b-Tagging with Boosted Decision Trees

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Physics 290E

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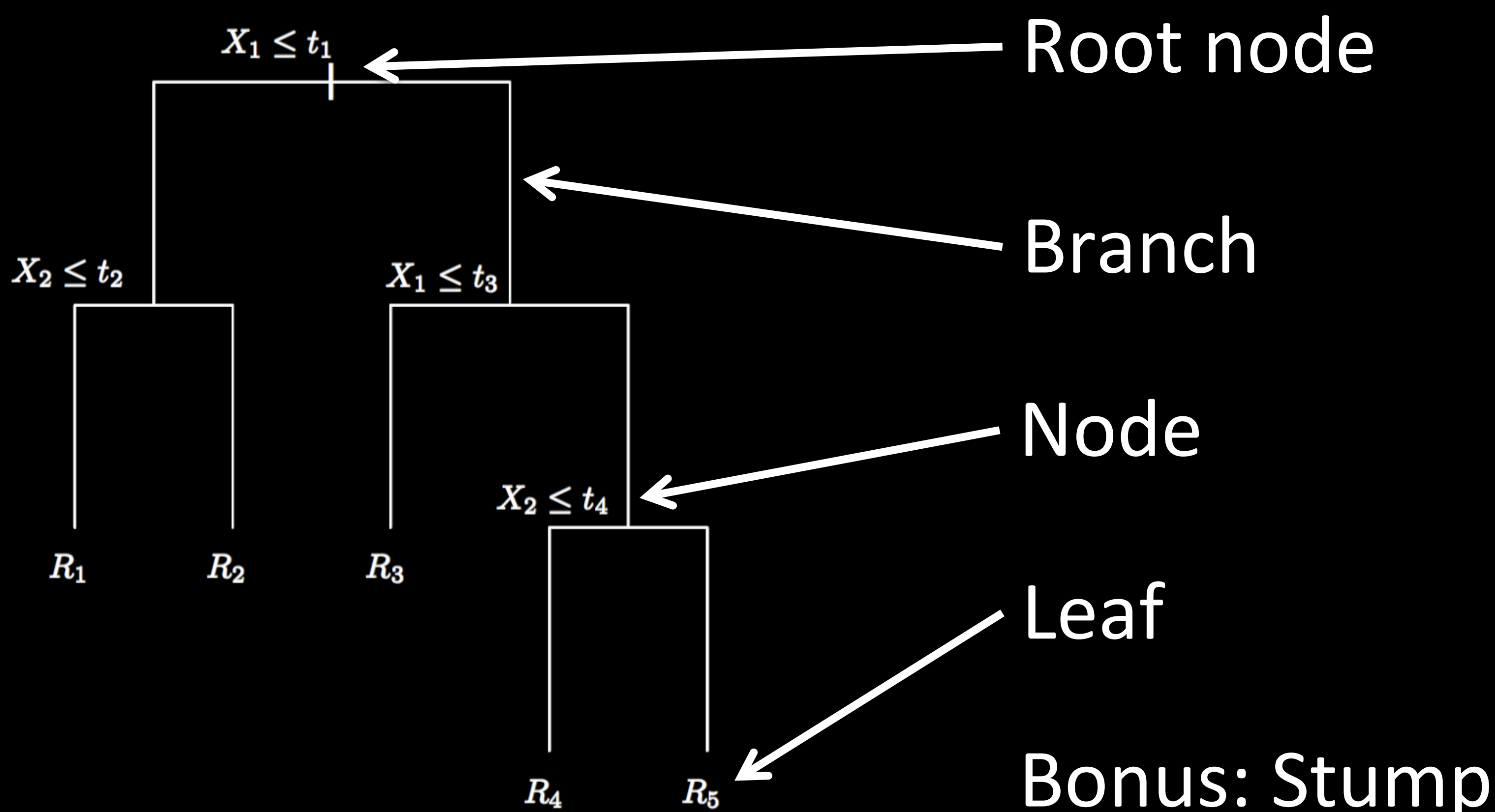
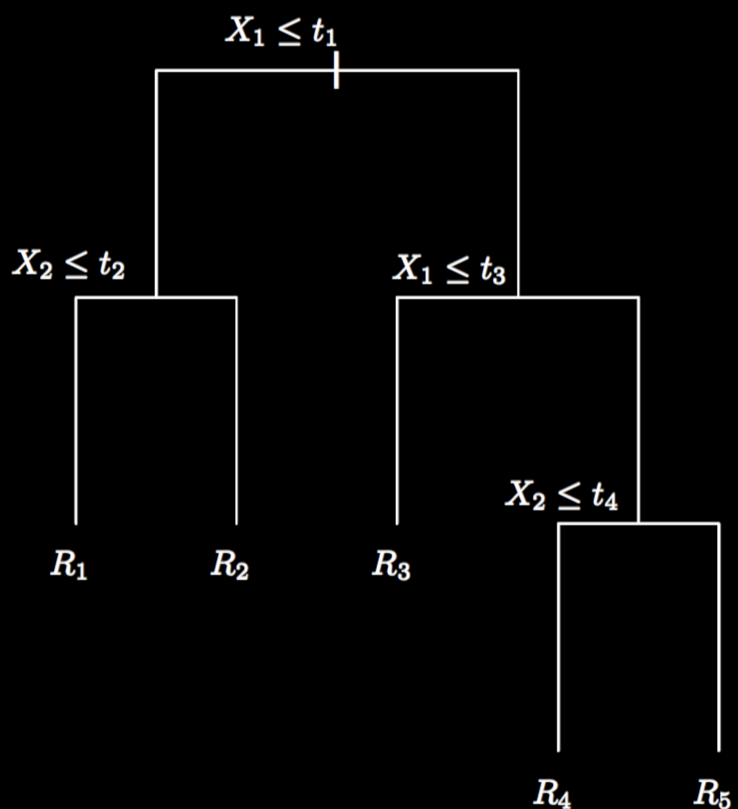
Decision Tree Basics



G. James, et al. *An Introduction to Statistical Learning*.

Decision Tree Basics



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Decision Tree Details

- Growing process
  - Top-down: begin with whole data set; split once
  - Recursive: repeat on two new data sets
  - Greedy: make best split at the current step; don't consider future trees
- Decision-making parameter:

$$E = 1 - \max_k(\hat{p}_{mk})$$

Classification Error

$$D = -\sum_{k=1}^{K} \hat{p}_{mk} \log \hat{p}_{mk}$$

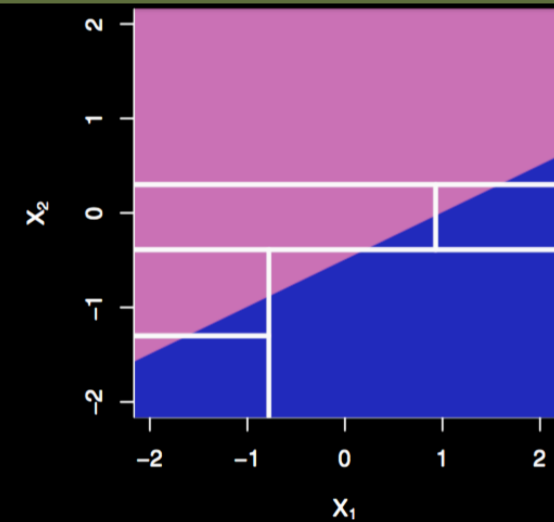
Entropy

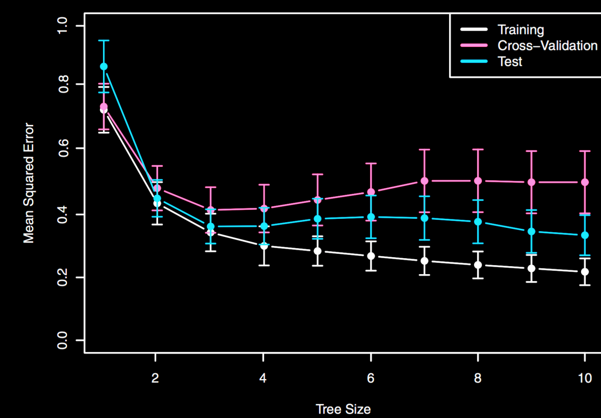
$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk})$$

