

Machine Learning for analysis

- Personal related

Bo Liu



Usage of Machine Learning for physics

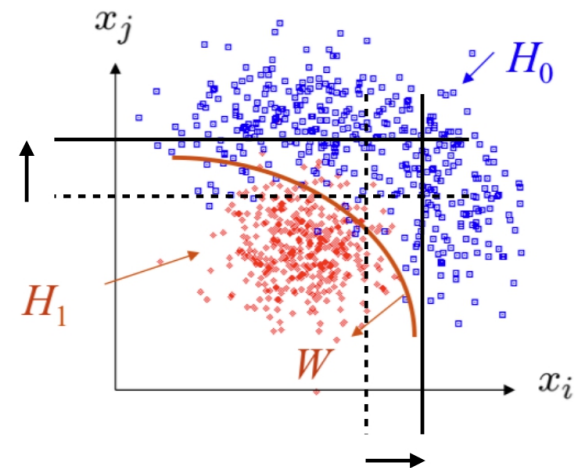


❖ Classification

■ Objection tagging

- ✓ Btagging
- ✓ Electron/photon identification
- ✓ q/g tagging
- ✓ Fatjet tagging

■ Event selection and tagging



❖ Regression

■ Correction to truth objection

- ✓ B-jet energy correction

■ Background estimation

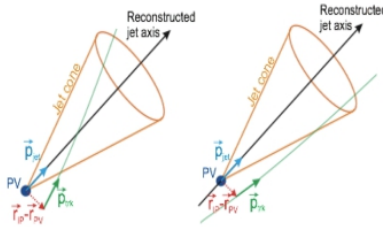
- ✓ Reweight from CR to SR

ML for btagging



- **IP3D / IP2D:**

- Impact parameter algorithm
- Exploit (in)compatibility of track with PV



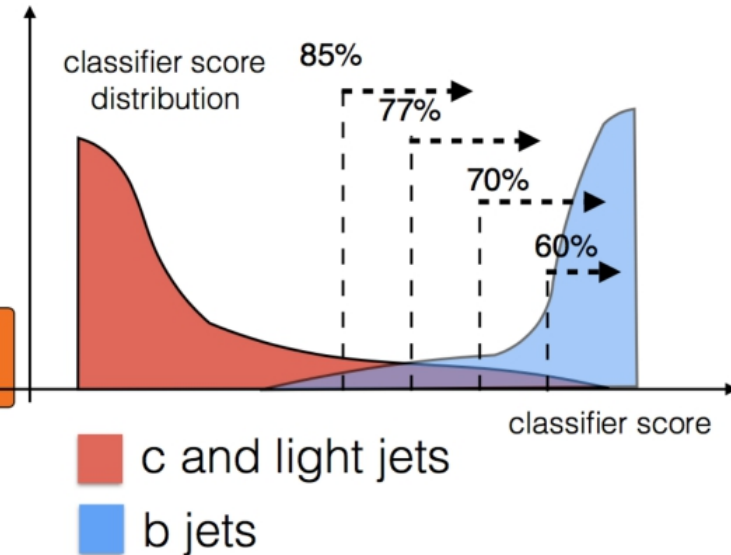
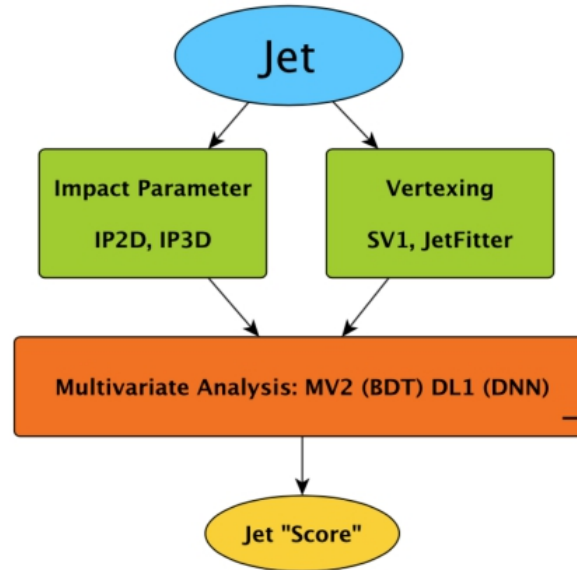
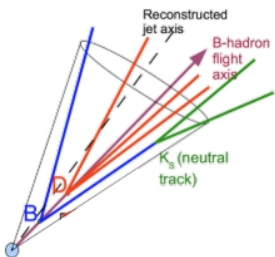
- **SV:**

