Feature ranking

Showcase of subtraction method for ttH(H->bb) classification

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18 April 2019
3rd IML Workshop

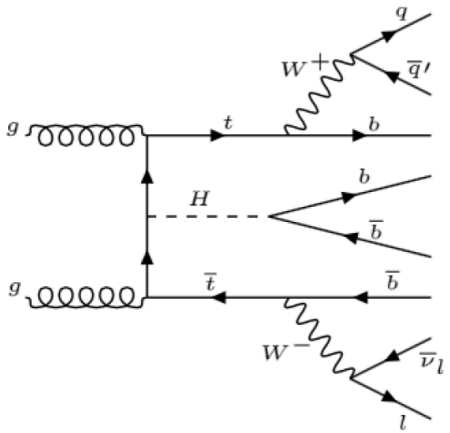
HELMHOLTZ ASSOCIATION

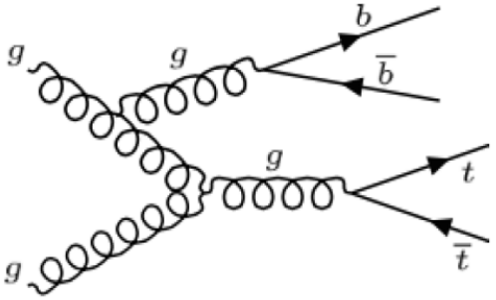
ATLAS EXPERIMENT

DESY

Intro

- For the example of a classification BDT for ttH(H->bb) vs ttbar+b-jets we will present different methods of ranking the relative importance of training features.
  - Test subtractive method: start with all variables and remove the least important
- The classification problem and event selection are inspired by the ATLAS ttH(H->bb) 1712.08895 paper.
  - Using open-data MC with Delphes simulation





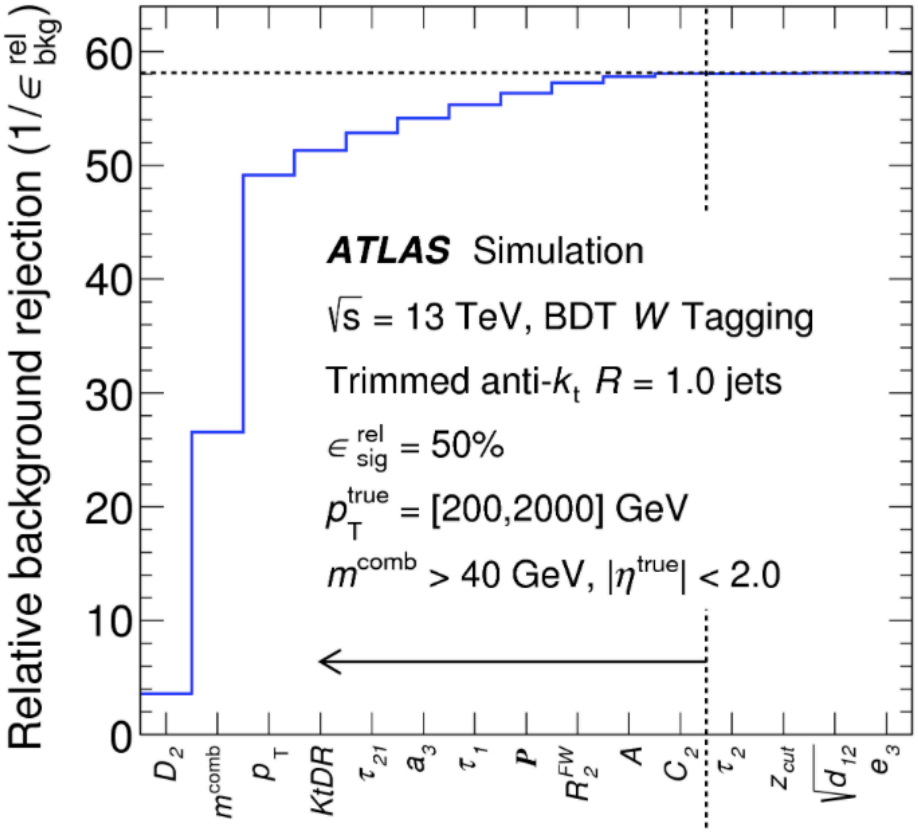
Motivation

- Feature ranking can help reduce unnecessary dimensionality
- Quicker run time and optimisation
- Improve insight into physical importance of the few selected variables
- Focus efforts of validating the modelling of inputs (time consuming)
- Help understand model response to different MC generators
- Not an issue for BDTs, but arbitrarily large number of inputs can compromise other learning algorithms.

- How to select the best N variables to use in the training?
  - Question of which training features are most important in the classification has no unique answer, particularly when they are highly correlated.

Example of additive ranking

- ATLAS Top and W tagger CERN-EP-2018-192
- Sequentially add variable that gives largest increase in performance
- The set variables that reaches saturation in performance (within stat. uncertainty) is selected
- Ranking complexity scales with number of variables n as $O(n^3)$ (assuming product of #trainings and #variables/training)
- Not clear if additive method correctly ranks correlated variables, e.g two individually useless variable that have separating power only when used together