Gini Index

Decision Tree Details

- Overfitting
  - Growing a tree to arbitrary depth can pick up spurious features
- Pruning
  - Cost complexity function: $R_\alpha(T) = R(T) + \alpha N_T$
  - Prune worst subtree at each node and generate list of subtrees. Pick one through validation sample





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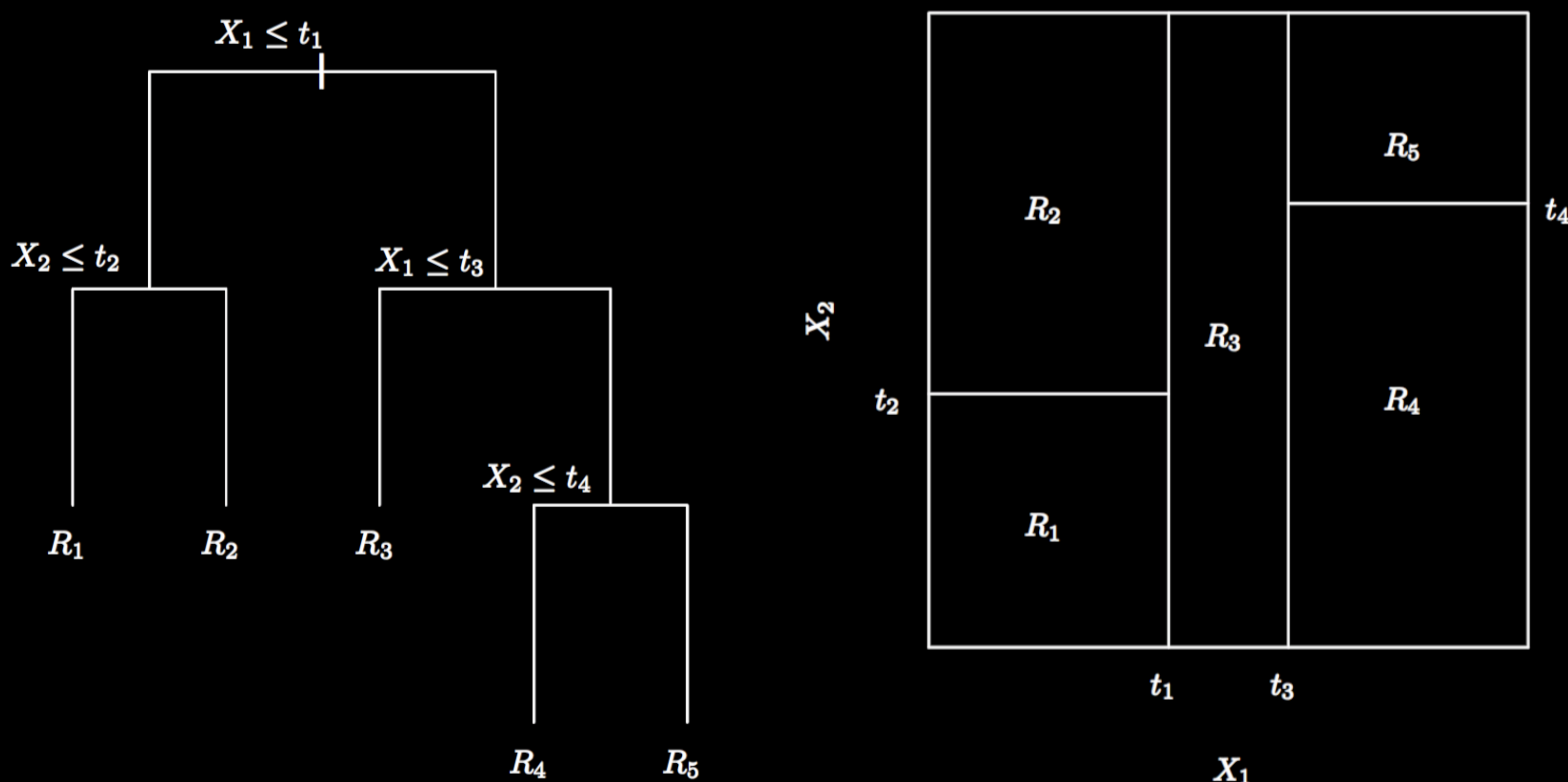
Decision Trees



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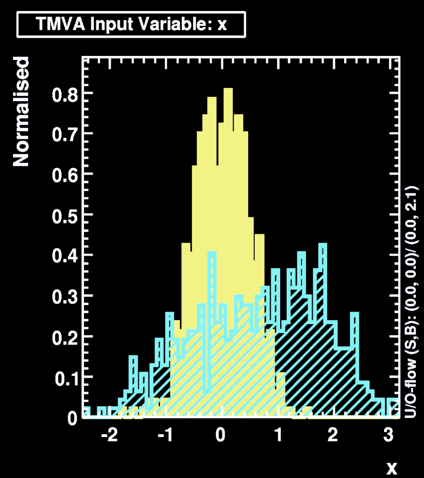
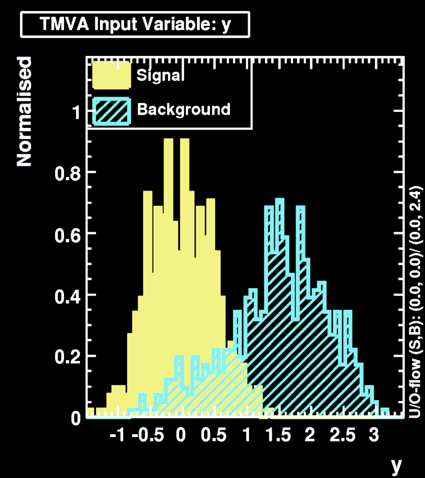
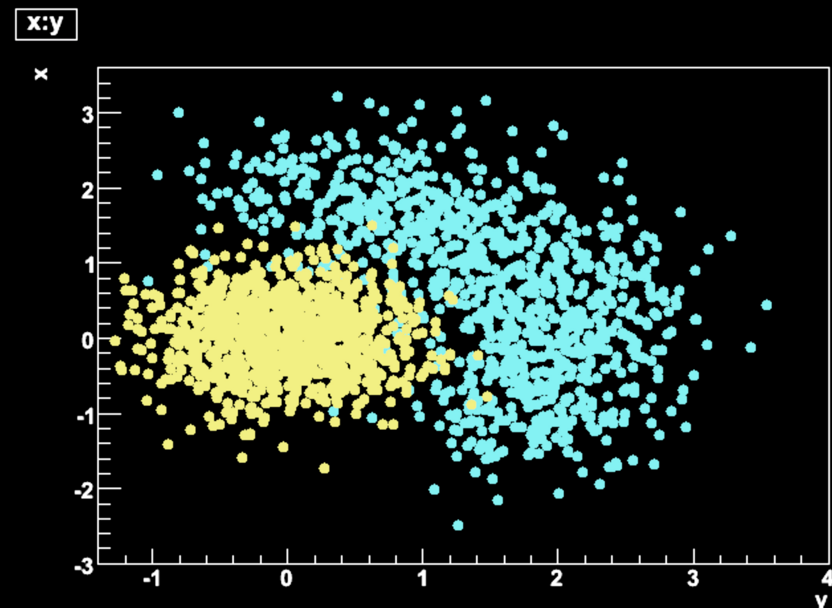
Decision Tree Walkthrough







