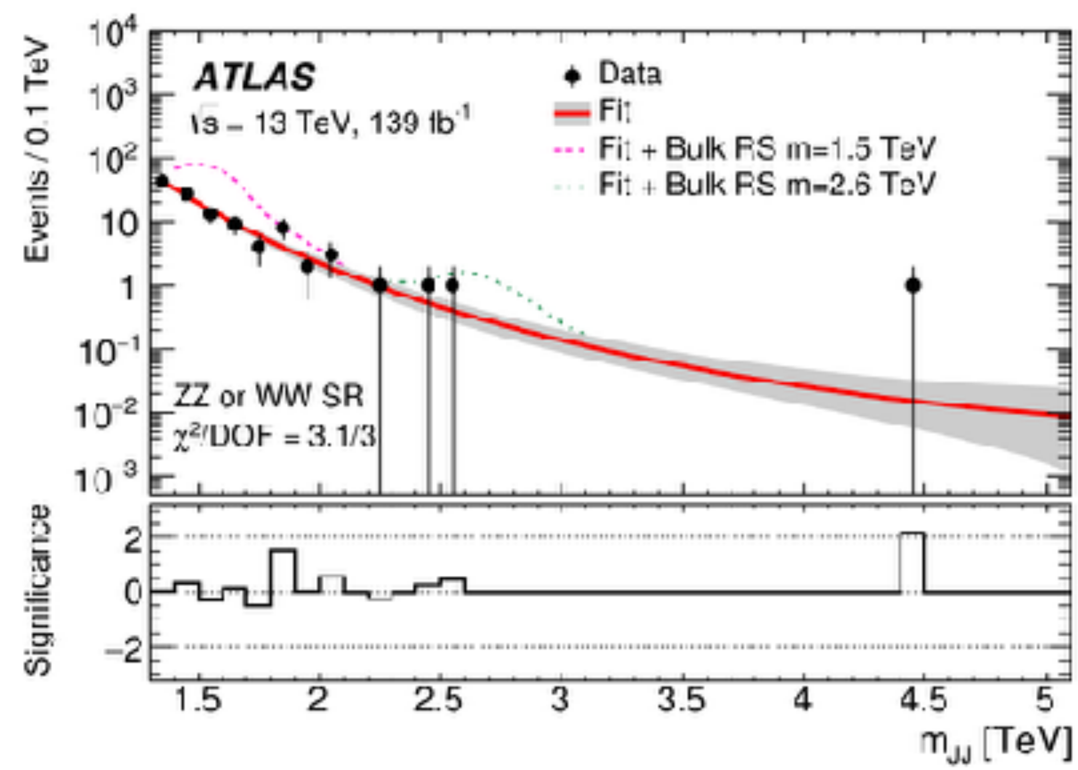
- If we want to test **a specific model**, ML classifier is a powerful tool to enhance signals
  - e.g. H→bb
    is “observed” at ATLAS
  - Using BDT: 3σ → 5σ (!!)