Data sets and BDT setup

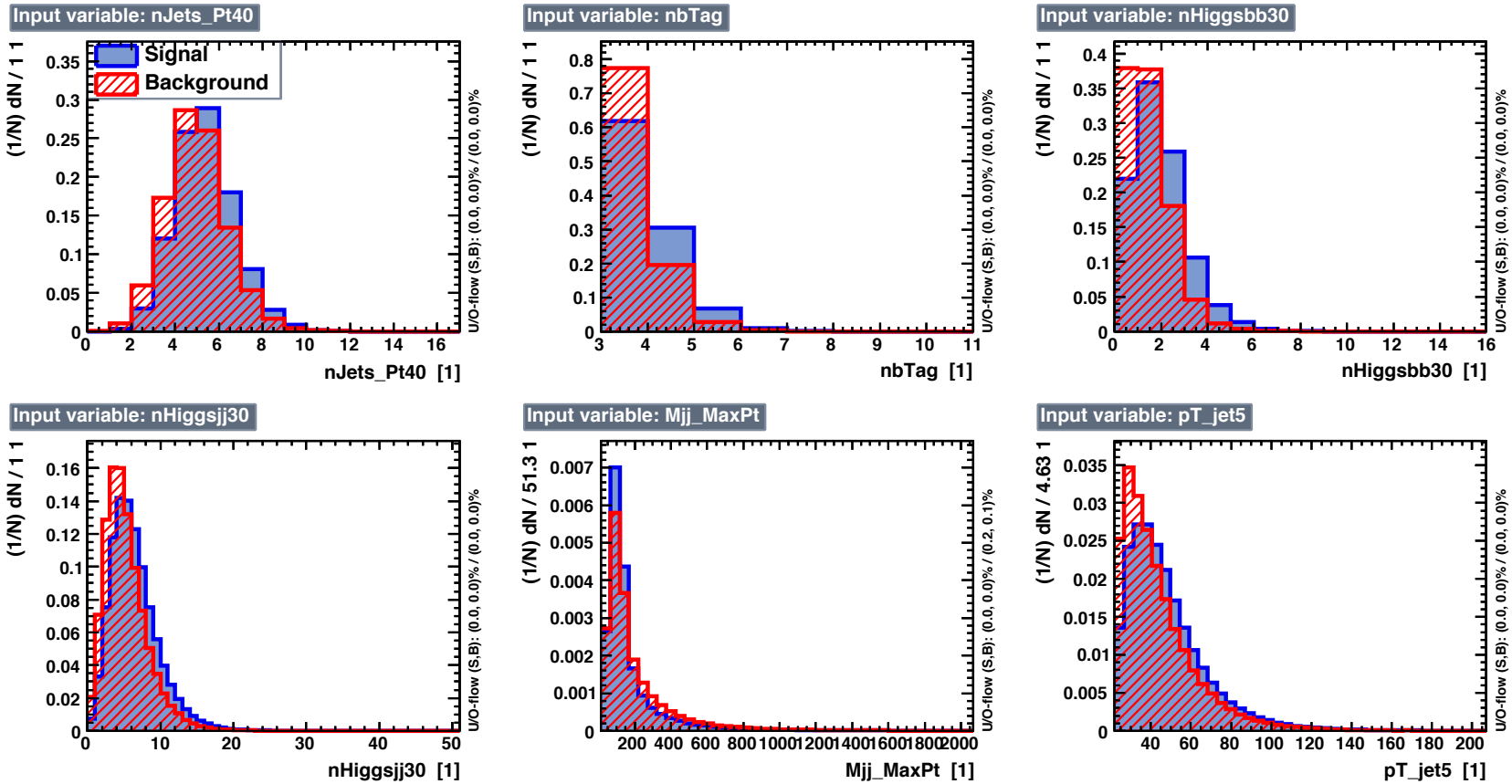
- Open data MC:

  tev13pp_mg5_ttbar_jet_ MadGraph/HW6. 2M events
  tev13pp_mg5_ttbar_bjet_ MadGraph/P6 10M events
  tev13pp_mg5_ttH MadGraph/HW6 13M events
  from https://hepsim.jlab.org
  The ttbar+jet and ttbar+bjet background samples are orthogonal, weighted by their cross section.

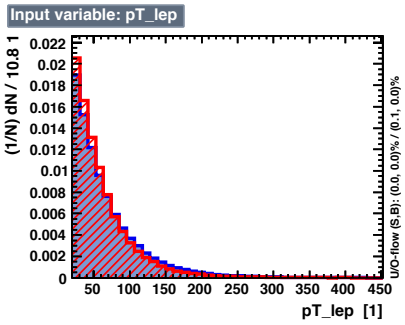
- Delphes simulation with atlas-like geometry https://cp3.irmp.ucl.ac.be/projects/delphes/
- Event selection, type of variables chosen similar to single lepton channel of ATLAS-CONF-2016-080 (some cuts loosened to gain stats)
  - 1 lepton with pt> 20 GeV and ≥5 jets with pt>25 GeV
  - ≥3 b-jets, with 70% WP, b-efficiency, light/c-rejection is parameterised according to JHEP08(2018)089
  - selects: 700k ttH signal and 275k tt+jets background events
  - Train on 2/3, test on 1/3 of events
- TMVA implementation of BDT:
  - 400 trees, MaxDepth=5, AdaBoostBeta=0.15, nCuts=80

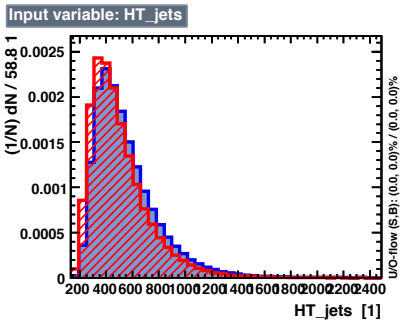
Training variables

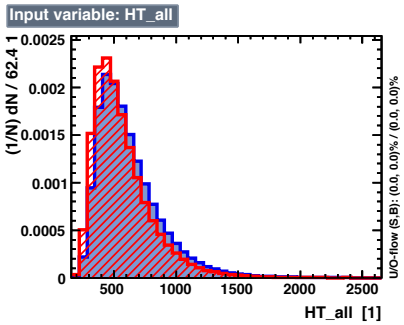
- Choice of variables inspired by reference paper, but also added additional ones and left those out that could not easily be reproduced
- 39 variables are computed, from which 26 are considered which have at least 1% separation in signal vs background shapes