Y. Coadou. European School of Instrumentation in Particle and Astroparticle Physics, Feb. 2016.

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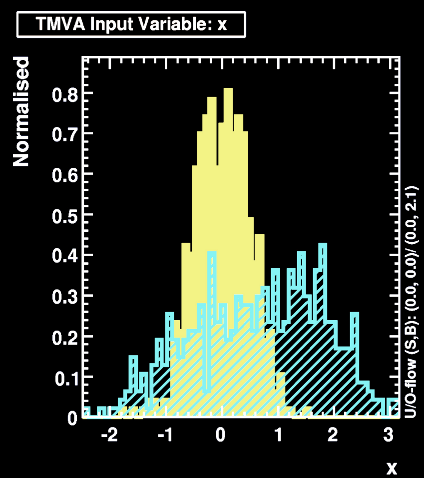

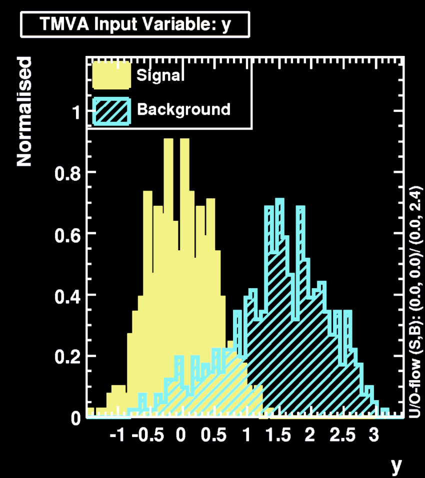

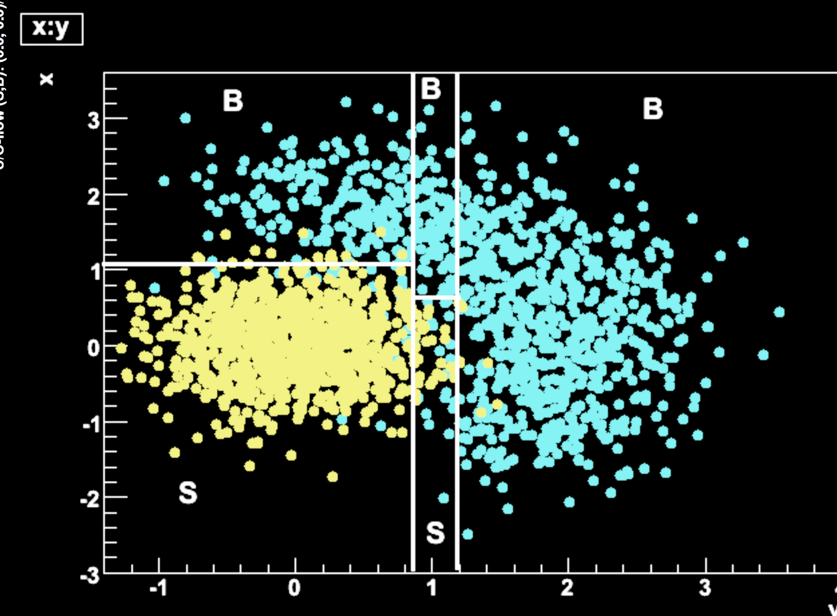

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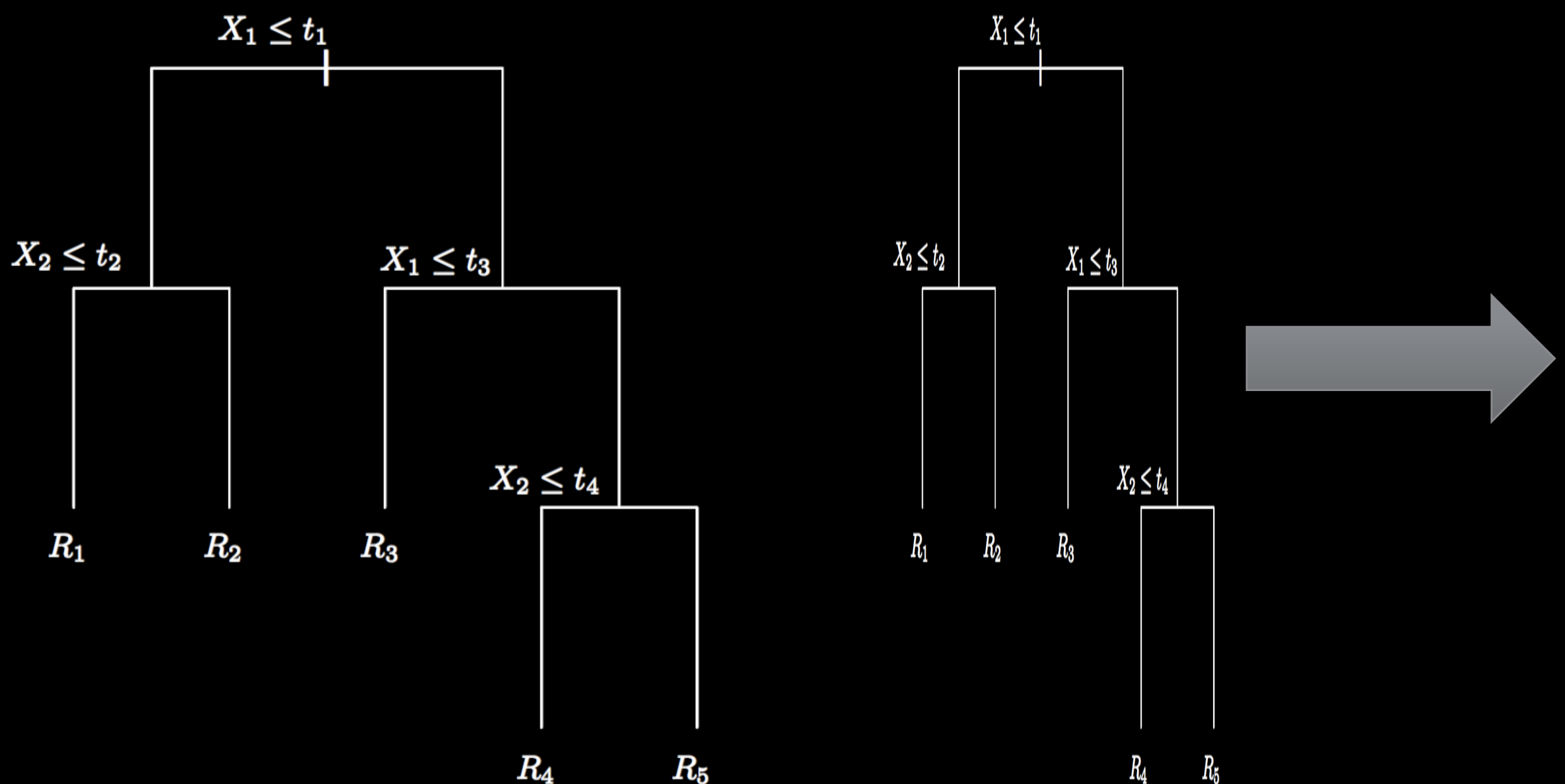
Boosted Decision Trees (BDTs)



