Improving Background Estimation for Di-Higgs Searches with ATLAS

PHYS 437B Presentations

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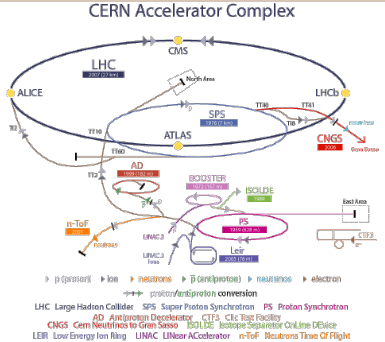
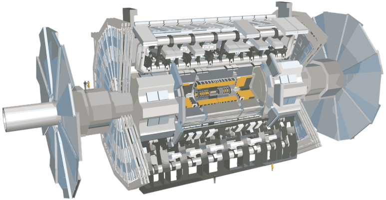
Overview: Higgs Research with ATLAS





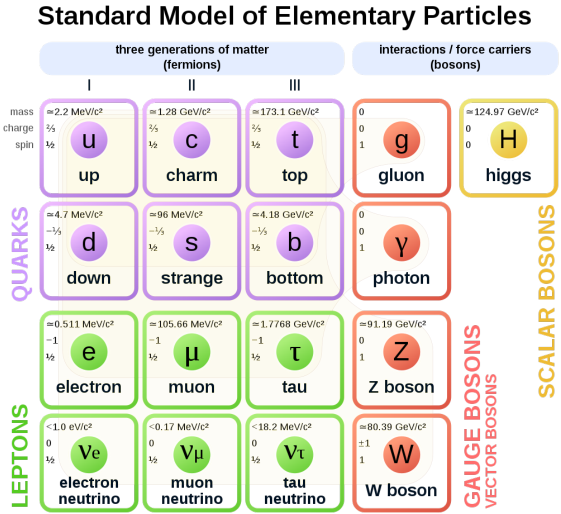


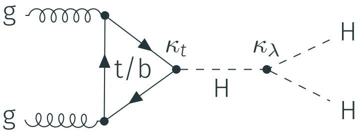
Image sources: Accelerator Complex, ATLAS, Standard Model

The Larger Project: Measuring the Higgs Self-Coupling

Relevant section of the SM Lagrangian for Higgs potential:

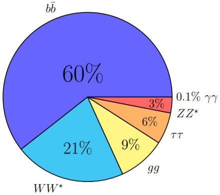
$$V(\phi) = -\mu^2\phi^2 + \lambda\phi^4 + \ldots \text{ Taylor exp. at min } \rightarrow V_T(\phi) = -\frac{\mu^4}{4\lambda} + \frac{\sqrt{2}\mu^3}{\lambda}\phi - 4\mu^2\phi^2 + 2\sqrt{2\lambda}\mu\phi^3 + \ldots$$

Constant and ϕ terms: can eliminate with change of coordinates, ϕ^2: mass term,
ϕ^3: self-interaction or self-coupling term, not well constrained
(current best: $\kappa_\lambda = (2\sqrt{2\lambda}\mu)/(2\sqrt{2\lambda}\mu)_{\text{SM}}$, $\kappa_\lambda \in [-2.3, 10.3]$ at 95% confidence)



To find κ_λ we need *HH* events, and we can find them using jets!

Background: Jets and Pairing



$H \rightarrow 60\% b\bar{b} \rightarrow 2 \times b$ hadrons $\rightarrow 2 \times b$-jets

- Jets are collections of particles with appx. the same direction
- ATLAS can't directly detect H or b. Instead, use b-jets, which can be directly detected (using secondary vertices)
- b-jet detection is not a perfect process (hence 437A report), and neither is pairing – identifying which jets came from which H

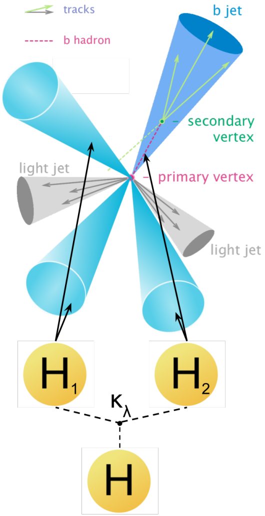


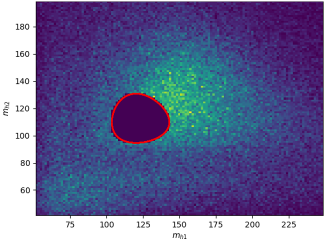
Image sources: branching ratios, b-tagging image adapted from here

HH Backgrounds

- When looking at HH events, singal = 4 b-jets, background = other QCD processes
- In 95% of LHC analyses, backgrounds can be simulated (e.g. with GEANT)
- But QCD modelling is difficult
  (computationally and physics-wise, especially for many-jet events)
- Motivates using data for background estimation
- But how?