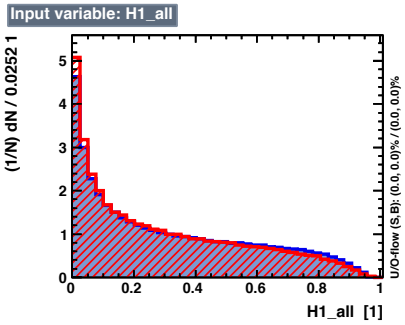


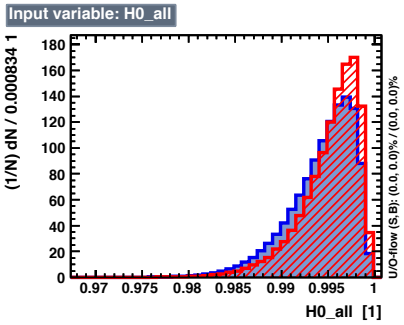
Training variables

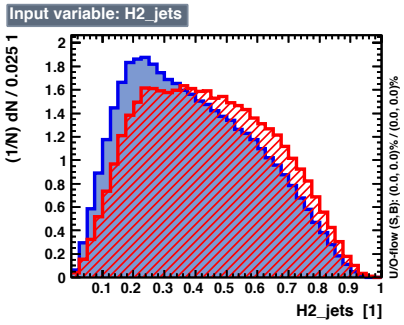




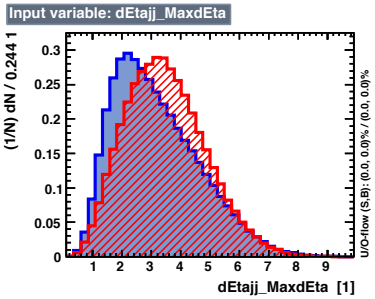


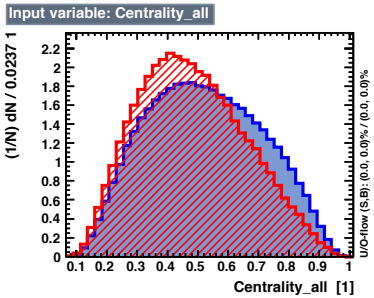


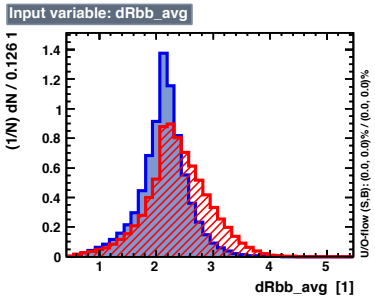


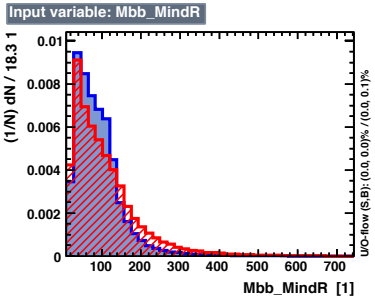


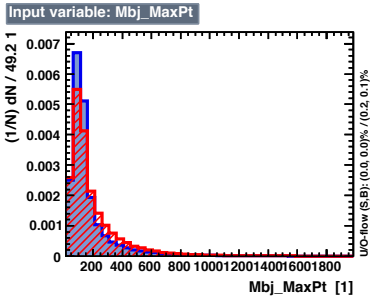
Mainly high level quantities.
Invariant mass and dR e.g., probably high redundancy among them.