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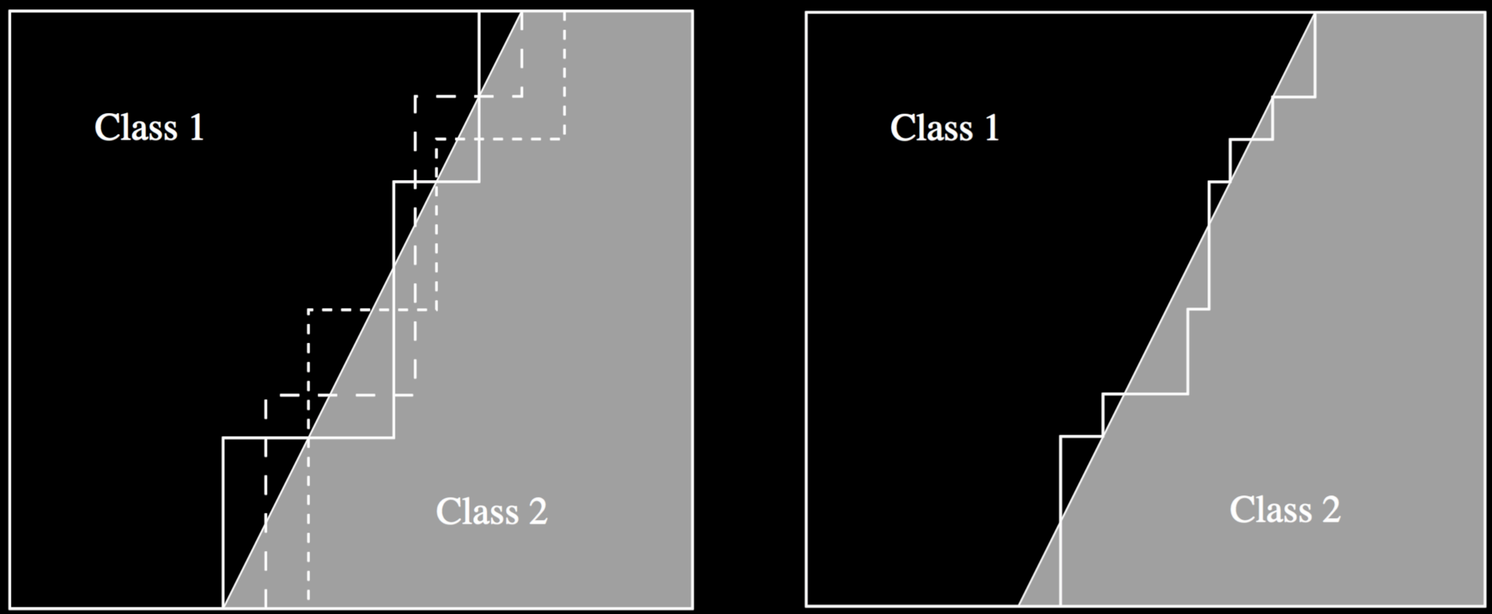
Ensemble Learning



- Have multiple trees vote on final output.
  - Need a way to produce varied trees.
  - Random forests; bagging

T Diettrich. AI Magazine, 18(4): 97–136, 1997.

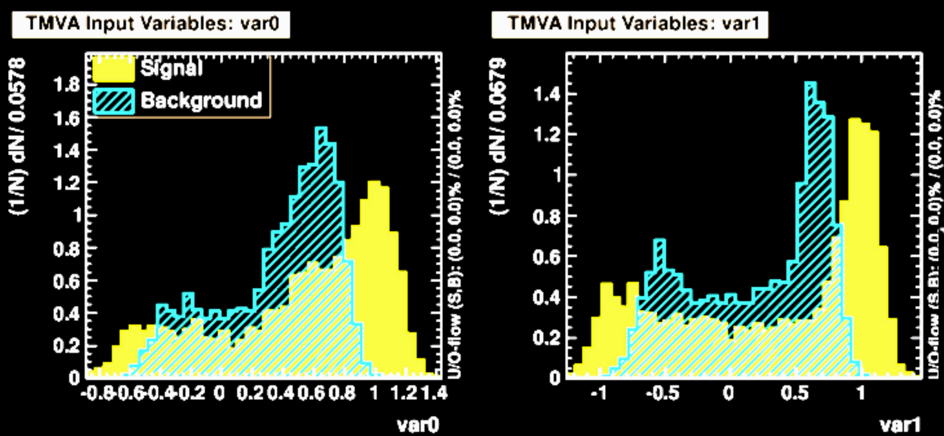
Boosting

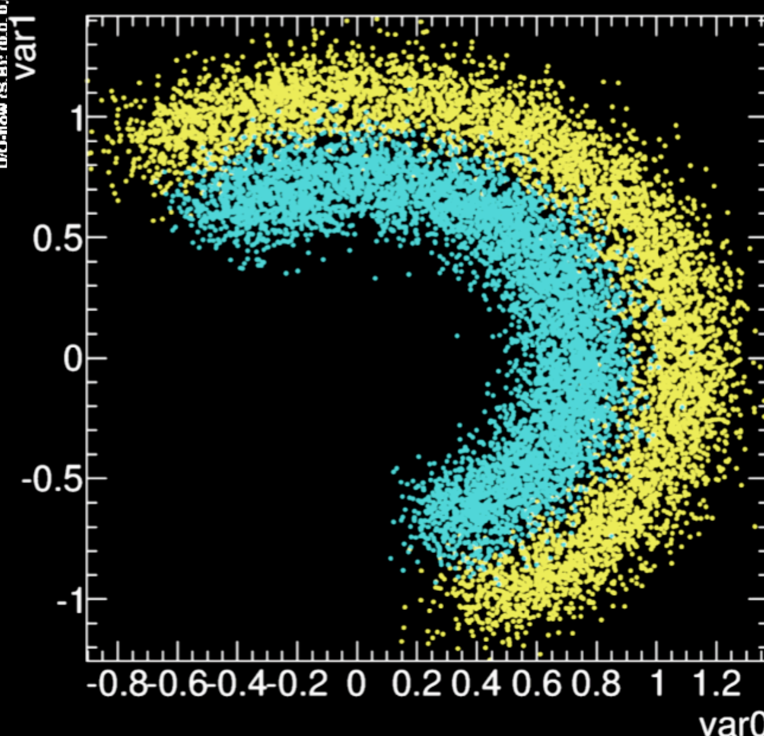
- The logic is to increase weight of misclassified data after building a tree.
  - For example, AdaBoost algorithm has weights w_i^k for the *i*-th datapoint in the *k*-th tree.
  - After each tree, update weights by

$$w_i^k \to w_i^{k+1} = w_i^k \times e^{\alpha_k}, \;\; \alpha_k = \beta \times \ln((1-\varepsilon_k)/\varepsilon_k)$$

  where ε_k is the misclassification rate and β scales tree weights α_k.
  - Boosted result: $T(i) = \frac{1}{\sum_{k=1}^{N_{\mathrm{tree}}} \alpha_k} \sum_{k=1}^{N_{\mathrm{tree}}} \alpha_k T_k(i)$