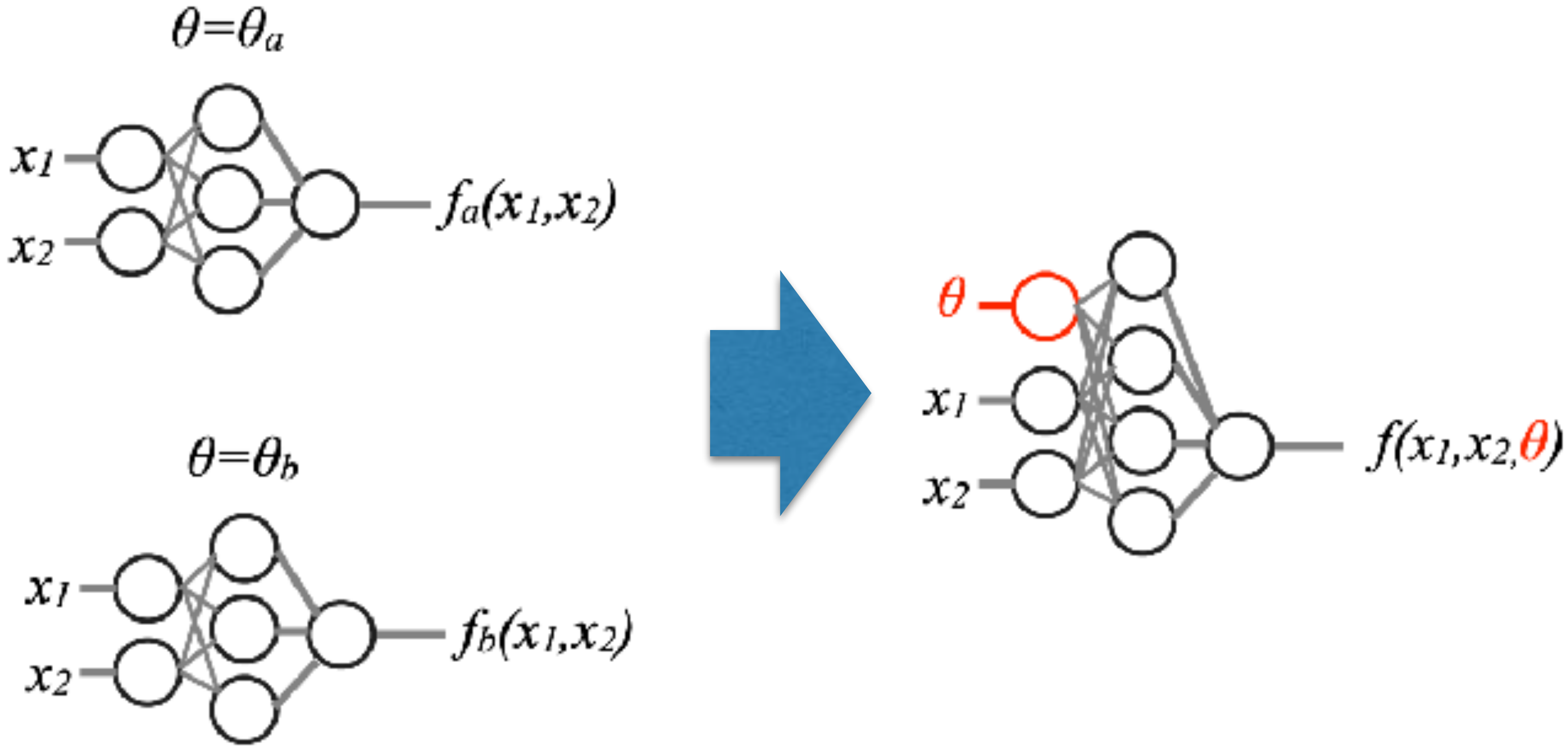


- Search for **hypothetical new particles** <u>with unknown parameters</u> e.g. resonant mass
  - Training at each mass point? probably no sensitivity at mass points not used in the training
  - We must *NOT* overlook these signals



Parameterized NN (pNN)