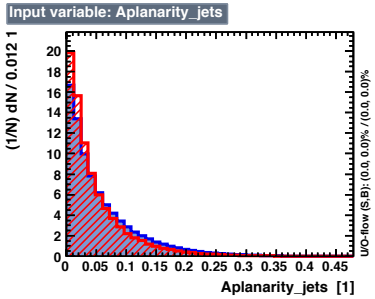




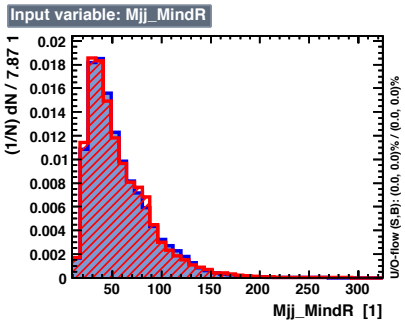


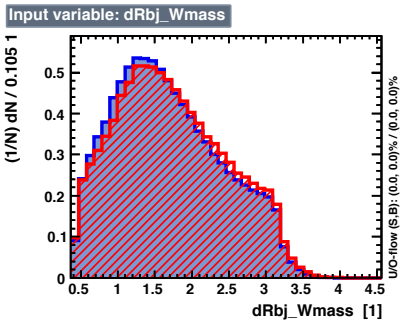


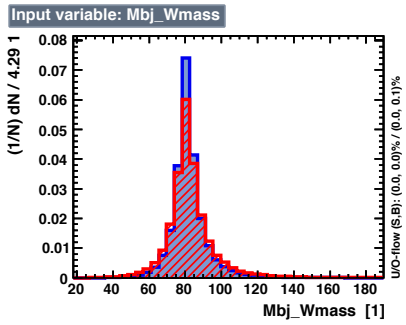


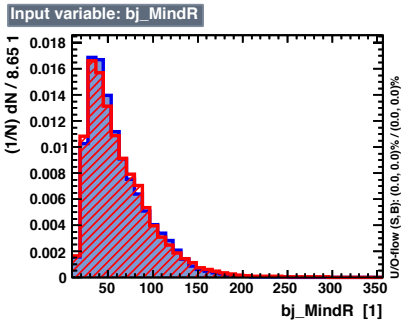


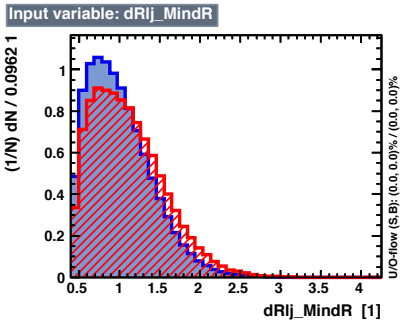
Training variables

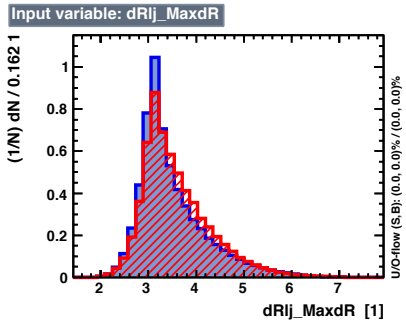


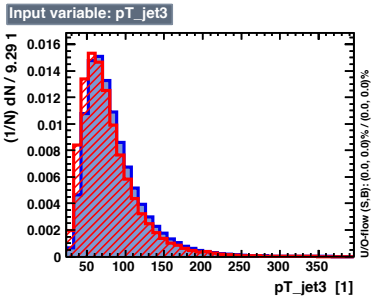


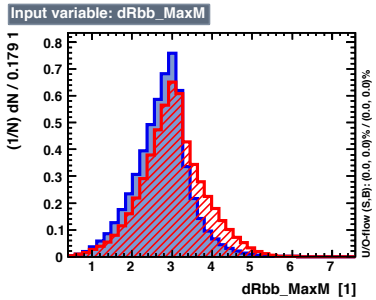


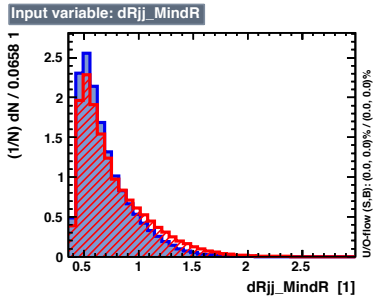


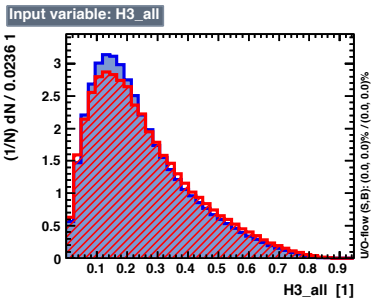


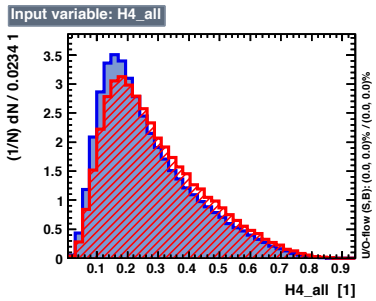


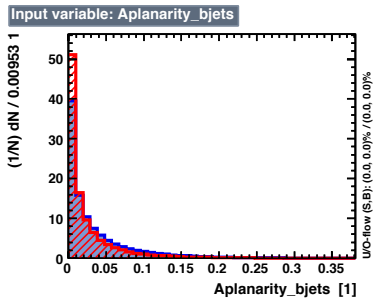




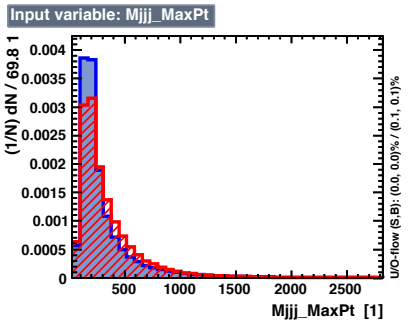


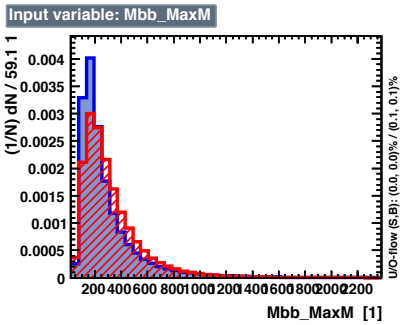


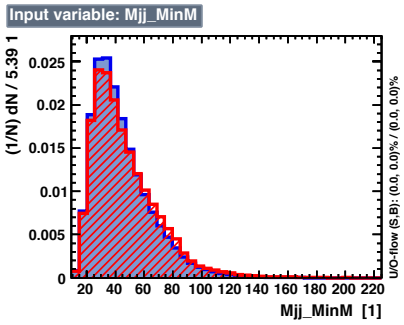


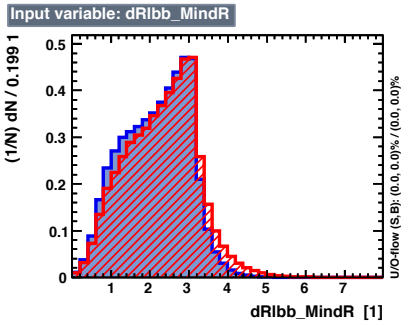


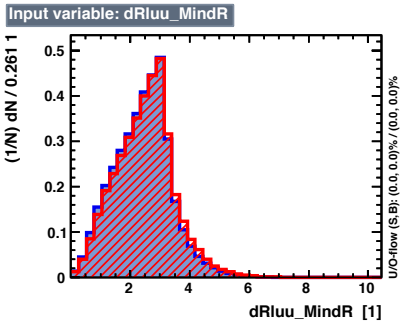
Training variables

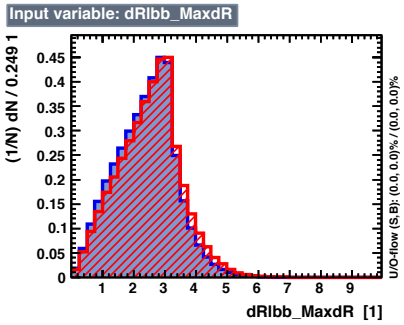


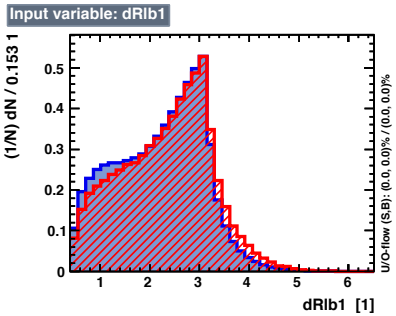


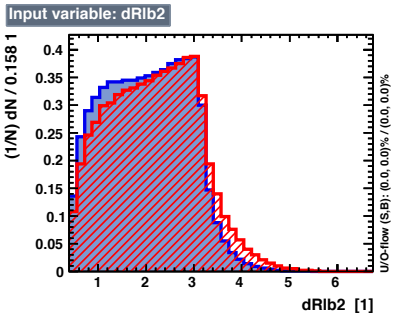


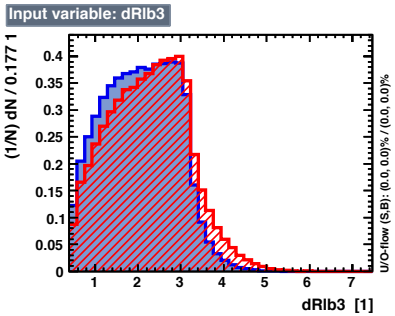










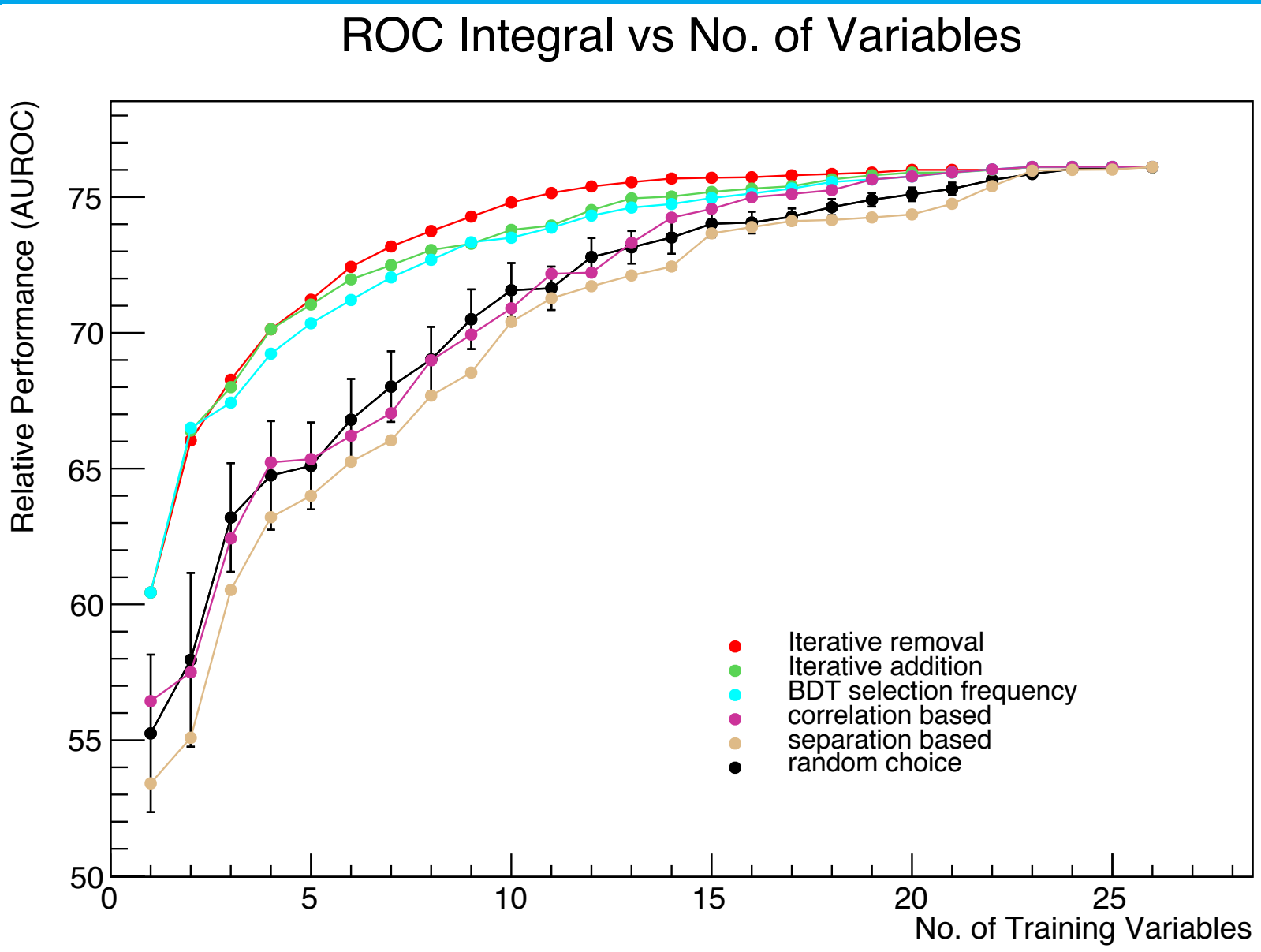


Ranking Methods tested