Boosting Walkthrough





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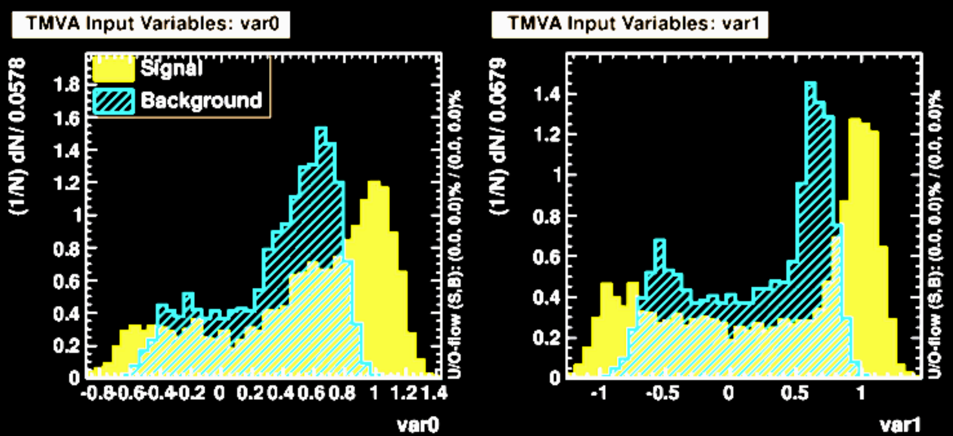
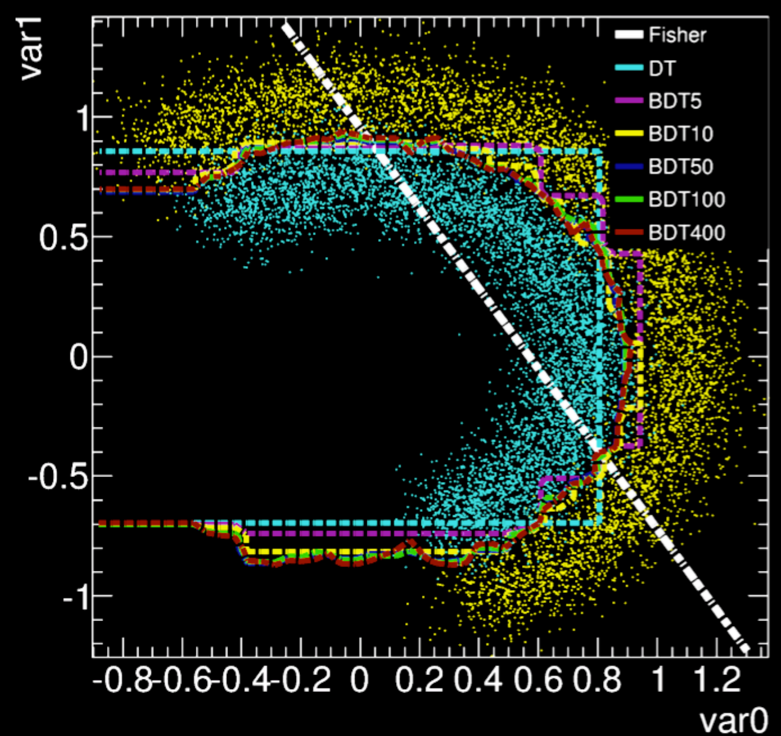
Boosting Walkthrough





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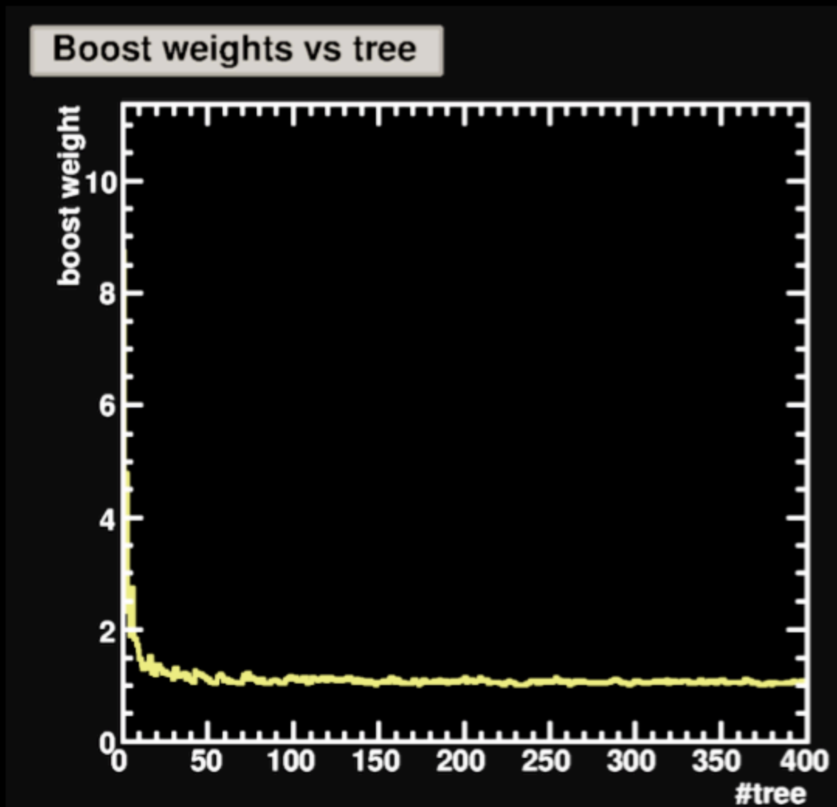
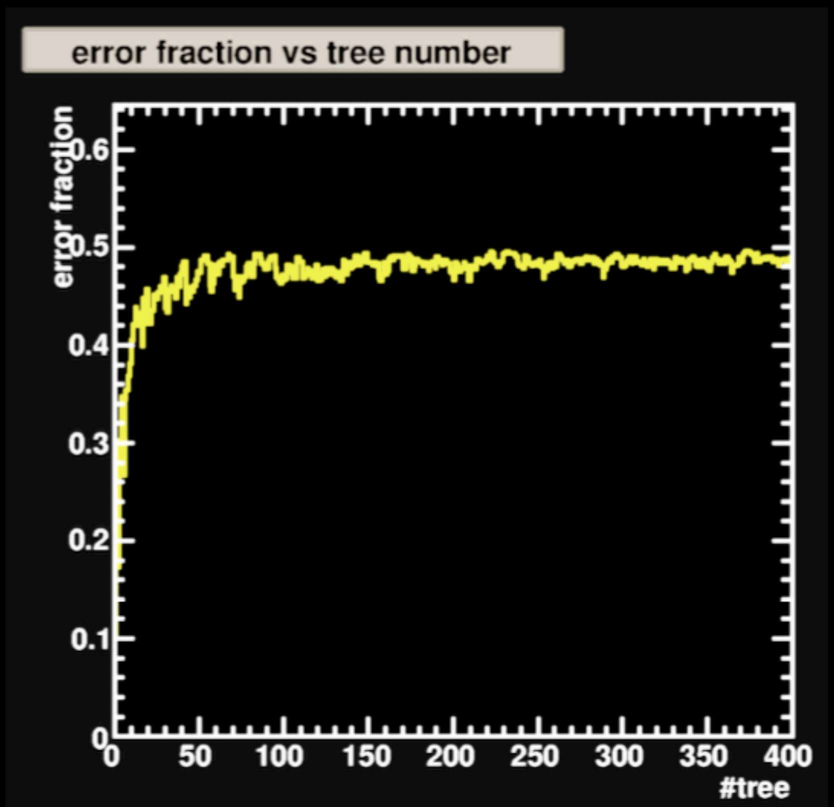