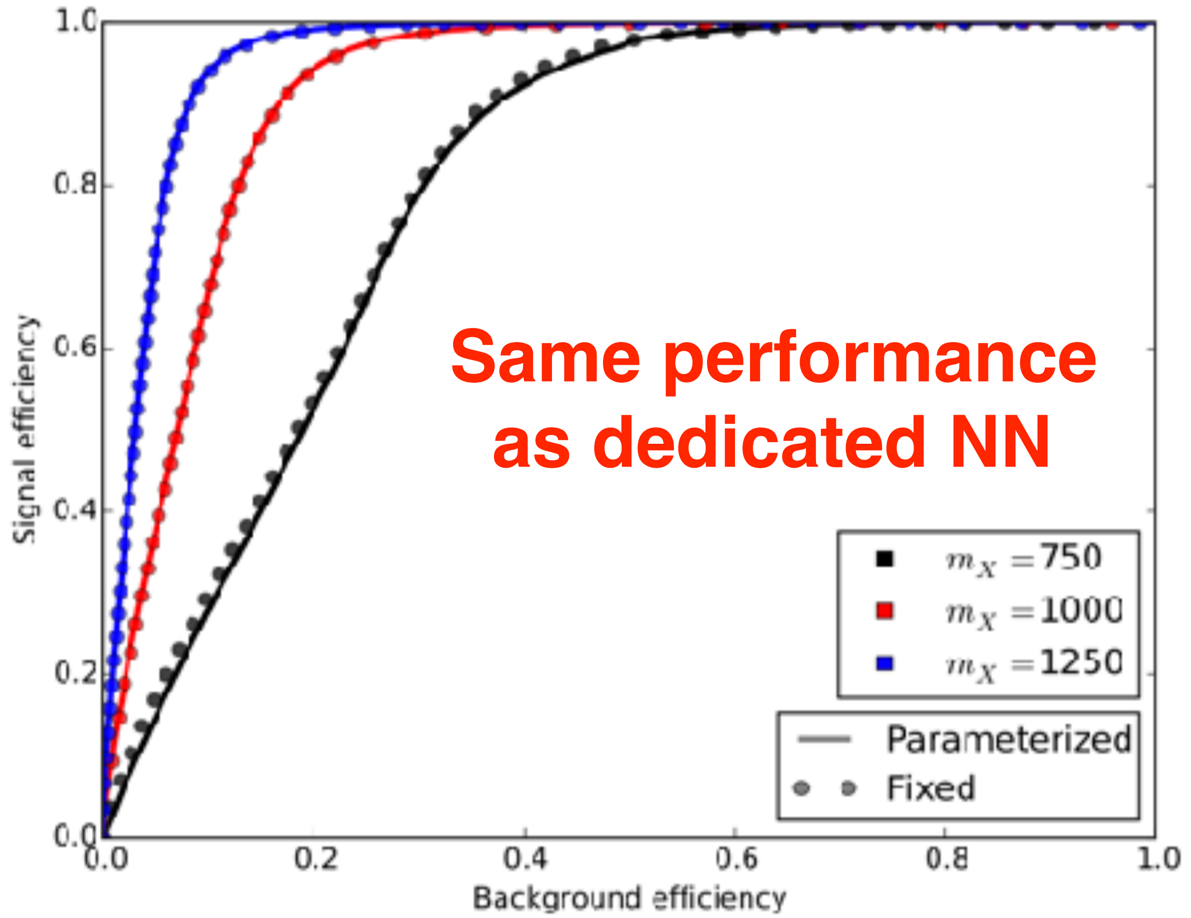
Baldi et. al.



- Adding a parameter of the physics model (θ; for example mass) to the input of Neural Network
- (x_1, x_2, …) is the input variables (e.g. p_T, η, ϕ, E, etc.)
- Signal: all generated mass points are mixed up and used in the training
- Background: θ is **randomly assigned** to reproduce the same distribution used for the signal sample in the training

pNN -cont'd

- An example of narrow ttbar resonance (X→tt) search
  - Solid black line: pNN trained with signals with m_X=500, 1000, 1250 and 1500GeV (without 750GeV)
  - Black dots: a single NN trained at m_X = 750GeV



- Since m_X is randomly assigned for bkg sample, the "effective" MC statistics of bkg depends on number of mass points used in the training