- Iterative addition: start with n=1, take best training of all n options. Then take best option of adding one more from remaining n-1 variables, etc. Ranking complexity scales as $O(n^3)$.
- Iterative removal: start with training on all variables and remove iteratively remove the one that degrades the performance the least, scales as $O(n^3)$.
  - Hypothesis: better consideration of variables that only add to performance in combination with others.
- Correlation based: rank the variables based on their correlation to the BDT score computed with all variables. Computationally cheap, scales as O(n).
- BDT selection frequency 'TMVA ranking': train once on all variables, rank by how often a variables provided the optimal decision in the BDT, scales as O(n).
- Separation based: rank by overlap of signal vs background shapes. Only method that establishes ranking without performing any training.
- Random choice: serves as reference, use a random subset of the variables. Repeat and average over 1000 trials.

Here performance is measured as integral of the ROC curve.

Ranking results



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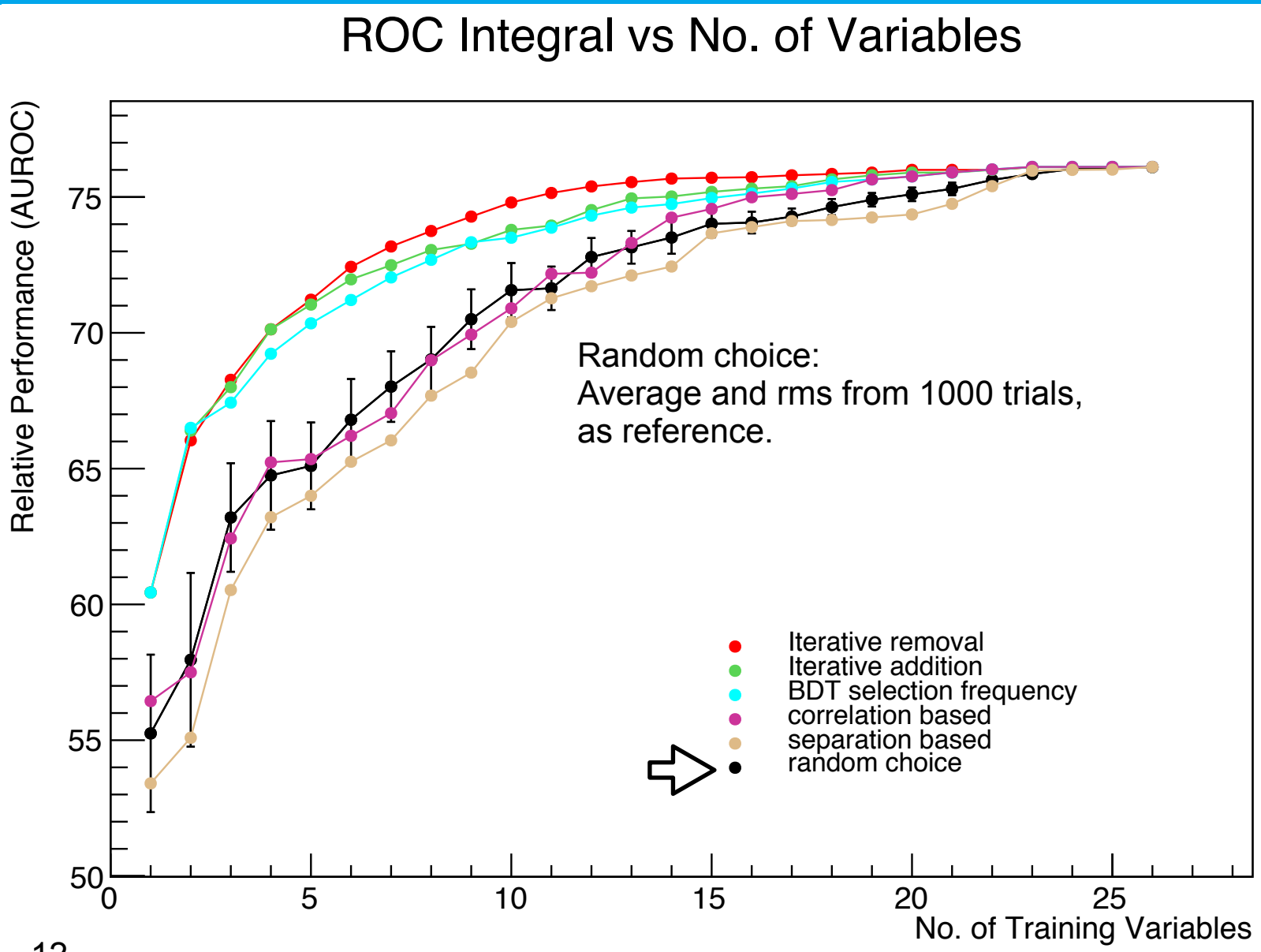

