Parameter Inference from Event Ensembles and the Top-Quark Mass

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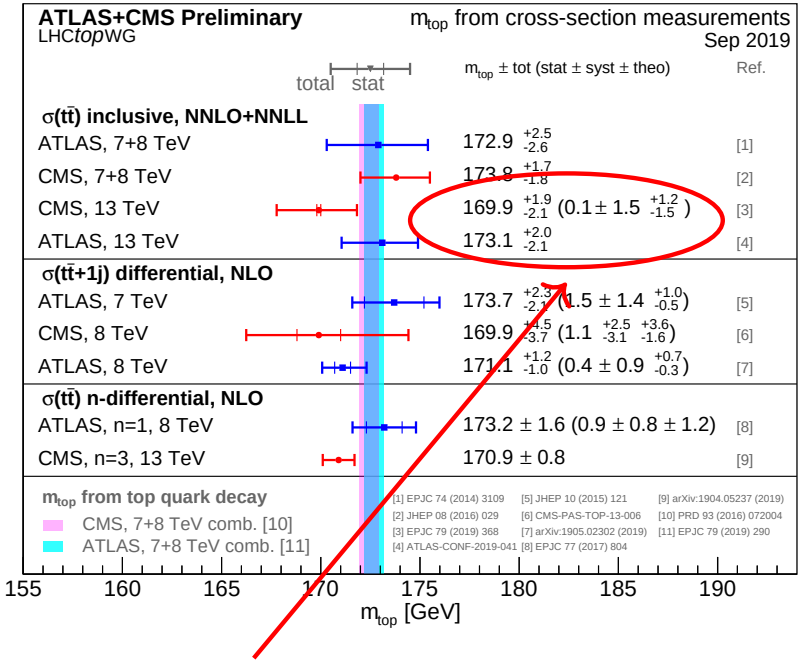
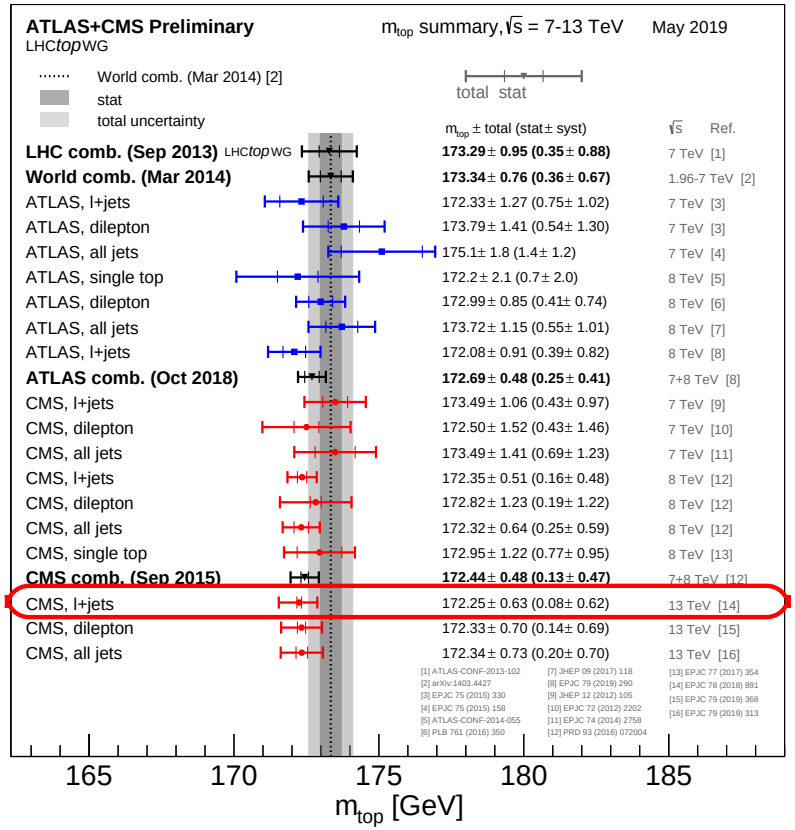
Motivation

Why the MC mass?