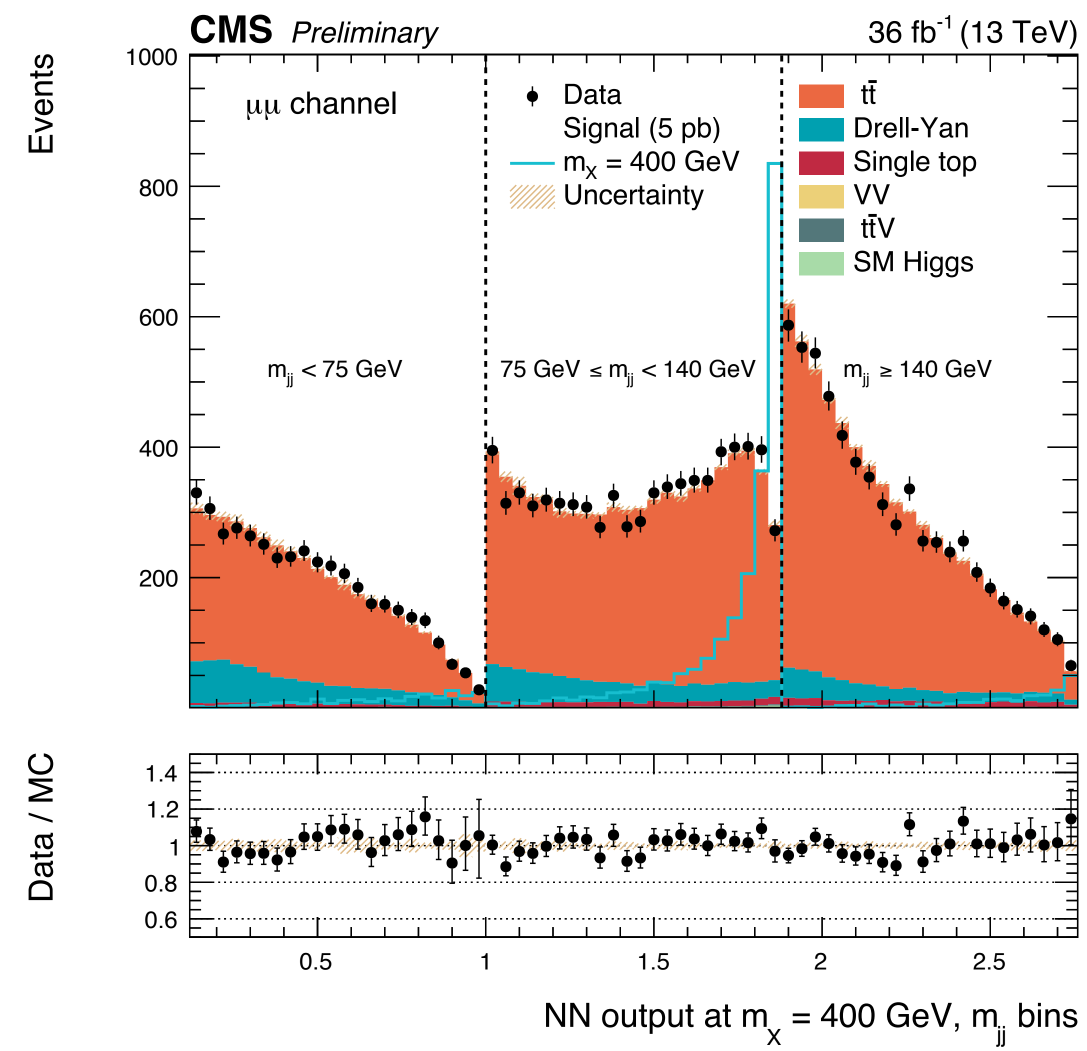
- But it doesn't mean we have to reduce number of mass points in the training. If we can't ensure the linearity of kinematic variables between 2 mass points, the performance at the intermediate mass region may deteriorate

CMS HH→bbWW search

[CMS-PAS-HIG-17-006]