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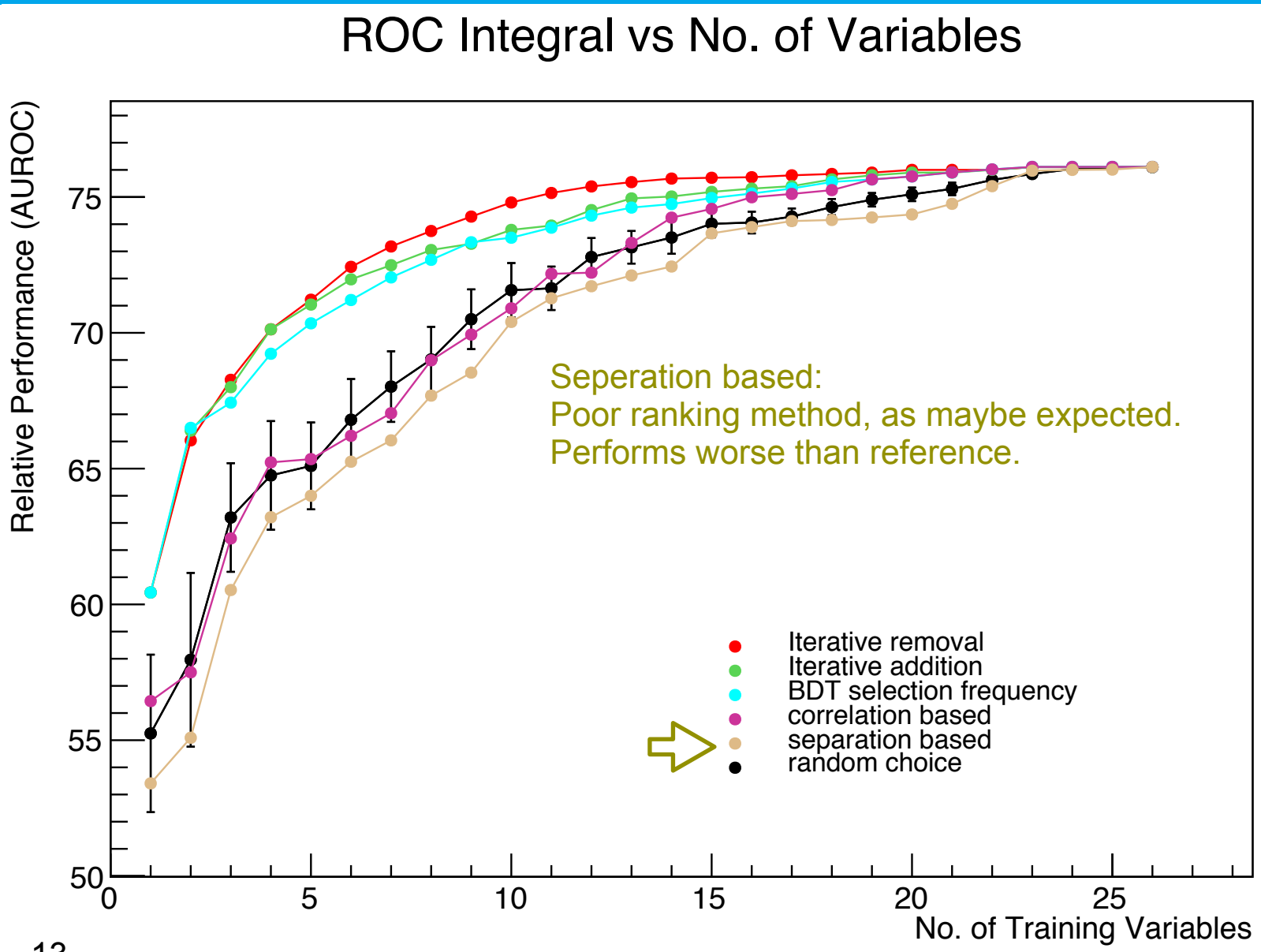

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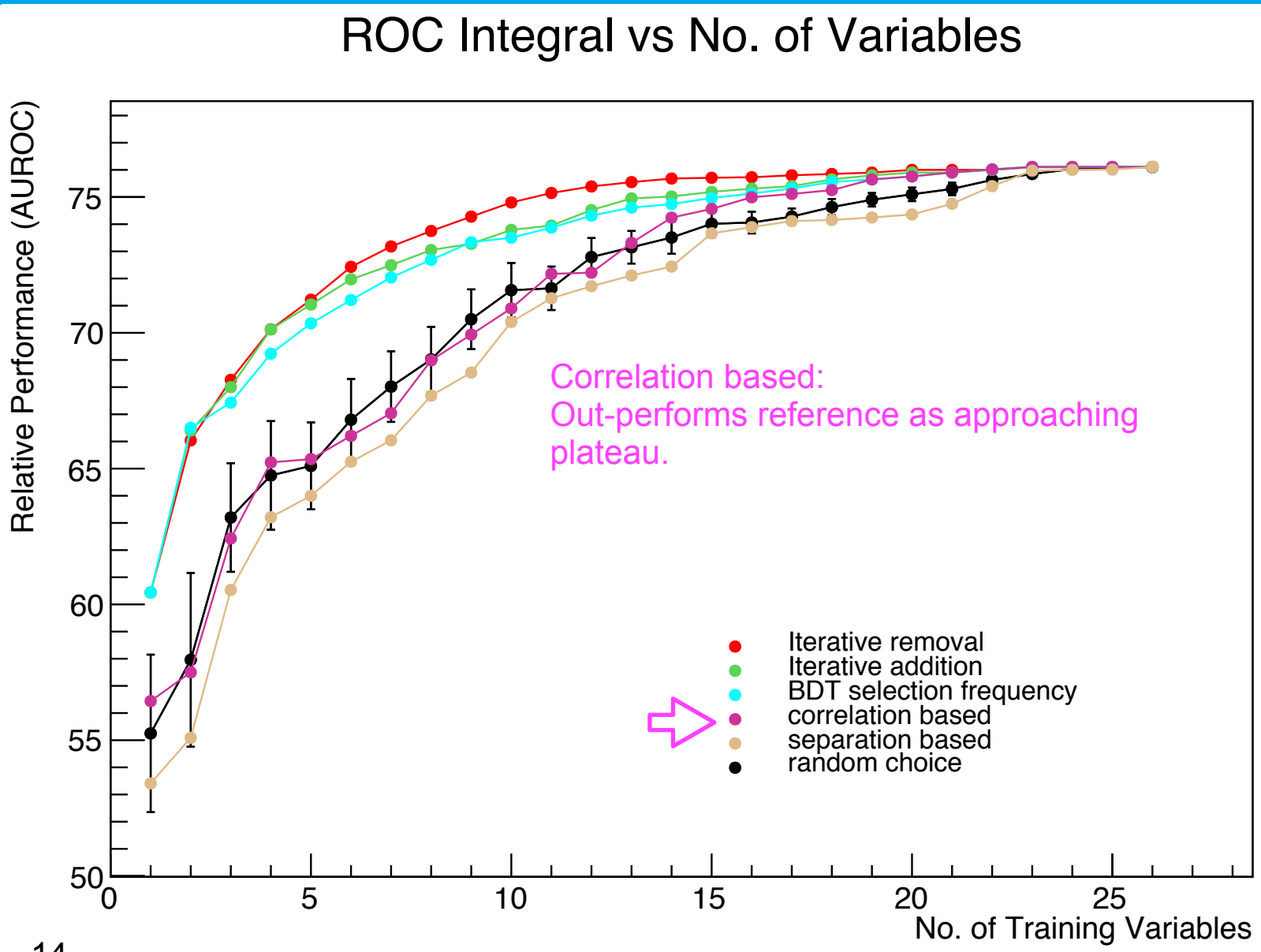