- Inclusive Secondary vertexing
- Determination of single inclusive weak b-hadron decay vertex



- **JetFitter:**

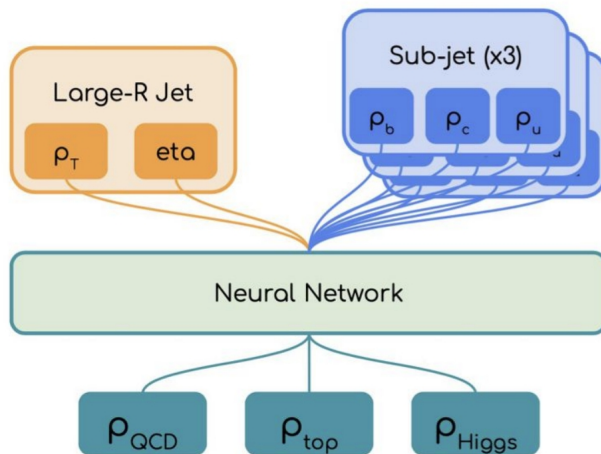
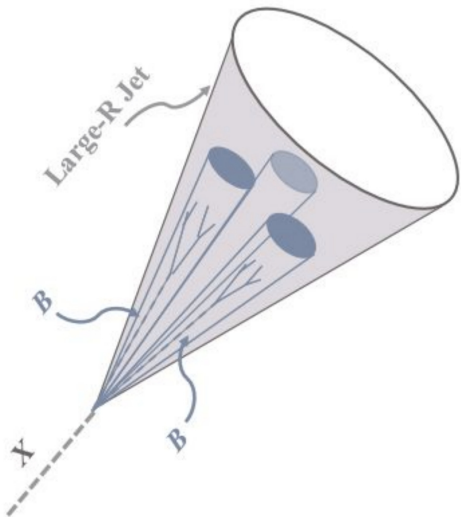
- PV → B → D decay chain finding
- More detailed determination of decay vertex topology



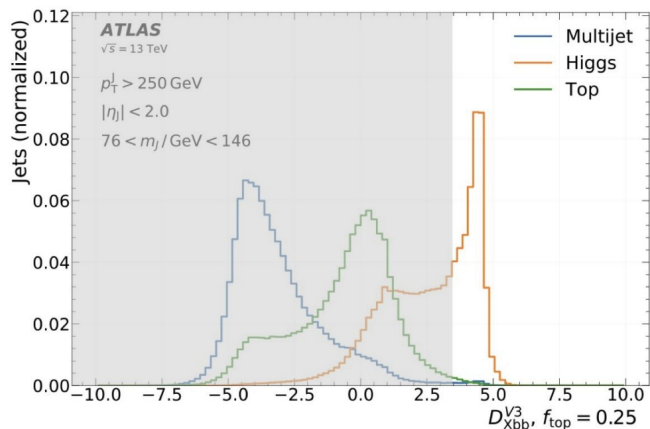
- Train models utilizing the outputs of impact parameter taggers and properties of vertices from vertexing algorithms
- MV2 - Boosted Decision tree based model
- DL1 - 8-hidden layer Deep Neural Network, multi-class classification

- Now ATLAS default btagging is based DNN (DL1)
 - ✓ Potential new ML algorithm? GNN?
- Potential multi-b-jet tagging?
 - ✓ Including color flow?
 - ✓ Better for H → bb event tagging