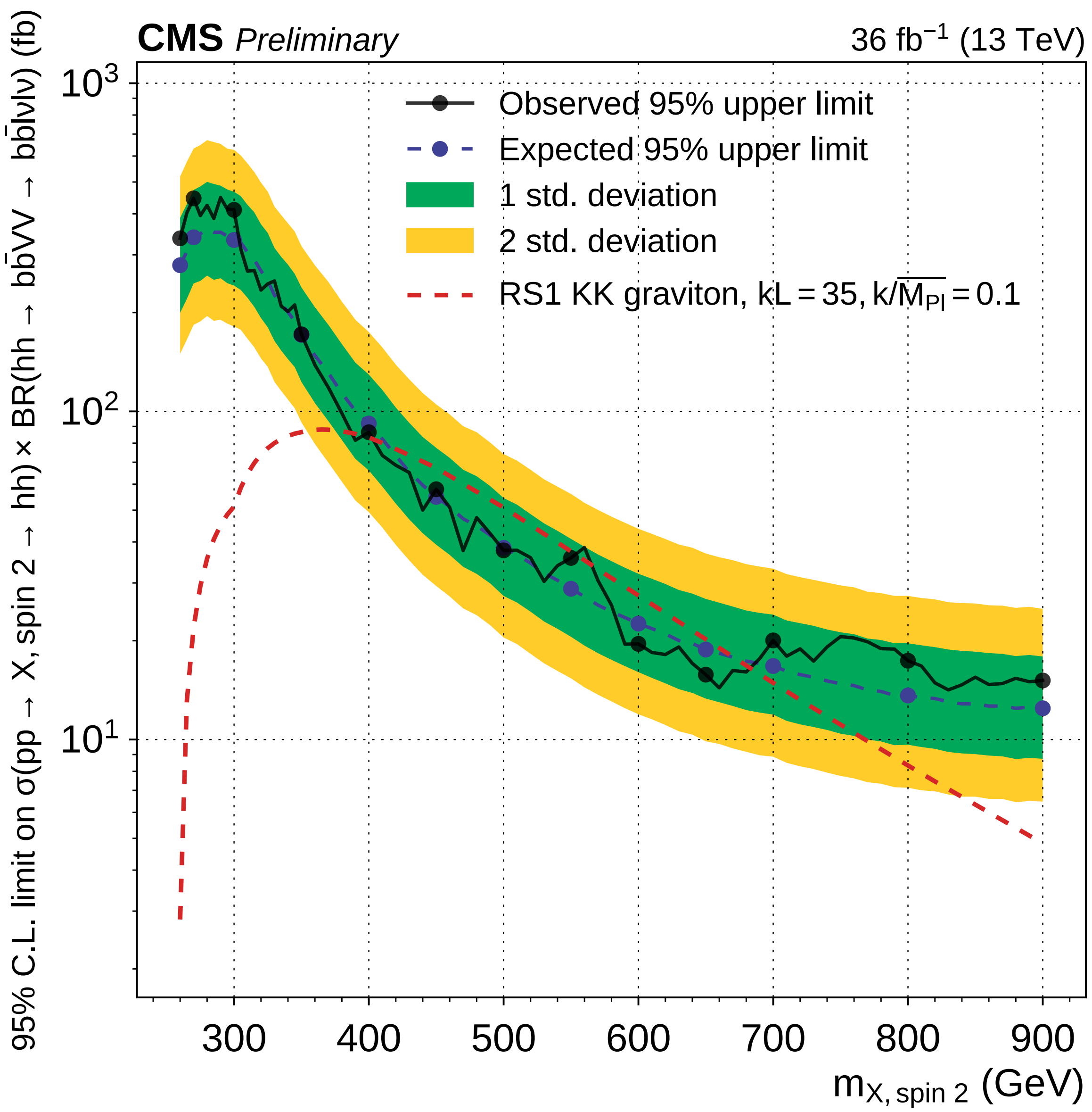
- Using pNN
  - Input variables: dijet and dilepton kinematics + missing E_T
  - m_X=(260, 270, 300, 350, 400, 450, 500, 550, 600, 650, 750, 800, 900)GeV are used in the training
- Background normalization is constrained in $m_{h\to bb}$ sideband region
- Background modeling study should be repeatedly done at each mass point scanned in the interpretation

f(*x*, 400GeV) in μμ ch.