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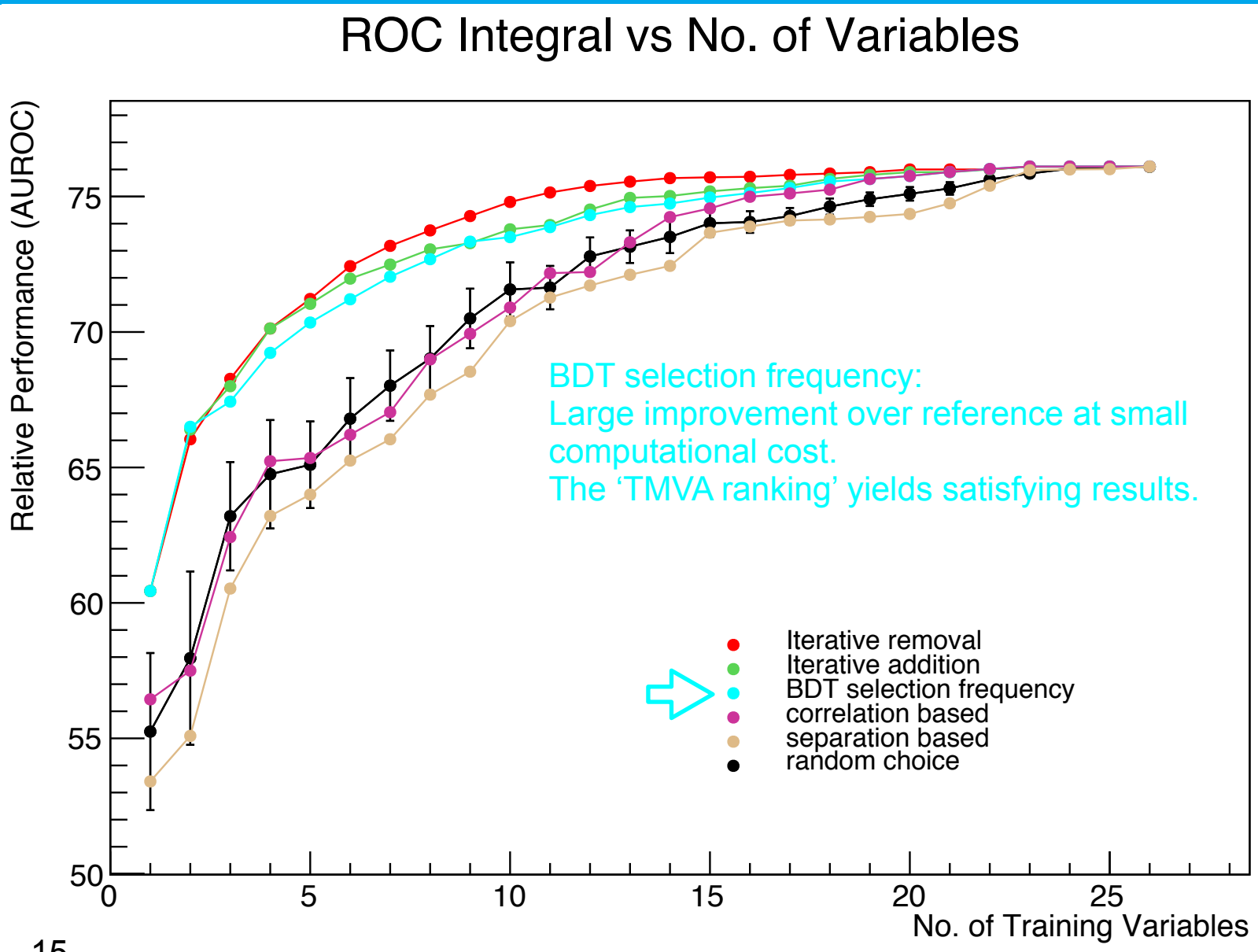

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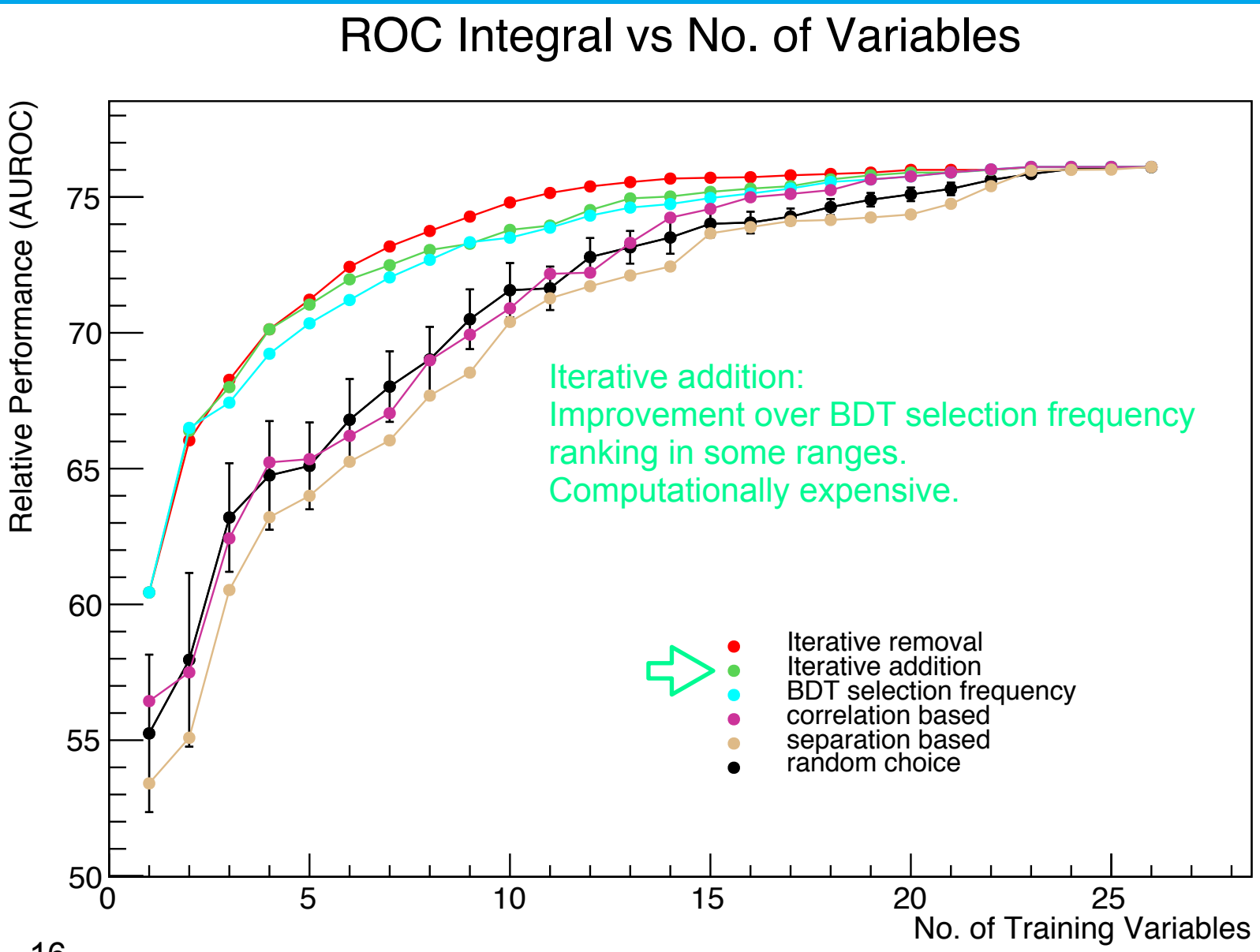