Boosted $X \rightarrow b\bar{b}$



- Double bjet tagging in boosted regime
- Reject top and QCD events



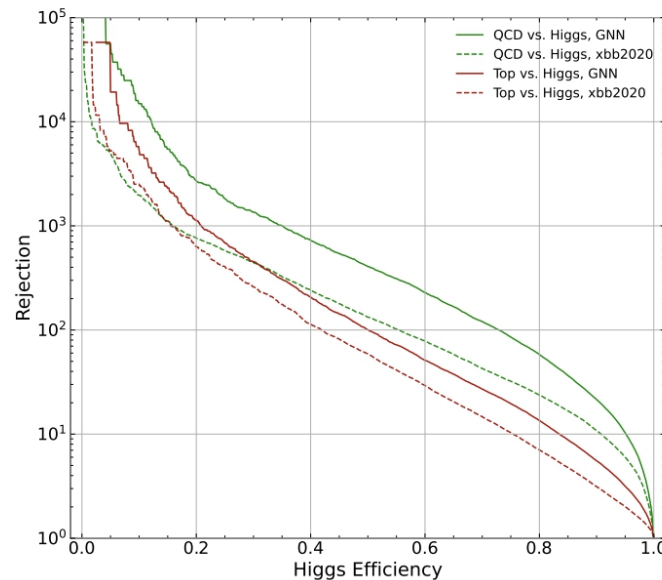
Grey shaded area 60% WP

$$D_{Xbb} = \ln \frac{P_{\text{Higgs}}}{f_{\text{top}} \cdot p_{\text{top}} + (1 - f_{\text{top}}) \cdot p_{\text{multijet}}}$$

<https://indico.cern.ch/event/1132691/timetable/#b-457079-tagging-techniques>

For future: GNN

✓ An overall better performance

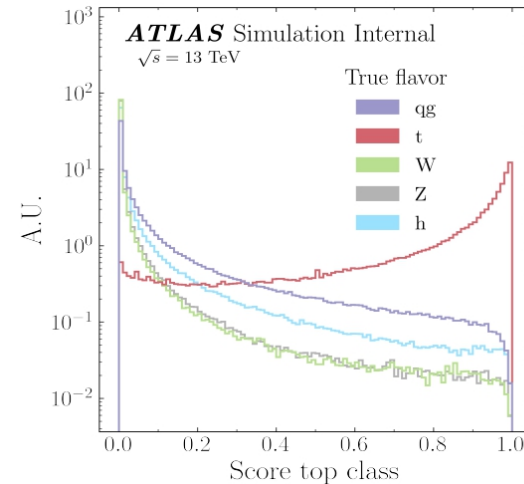
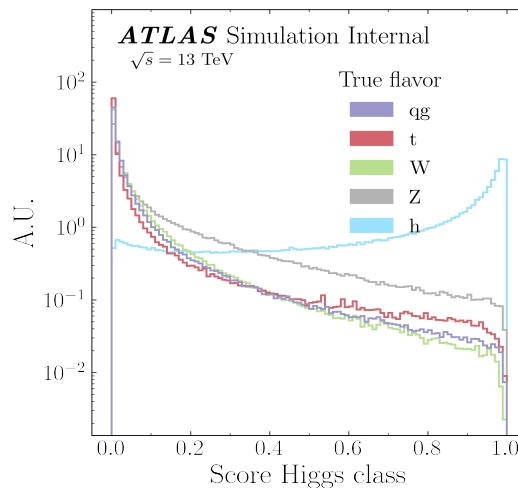
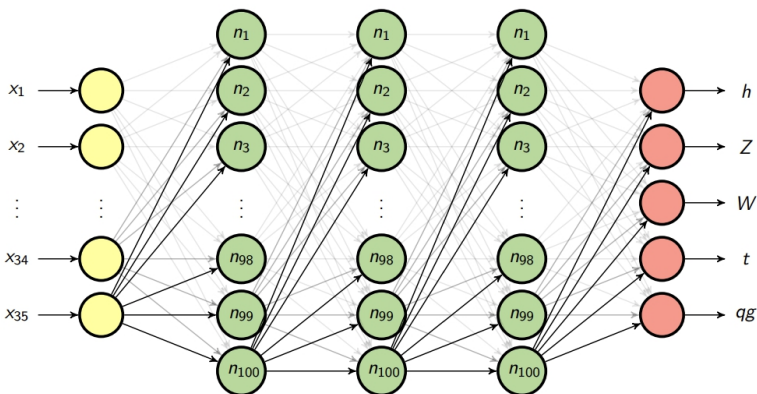




Boson/top tagger

https://indico.cern.ch/event/1132691/contributions/4989392/attachments/2503249/4300531/HD_BSUppsala22_MCT_mmazza.pdf