x65 sets of distributions

CMS HH→bbWW search -cont'd

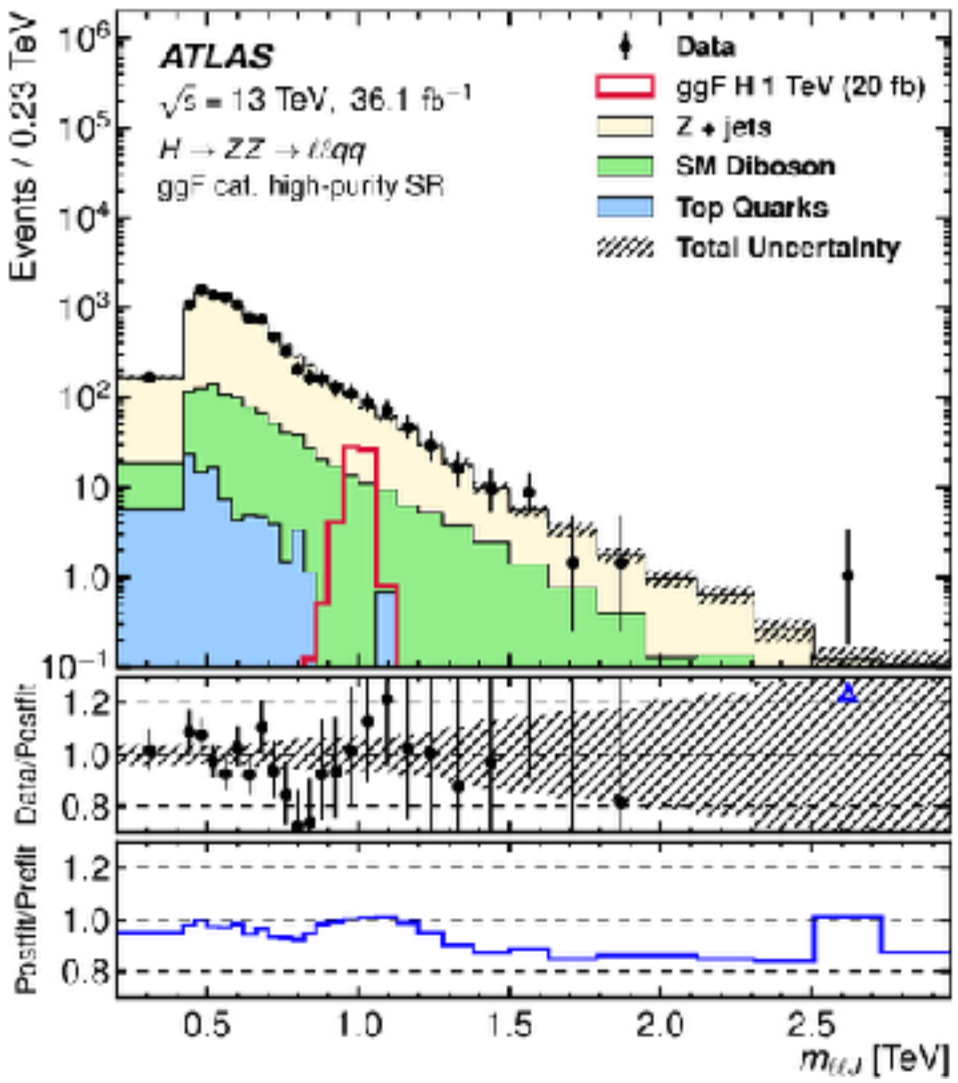


- Hypothetical test has been done in 10GeV step
  - i.e. **65 independent analyses** (260GeV to 900GeV) has been performed
  - i.e. background modeling of f(x, 260GeV), f(x, 270GeV), …, f(x, 900GeV) are carefully studied
- The same data are used repeatedly at each mass point
- Expected limit is smooth (*nice feature of pNN*)