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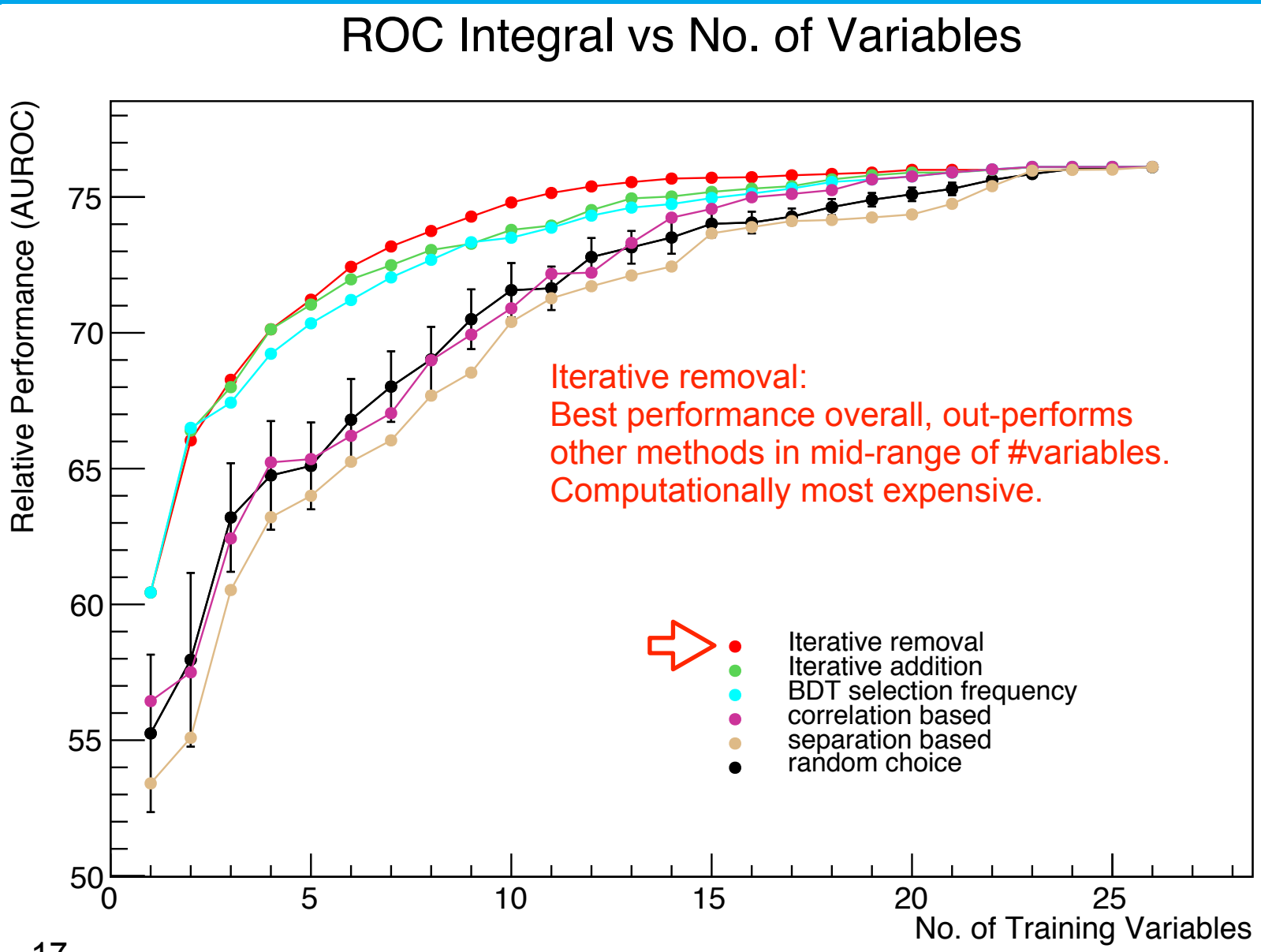

Variable ranking

- Top 10 variables selected by most promising methods
- Should only serve as indication, would not make physics conclusions on the basis of the sample and simulation used
- Difference in performance at most ~1% on AUROC

Rank	Iterative removal	Iterative addition	BDT selection freq.
1	dRbb_avg	dRbb_avg	dRbb_avg
2	HT_jets	Mbb_MaxM	Mbb_MaxM
3	nHigssbb30	nbTag	HT_jets
4	Mbb_MaxM	dRlb2	H0_all
5	nbTag	Mjjj_MaxPt	nJets_Pt40
6	Mbb_MinR	Pt_lep	dRlb2
7	dRlb3	dRbb_MaxM	Mjjj_MaxPt
8	H2_jets	dRlbb_minR	Pt_lep
9	H0_all	HT_all	Max_dEtajj
10	Mjjj_MaxPt	Mbb_MinR	dRlb1

Conclusions

- The example of the ttH(H->bb) vs tt+jets BDT classification was shown to demonstrate the difference of selected feature ranking methods.
- Identifying the top 5 or 10 most important variables is not straightforward in this case, given the high correlation among the variables.
- The computationally cheap BDT selection frequency ranking was found to be an adequate rough estimate
- The computationally costly (greedy) iterative addition and removal methods were compared, where the removal method yields the highest performance for any subset of variables.
- We recommend the iterative removal method for analogous cases where you want to prune the list training variables.

https://github.com/sitongan/vSearch