The Interplay of Machine Learning-based Resonant Anomaly Detection Methods

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Resonant anomaly detection as a search strategy



Many* ML techniques can construct the SM Template





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Study 0: do the methods reproduce the expected marginals?



Study 1: are the samples good proxies for SM background?



Study 2: do the samples agree on "anomalous" background?



Study 3: do the samples agree on signal?



Combination appears to stabilize and improve performance...



...across a range of signal efficiencies



Closing thoughts

- The LHC Olympics dataset has been almost exclusively used for resonant AD.
 We should be testing on a variety of signal models!
- SALAD appears* to beat the combined methods, but reweighting needs regions of overlapping support.
 - What signals could break individual methods?
 - Would the combination of samples still perform well on these models?
 - Note that sample combination can be **weighted** (though not explored here).

Backup slides

Number of generated samples

Method	Training data	Validation data	# samples	Oversampling
SALAD	793k SIM, 696k DAT	198K SIM, 174K DAT	1,045k	N/A
CATHODE	696k DAT	174K DAT	400k	3
CURTAINS	373k DAT	93k DAT	1,887k	4
FETA	793k SIM, 696k DAT	198K SIM, 174K DAT	732k	6

Background overlaps do not agree when there is signal



SIC at rejection = 1000



Classifier SIC for $n_{sig} = 750$



Classifier rejection for $n_{sig} = 750$



Around $n_{sig} = 500$, the AD task breaks down



Correlations of scores: background only





Correlations of scores: $n_{sig} = 1500$