Goal: To decrease the uncertainty on the top quark monte carlo (MC) mass. Why the MC mass? [Summary Plots from twiki]





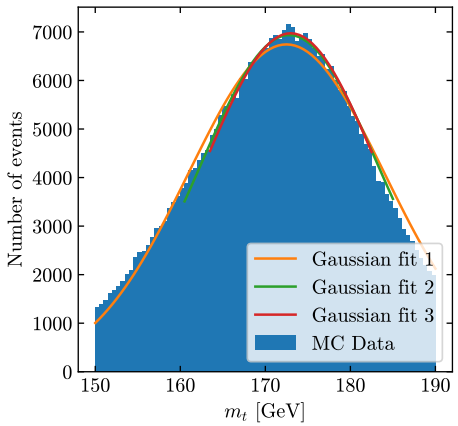
Large Error
$\mathcal{O}$(GeV)

Small Error
$\mathcal{O}$(600 MeV)

Motivation

Why the MC mass?

- Best measurements rely on curve fitting the invariant mass peak in $t\bar{t}$ events
- But MC is still a significant source of systematic error



	2D approach δm_t^{2D} [GeV]	δJSF^{2D} [%]	1D approach δm_t^{1D} [GeV]	Hybrid δm_t^{hyb} [GeV]	δJSF^{hyb} [%]
Experimental uncertainties					
Method calibration	0.05	<0.1	0.05	0.05	<0.1
JEC (quad. sum)	0.13	0.2	0.83	0.18	0.3
– InterCalibration	(−0.02)	(<0.1)	(+0.16)	(+0.04)	(<0.1)
– MPFInSitu	(−0.01)	(<0.1)	(+0.23)	(+0.07)	(<0.1)
– Uncorrelated	(−0.13)	(+0.2)	(+0.78)	(+0.16)	(+0.3)
Jet energy resolution	−0.20	+0.3	+0.09	−0.12	+0.2
b tagging	+0.03	<0.1	+0.01	+0.03	<0.1
Pileup	−0.08	+0.1	+0.02	−0.05	+0.1
Non-$t\bar{t}$ background	+0.04	−0.1	−0.02	+0.02	−0.1
Modeling uncertainties					
JEC Flavor (linear sum)	−0.42	+0.1	−0.31	−0.39	<0.1
– light quarks (uds)	(+0.10)	(−0.1)	(−0.01)	(+0.06)	(−0.1)
– charm	(+0.02)	(<0.1)	(−0.01)	(+0.01)	(<0.1)
– bottom	(−0.32)	(<0.1)	(−0.31)	(−0.32)	(<0.1)
– gluon	(−0.22)	(+0.3)	(+0.02)	(−0.15)	(+0.2)
b jet modeling (quad. sum)	0.13	0.1	0.09	0.12	<0.1
– b frag. Bowler–Lund	(−0.07)	(+0.1)	(−0.01)	(−0.05)	(<0.1)
– b frag. Peterson	(+0.04)	(<0.1)	(+0.05)	(+0.04)	(<0.1)
– semileptonic B decays	(+0.11)	(<0.1)	(+0.08)	(+0.10)	(<0.1)
PDF	0.02	<0.1	0.02	0.02	<0.1
Ren. and fact. scales	0.02	0.1	0.02	0.01	<0.1
ME/PS matching	-0.08 ± 0.09	+0.1	$+0.03 \pm 0.05$	-0.05 ± 0.07	+0.1
ME generator	$+0.15 \pm 0.23$	+0.2	$+0.32 \pm 0.14$	$+0.20 \pm 0.19$	+0.1
ISR PS scale	$+0.07 \pm 0.09$	+0.1	$+0.10 \pm 0.05$	$+0.06 \pm 0.07$	<0.1
FSR PS scale	$+0.24 \pm 0.06$	−0.4	-0.22 ± 0.04	$+0.13 \pm 0.05$	−0.3
Top quark p_T	+0.02	−0.1	−0.06	−0.01	−0.1
Underlying event	-0.10 ± 0.08	+0.1	$+0.01 \pm 0.05$	-0.07 ± 0.07	+0.1
Early resonance decays	-0.22 ± 0.09	+0.8	$+0.42 \pm 0.05$	-0.03 ± 0.07	+0.5
Color reconnection	$+0.34 \pm 0.09$	−0.1	$+0.23 \pm 0.06$	$+0.31 \pm 0.08$	−0.1
Total systematic	**0.75**	**1.1**	**1.10**	**0.62**	**0.8**
Statistical (expected)	0.09	0.1	0.06	0.08	0.1
Total (expected)	**0.76**	**1.1**	**1.10**	**0.63**	**0.8**