Improvement by ML v.s. simplicity

- If we expect clear peak of new physics signal

- 10-30% sensitivity gain by using NN
  ⇔ $\times N$ background modeling studies (N: number of mass points)



e.g. JHEP03(2018)009

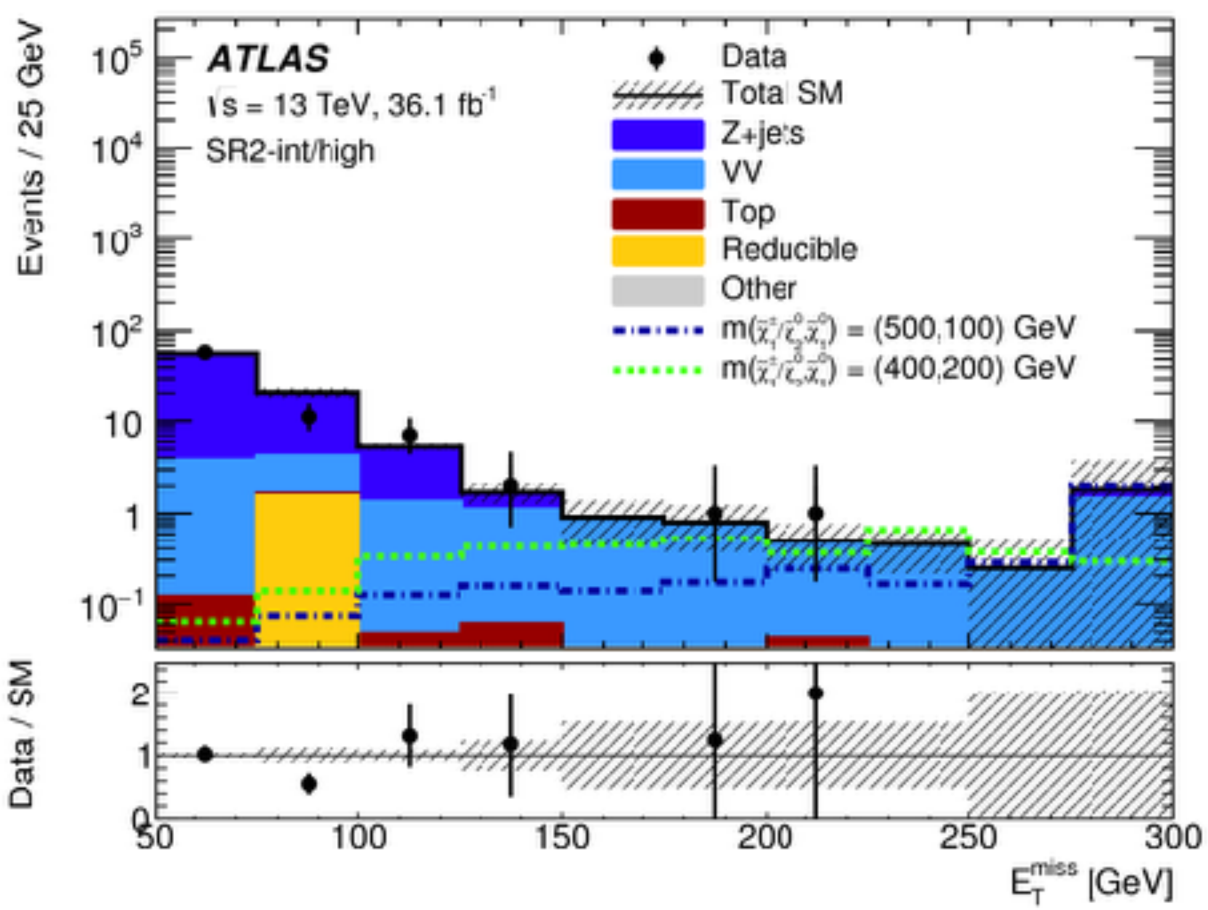
- e.g. anomaly detection (anti-background tagger) with adversarial NN is a better approach in that case?

Good use case of pNN?