Y. Coadou. European School of Instrumentation in Particle and Astroparticle Physics, Feb. 2016.

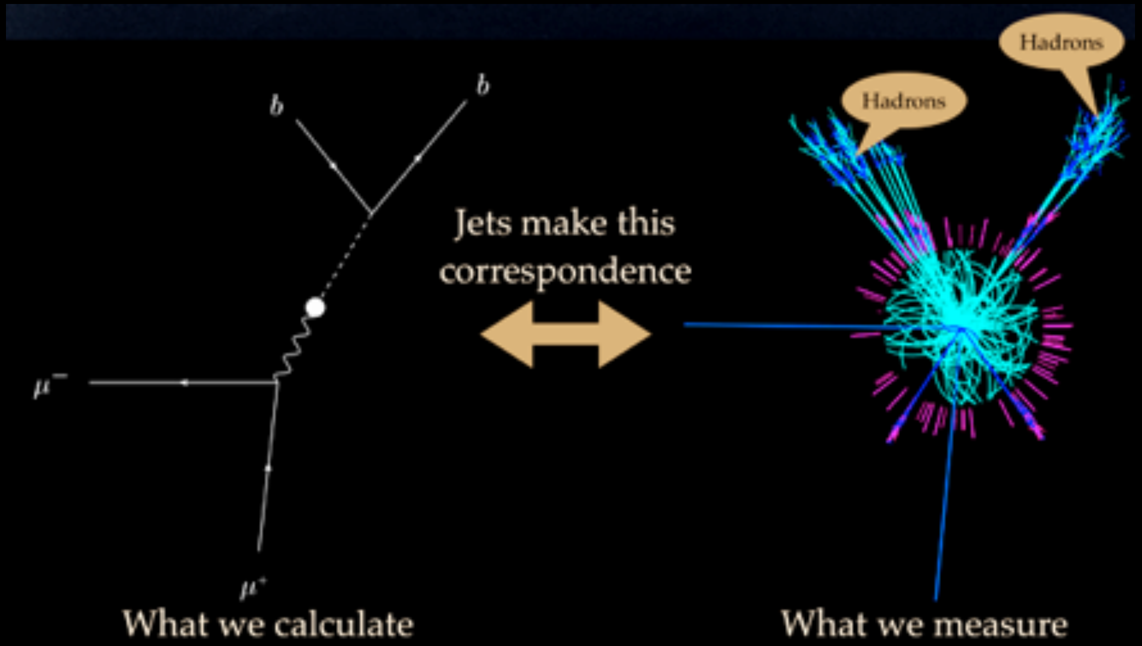
BDTs in Particle Physics

- ATLAS
- CMS
- MiniBooNE
- D0
- BaBar
- LHCb

BDTs in Particle Physics

- ATLAS b-tagging
- CMS
- MiniBooNE
- D0
- BaBar
- LHCb

Need For *b*-tagging



F. Tanedo. http://www.quantumdiaries.org/2011/04/22/when-youre-a-jet-youre-a-jet-all-the-way/

- t decay (t -> Wb)
- Higgs decay (h -> $b\bar{b}$)
- CP violation studies
- Beyond the standard model physics

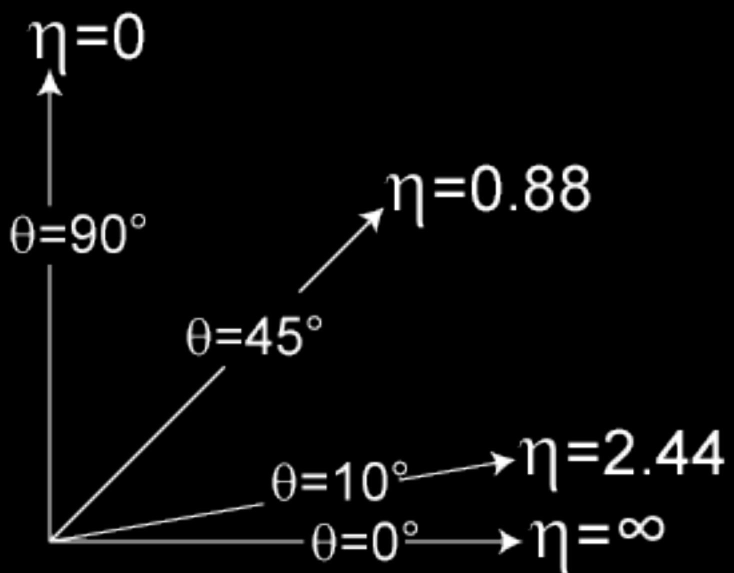
ATLAS Kinematics

$$\eta = -\ln \tan(\theta/2)$$

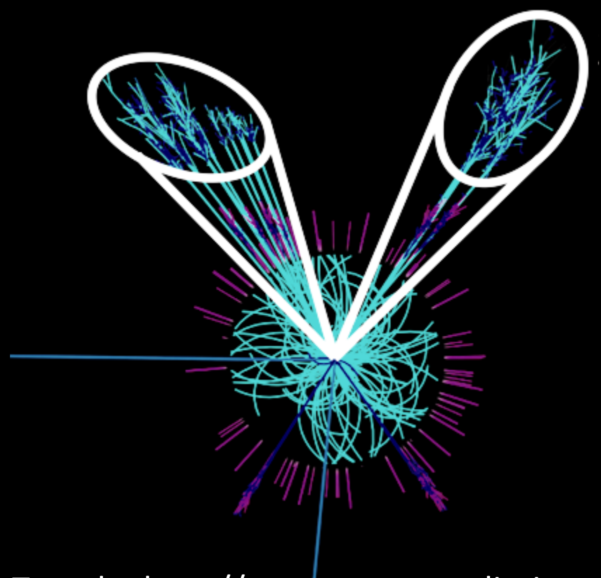
$|\eta|$ < 2.5 detected

$$\Delta R \equiv \sqrt{\Delta\eta^2 + \Delta\phi^2}$$

ΔR < 0.3 in jet



https://en.wikipedia.org/wiki/Pseudorapidity



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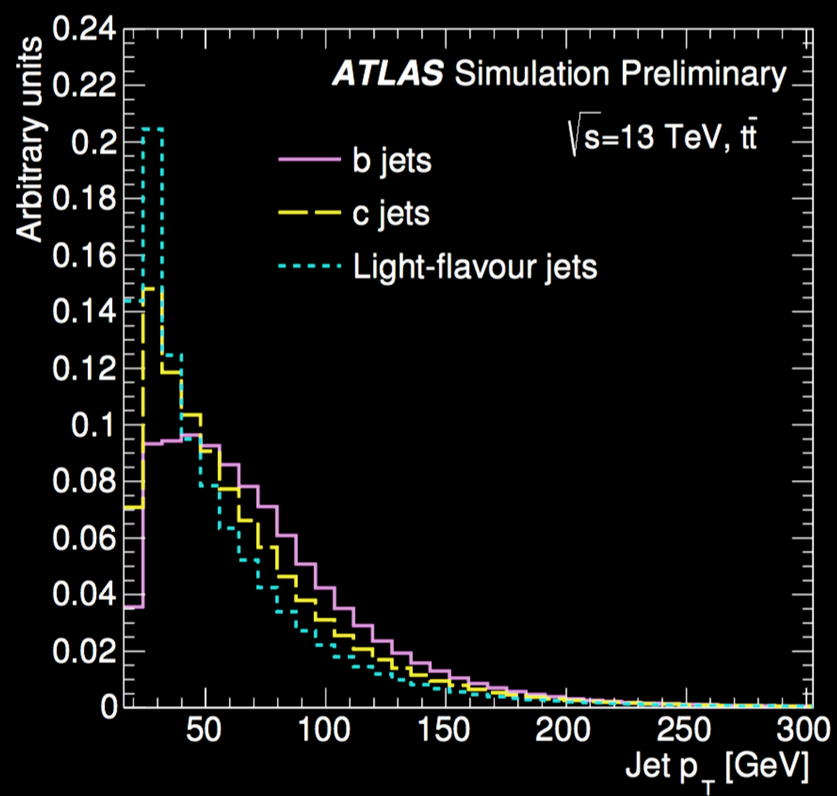
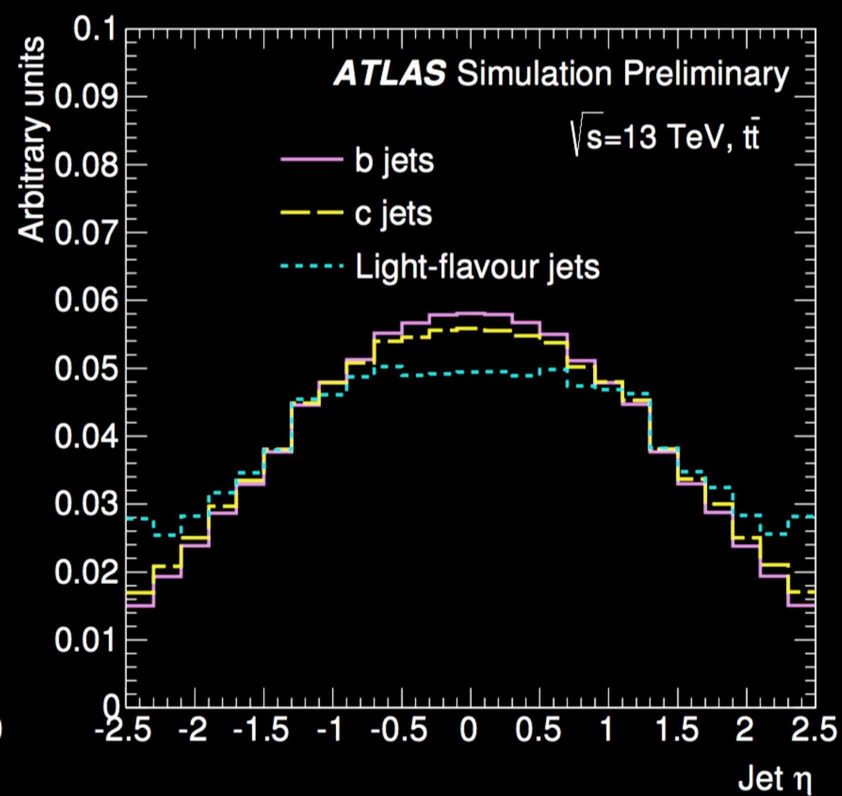
BDT b-tagging in ATLAS