[CMS: EPJC 78 (2018) 891 (1805.01428)]

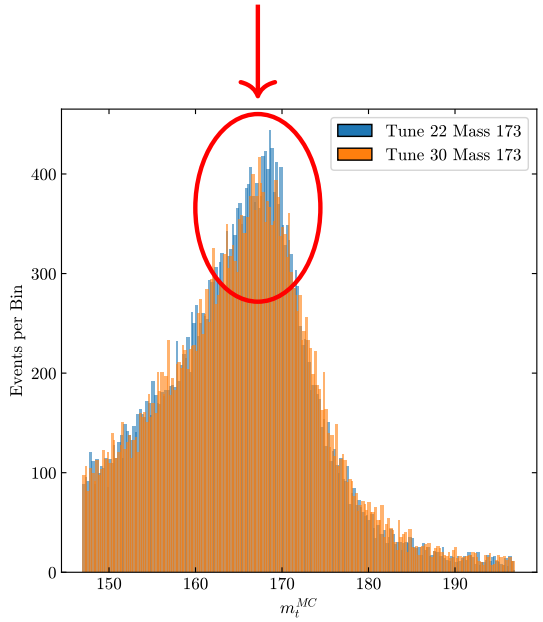
MC Tunes

- MC mass is the fit to the peak in MC
- Error exists because the mass that fits the peak depends on MC parameters (tunes)
- Need to eliminate dependence to get a well defined mass

Variation	Tunes	ColorRec	α_S^{MPI}	p_{T0}^{Ref}
VarPDF	19-22	1.71	0.126	1.56
Var1	21, 23, 24	[1.69,1.73]	[0.121,0.131]	1.56
Var2	21, 25, 26	1.71	0.126	[1.50,1.60]
Var3a	21, 27, 28	1.71	[0.125,0.127]	[1.51,1.67]
Var3b	21, 29, 30	1.71	0.126	1.56
Var3c	21, 31, 32	1.71	0.126	1.56

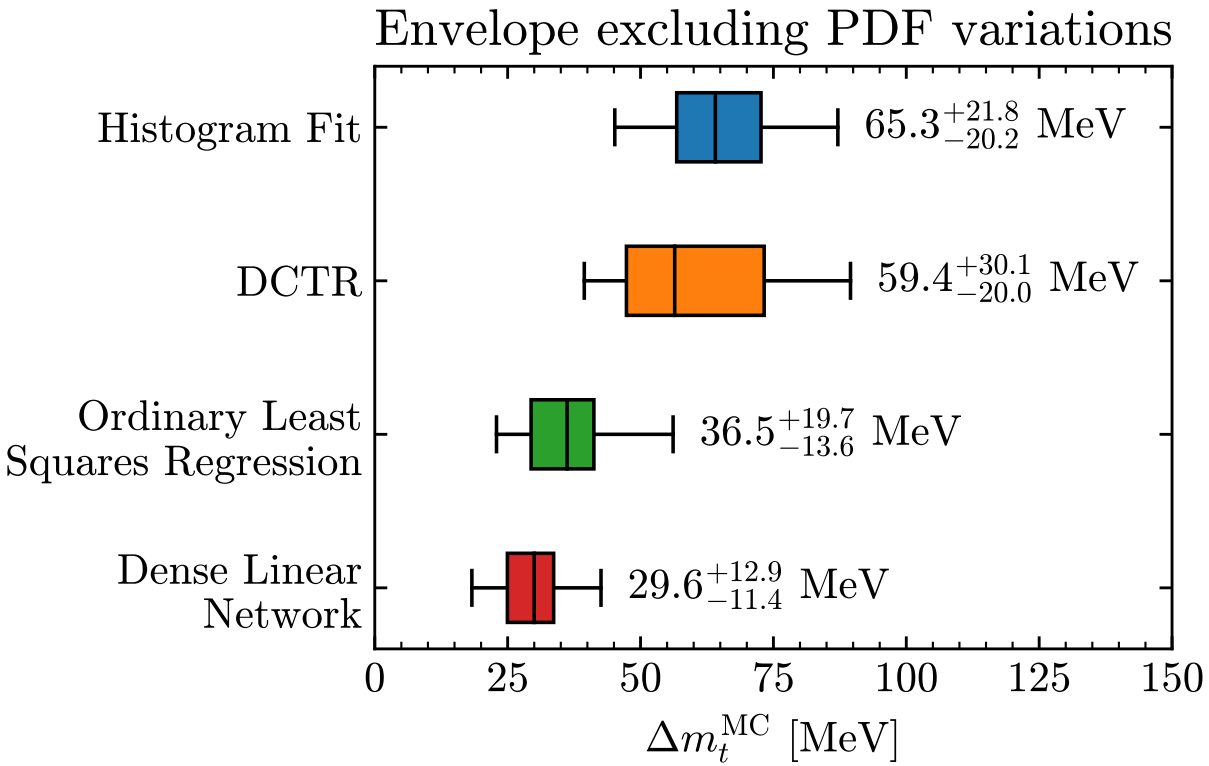
Variation	$p_T^{\mathrm{dampFudge}}$	α_S^{FSR}	p_T^{maxFudge}	α_S^{ISR}
VarPDF	1.05	0.127	0.91	0.127
Var1	1.05	0.127	0.91	0.127
Var2	[1.04,1.08]	[0.124,0.136]	0.91	0.127
Var3a	[0.93,1.36]	[0.124,0.136]	[0.88,0.98]	0.127
Var3b	[1.04,1.07]	[0.114,0.138]	[0.83,1.00]	[0.126,0.129]
Var3c	1.05	0.127	0.91	[0.115,0.140]