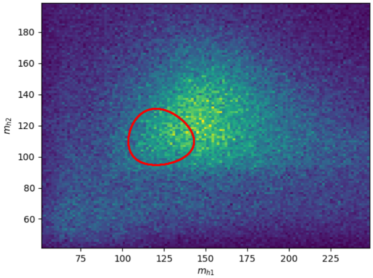
Our Project: Background Modelling

- Mass plane: reconstructed (m_{H_1}, m_{H_2}) values, m_{H_1} has higher transverse momentum
- We expect a peak around $(125, 125)$ (all masses in GeV)
- The Problem: how to estimate background around peak?
  Large source of error $(|\kappa_\lambda| < 7 \rightarrow |\kappa_\lambda| < 9)$
- Signal Region (SR, in red): blinded to reduce study bias
- We want to "fill in" the SR



Current Approach: $2b$RW

- All jets are similar to a rough approximation
- $2b$ data: uses 2 b-jets and 2 other jets
- Similar to $4b$ data outside of SR, but no peak
- $2b$RW: derive a scaling (“ReWeighting”) function outside of SR, apply inside
- Provides a good first background estimate
- Assumes RW function applies in SR, may be false
- This project: is there a better approach?

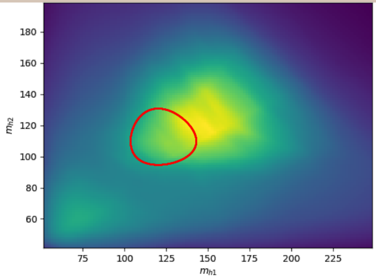


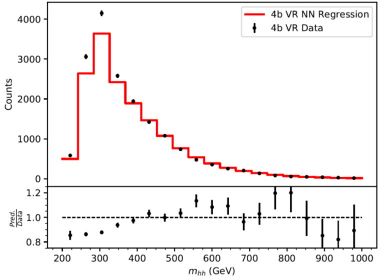
Note

Don’t forget $2b$ data is physically different from $4b$ and $2b$RW are not **real** SR values. $2b$RW is thought to be correct within around $\pm 10\%$.

New Approach: Neural Network

- Given enough data, neural networks can learn arbitrary functions
- Goal: fill in the SR, and reproduce 2bRW $\pm 10\%$ using only 4b data
- Inputs: $(m_{H_1}, m_{H_2}, m_{HH})$, output: $P(m_{H_1}, m_{H_2})$
- Initially: good-looking mass plane predictions, 2bRW agreement is not great though





Histogram image from Todd Seiss. Note: this is 4b VR, most plots will use 2bRW SR

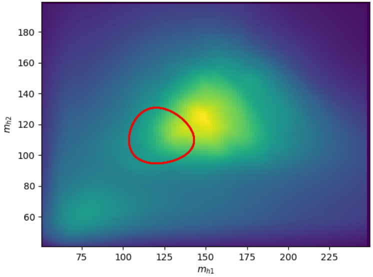
Neural Network Optimization

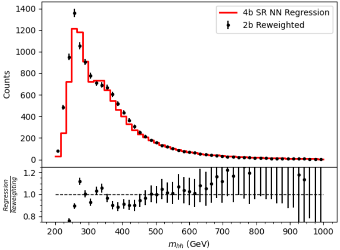
What if we...

- Further optimize network hyperparameters?
- Add more bins?
- Add other variables (e.g. more masses, NTag)?
- Smooth the data (fit a polynomial, KDE, ...)?