- Model trained on $t\bar{t}$ events corresponding to 13 TeV proton-proton collisions.
  - Trained on *b*-jets as signal and a background of 80% light-flavor jets and 20% *c*-jets.
- Variables are basic kinematic variables η and p_T, and features from 3 reconstruction algorithms.

Basic Jet Observables





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BDT Variable List

Input	Variable	Description
Kinematics	$p_T(jet)$	Jet transverse momentum
	$\eta(jet)$	Jet pseudo-rapidity
IP2D, IP3D	$\log(P_b/P_{\mathrm{light}})$	Likelihood ratio between the *b*- and light jet hypotheses
	$\log(P_b/P_c)$	Likelihood ratio between the *b*- and *c*-jet hypotheses
	$\log(P_c/P_{\mathrm{light}})$	Likelihood ratio between the *c*- and light jet hypotheses
SV	$m(\mathrm{SV})$	Invariant mass of tracks at the secondary vertex assuming pion masses
	$f_{\mathrm{E}}(\mathrm{SV})$	Fraction of the charged jet energy in the secondary vertex
	$N_{\mathrm{TrkAtVtx}}(\mathrm{SV})$	Number of tracks used in the secondary vertex
	$N_{\mathrm{2TrkVtx}}(\mathrm{SV})$	Number of two track vertex candidates
	$L_{xy}(\mathrm{SV})$	Transverse distance between the primary and secondary vertices
	$L_{xyz}(\mathrm{SV})$	Distance between the primary and secondary vertices
	$S_{xyz}(\mathrm{SV})$	Distance between the primary and secondary vertices divided by its uncertainty
	$\Delta R(\mathrm{jet},\mathrm{SV})$	ΔR between the jet axis and the direction of the secondary vertex relative to the primary vertex
Jet Fitter	$N_{\mathrm{2TrkVtx}}(\mathrm{JF})$	Number of 2-track vertex candidates (prior to decay chain fit)
	$m(\mathrm{JF})$	Invariant mass of tracks from displaced vertices assuming pion masses
	$S_{\mathrm{xyz}}(\mathrm{JF})$	Significance of the average distance between the primary and displaced vertices
	$f_{\mathrm{E}}(\mathrm{JF})$	Fraction of the charged jet energy in the secondary vertices
	$N_{\mathrm{1\text{-}trk\ vertices}}(\mathrm{JF})$	Number of displaced vertices with one track
	$N_{\geq 2\text{-}\mathrm{trk\ vertices}}(\mathrm{JF})$	Number of displaced vertices with more than one track
	$N_{\mathrm{TrkAtVtx}}(\mathrm{JF})$	Number of tracks from displaced vertices with at least two tracks
	$\Delta R(\vec{p}_{\mathrm{jet}},\vec{p}_{\mathrm{vtx}})$	ΔR between the jet axis and the vectorial sum of the momenta of all tracks attached to displaced vertices

Impact parameter based algorithms

Secondary vertex finding algorithm

Decay chain multi-vertex algorithm

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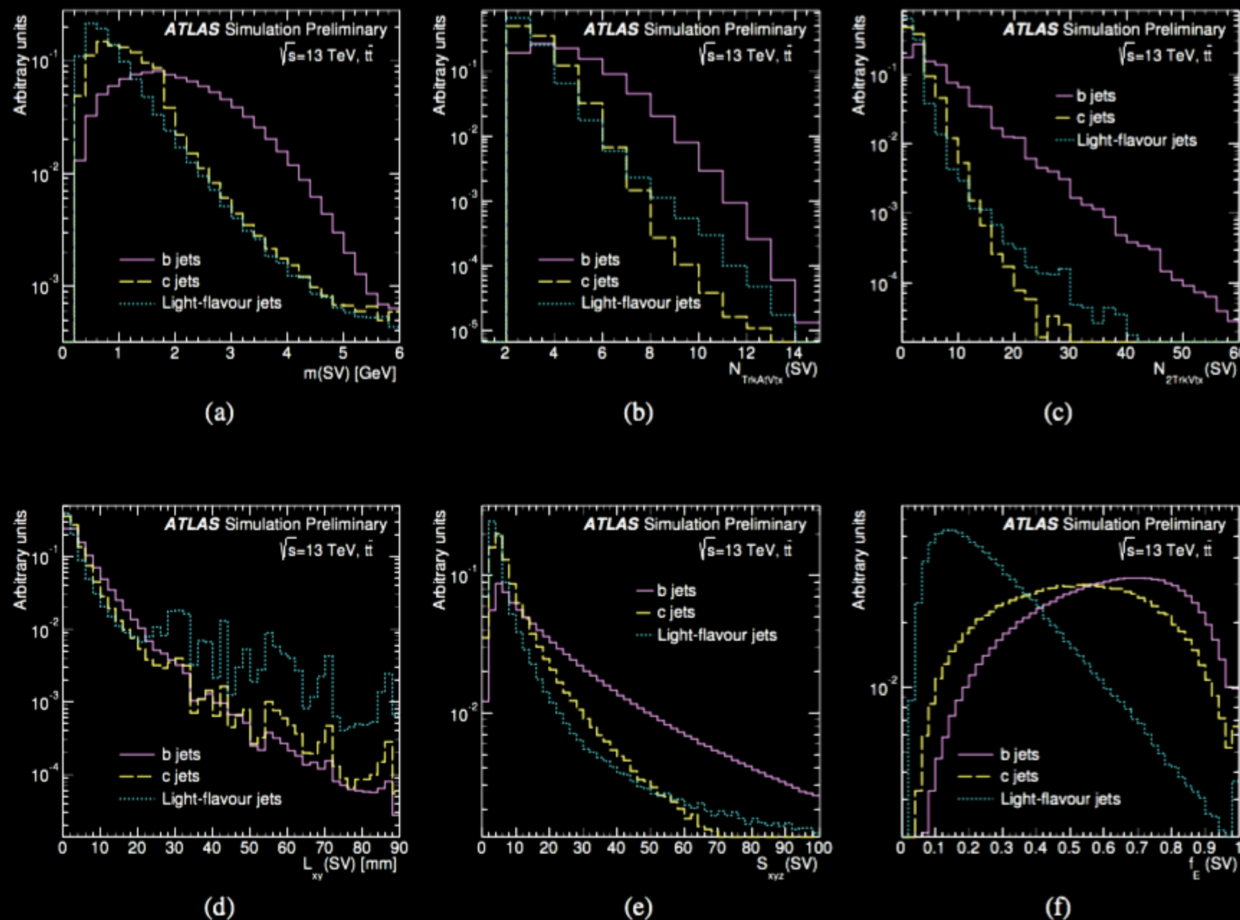
SV Algorithm Variables