- Classification for multiple classes



- ❖ For future: polarization-wised tagger?
 - ✓ More classes



Regression for background

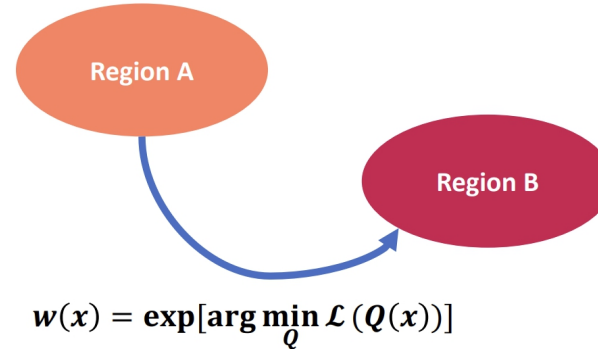
Reweighting with Neural Networks

A Brief Introduction

- Histogram-based reweightings suffer from “curse of dimensionality”
 - Prone to over- or under-fitting depending on choice of bin width
- Goal: determine an event-by-event reweighting to transform data from Region A into Region B
 - $p_A(x) w(x) = p_B(x) \rightarrow w(x) = \frac{p_B(x)}{p_A(x)}$
- Utilize dedicated loss function:

$$\mathcal{L}(Q(x)) = \mathbb{E}_{x \sim p_A} [\sqrt{e^{Q(x)}}] + \mathbb{E}_{x \sim p_B} \left[\frac{1}{\sqrt{e^{Q(x)}}} \right]$$

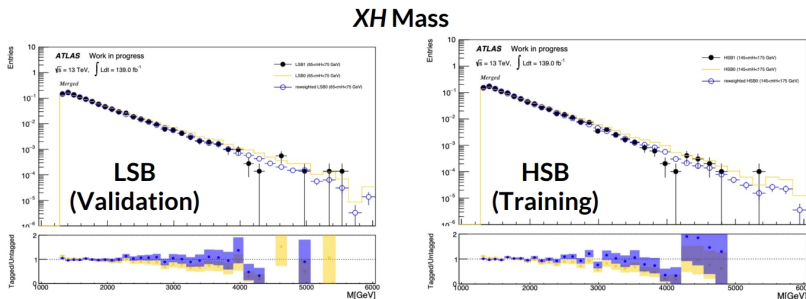
$$\arg \min_Q \mathcal{L}(Q(x)) = \log \frac{p_B(x)}{p_A(x)}$$



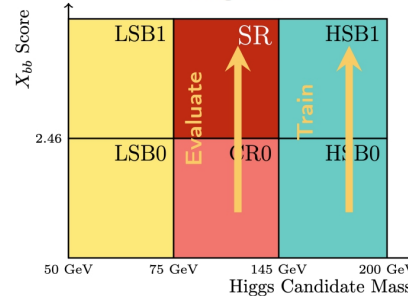
Methodology adapted from [arxiv:1911.00405](https://arxiv.org/abs/1911.00405)

DBL $Y \rightarrow XH \rightarrow qqbb$

- Use DNN to derive reweighting from “fail”- D_{Hbb} region to “pass”- D_{Hbb} region
 - Expect consistent m_H dependence on X_{bb} (60% WP) cut \rightarrow create CR by inverting X_{bb} cut



Training (HSB), Validation (LSB), and Evaluation (CR0/SR) Regions



- Data driven BKG estimation based on ML
- Better for densing events



Other interesting thought

<https://indico.cern.ch/event/1132691/timetable/#b-457081-new-machine-learning>

New machine learning approaches

Conveners: Nicole Michelle Hartman (SLAC National Accelerator Laboratory (US)), Rafael Coelho Lopes De Sa (University of Massachusetts (US))

[Zoom recording](#)

19:30

Recent developments for autodiff and analysis optimization in pyHF (15'+3')

🕒 15m

Speaker: Matthew Feickert (University of Wisconsin Madison (US))

[Feickert_2022-09-0...](#)

[Source GitHub repo...](#)

[talk: pyhf and analy...](#)

19:48

Analysis optimization with pyHF and NEOS (15'+3')

🕒 15m

Speaker: Mr Nathan Daniel Simpson (Lund University (SE))

[Link to Google Slides](#)

20:06

ML methods for parton-object assignment (15'+3')

🕒 15m

Speaker: Yuan-Tang Chou (University of Massachusetts (US))

[JetPartonAssignme...](#)

Regression

20:24

Study on Different Machine Learning Algorithms Used in the Search for di-Higgs in the Multi-lepton Final State (7'+3')

🕒 7m

Speaker: Santosh Parajuli (Southern Methodist University (US))

[HDBS_Uppsala_202...](#)

20:34

Searches using a per-event likelihood approach (15'+3')

🕒 15m

Speaker: Jay Ajitbhai Sandesara (University of Massachusetts (US))

[HDBS_Uppsala_Jay...](#)

Classification