Overall impression: large improvements unlikely from non-drastic changes in approach

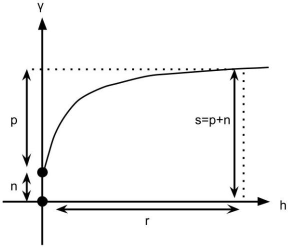
- (note: images are from different models, to show how many of them had similar performance to before)



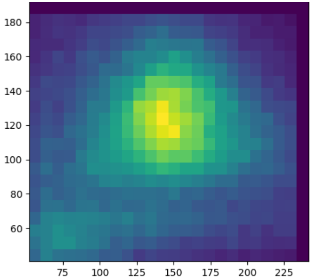


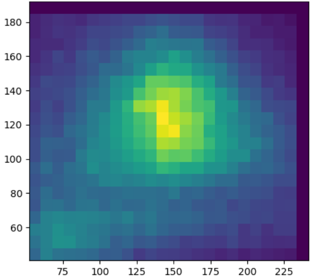
New Approach: Gaussian Process Regression

- Inputs: m_{H_1}, m_{H_2}, output: $P(m_{H_1}, m_{H_2})$
- Also gives estimator variance ($\exists$ assumptions)
- Relies on variogram (ideally could calculate, given finite data must guess)



- Tried a bunch of different "best-guess" variograms, e.g. linear and exponential:



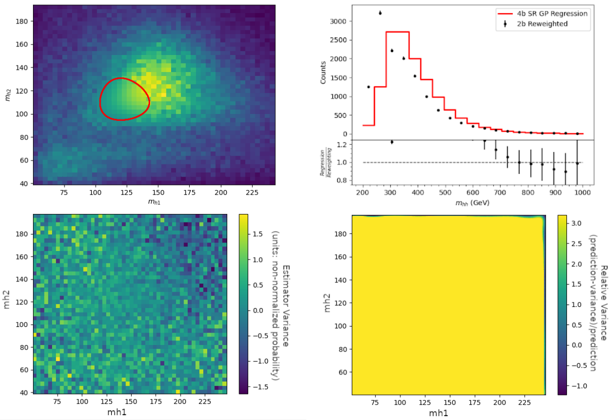


GPR Optimization

- Tested many variograms
- Selected low & flat variance
- Best ones still high relative to prediction ($\sim 1\times$)
- Tried 3D GPR, increases computation time too much

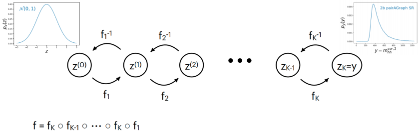
Impressions:

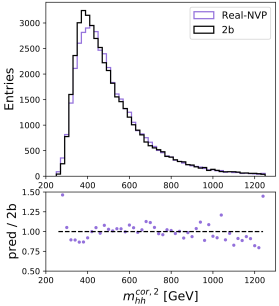
- Good mass plane, less-good histogram
- Interesting variances are always so large
- Figures: Gaussian variogram ($s = 800, r = 160, n = 10^{-8}$)



Flow Models

- The idea of flows: build arbitrary function from base function + invertible transformations
- R-NVP transformations: fast compute times
- Benefit: significantly smaller model space, can handle more variables
- Code was set up for 2*b* pairAGraph data + figures compare 2*b* SR prediction vs 2*b* SR data
- With larger models, some nice results are possible (e.g. 5-variable model in figure)

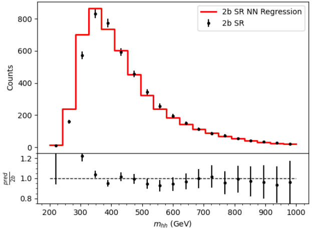




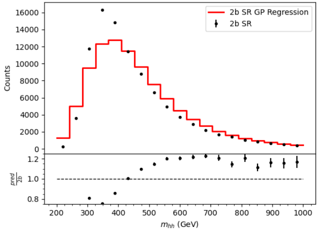
Comparison of FMs to NNs and GPR

Use $2b$ pairAGraph data on previous methods, compare with a FM with inputs (m_{H_1}, m_{H_2}):

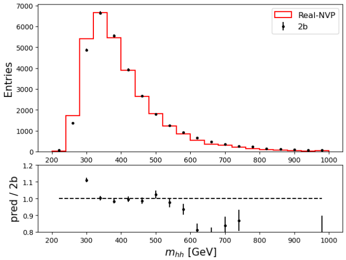
NN:



GPR:



FM:



Conclusion

- Direct NN regressions and GPR capture main features of the complicated background
- However, the existing $2b$RW procedure seems to perform better for the moment
- Flow models with more variables look promising
  (or potentially other similar techniques, e.g. variational auto-encoders)

Questions?
Comments?
Any other techniques we should try?

Backup Slides

Link to Google Slides with more details