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Predicted Performance

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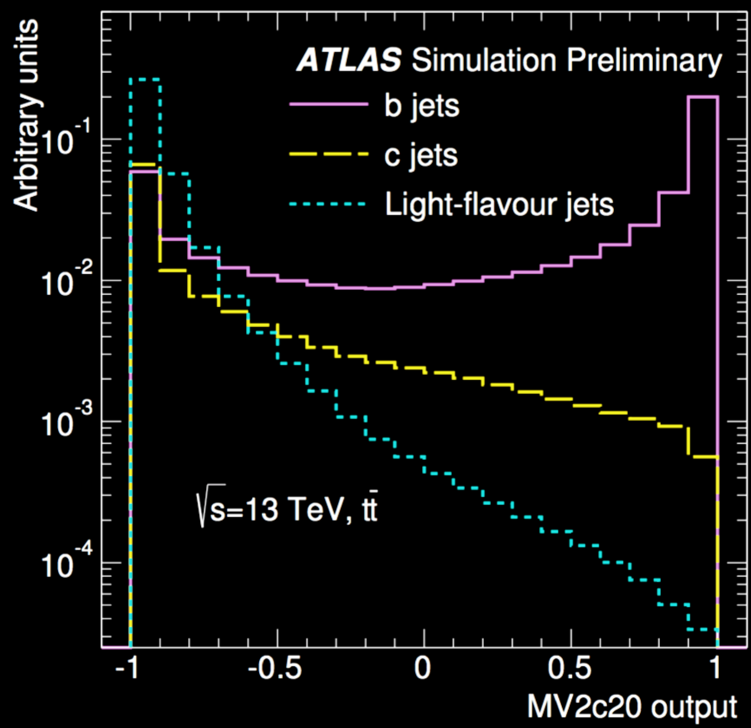
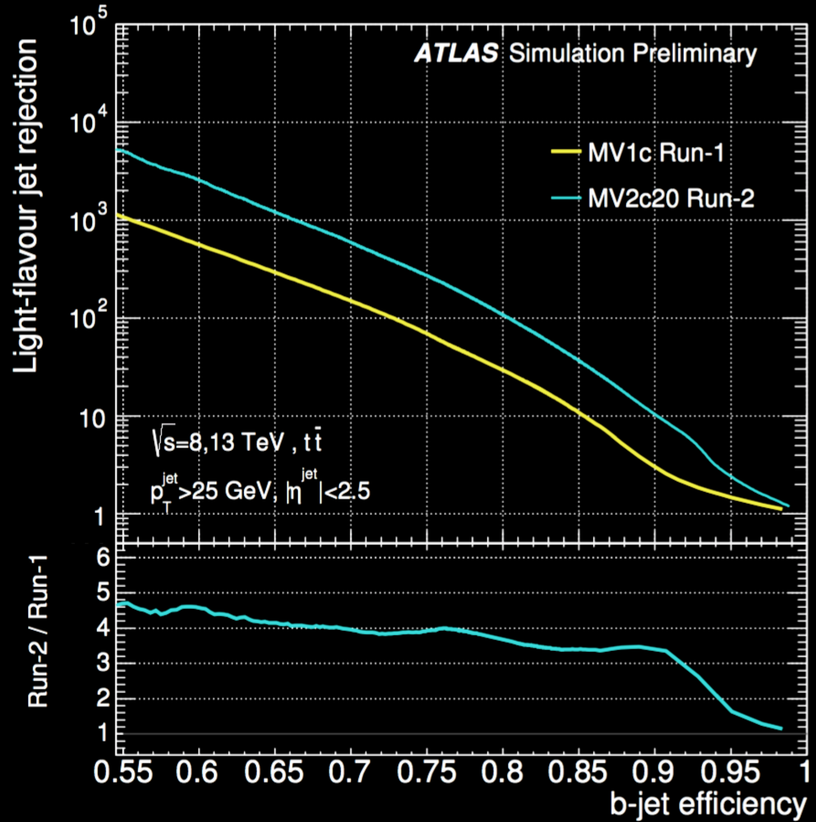
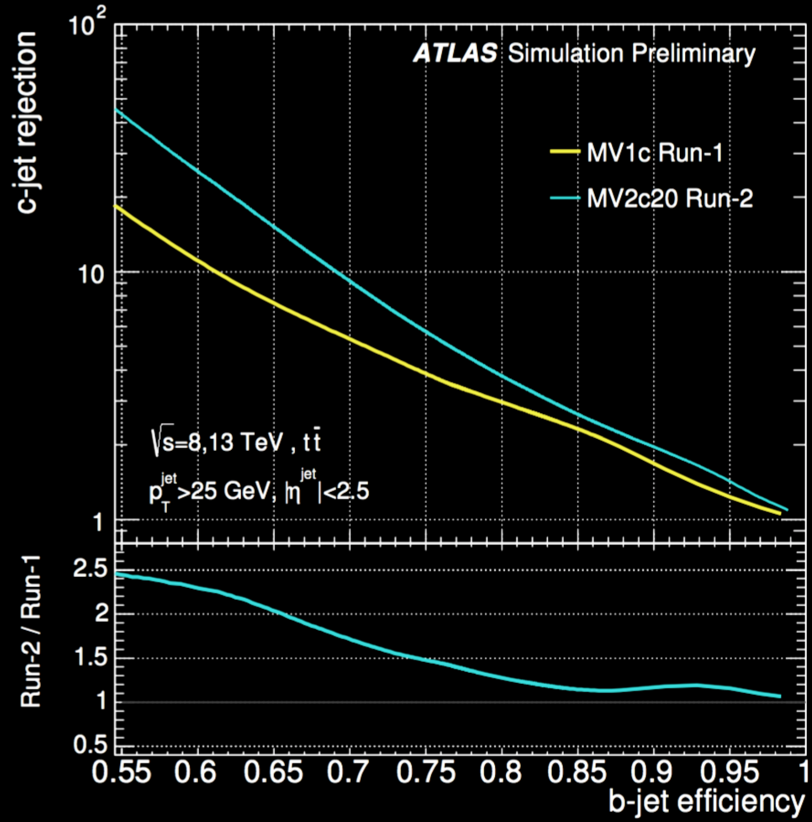


Cut Value	b-jet Efficiency [%]	c-jet Rejection	τ-jet Rejection	Light-jet Rejection
0.4496	60	21	93	1900
-0.0436	70	8.1	26	440
-0.4434	77	4.5	10	140
-0.7887	85	2.6	3.8	28

Predicted Improvement





- Some hardware, some software

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Final Thoughts

- Decision trees are fairly weak classifiers that are easy to understand.
- Boosting turns them into stronger classifiers but makes them more mysterious.
- BDTs show up a lot in particle physics.
- Propagating uncertainties difficult.
- <u>Still need to convince people your model produces good results.</u>

References

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- G. Cowan. Multivariate statistical methods and data mining in particle physics. CERN Academic Training Lectures, June 2008.
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