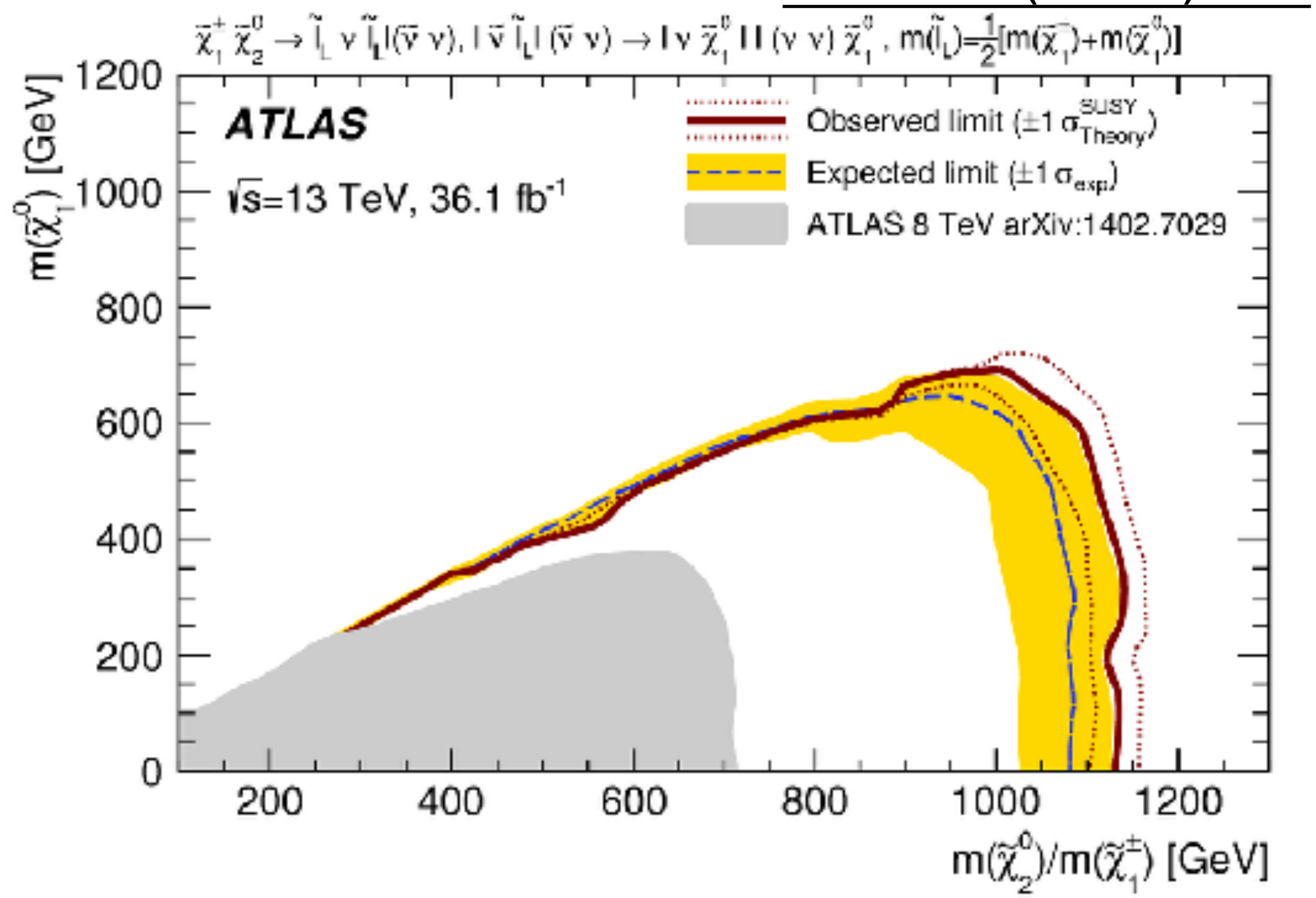
- If we can't reconstruct the theoretical parameters directly due to missing particles e.g. in SUSY and DM searches?

- Multi-dimensional pNN might be useful, but it depends on statistics of bkg samples

EPJC78(2018)995



Signal does not have "peak"



Signal kinematics depends on several parameters

Summary

- pNN expands input of NN to include not only experimental observables but also model parameters
- It can smoothly interpolate the sensitivity between parameters used in the training
- When the interpretation, anyway we need to perform independent analyses at each parameter point
  - x*N* efforts needed for background modeling study
  - In case we can reconstruct theoretical parameters directly, is it worth the cost?
- Might be useful for searches for invisible particles