Peak Depends on Tune



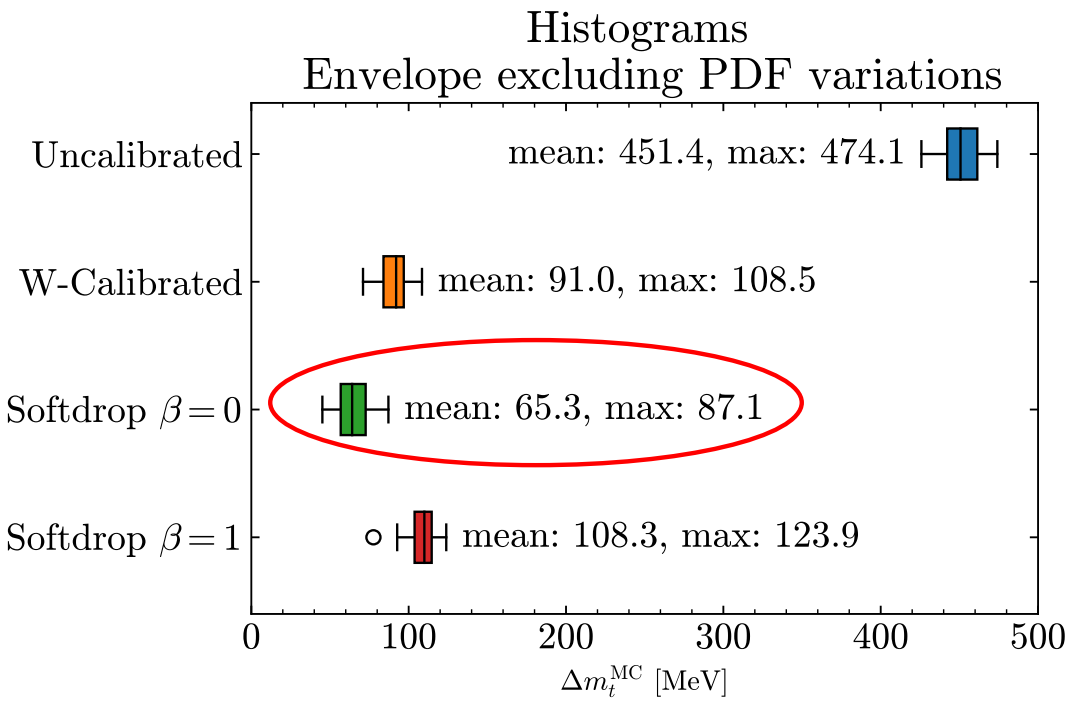
Results and Outline

Methods to decrease the uncertainty on the top quark monte carlo (MC) mass:



Previous Work - Histogram Fits with Grooming

- To extract the top-quark MC mass, iteratively fit histograms.
- Uncertainty $\sim 500 - 800$ MeV; ~ 100 MeV with W-calibration: ($m_{\text{calibrated}} = m_{3J}\frac{m_W}{m_{2J}}$)
- Error can be further reduced by grooming with soft drop ($\sim 30\%$) [Andreassen, Schwartz: 1705.07135]



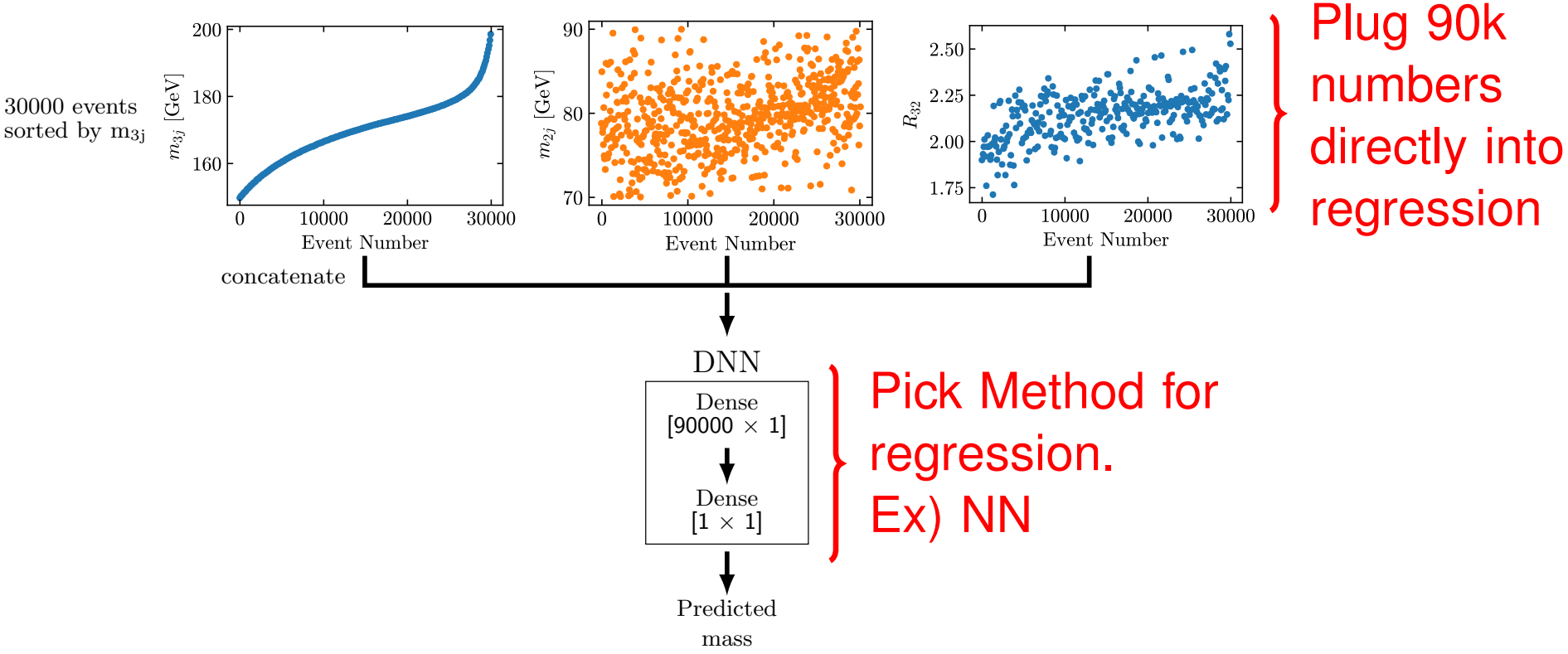
How can we do better?

Curve fitting reduces histograms to a very small number of parameters that are dependent on the parameterization.

Can we use more of the distribution? Eliminate dependence on parameterization?

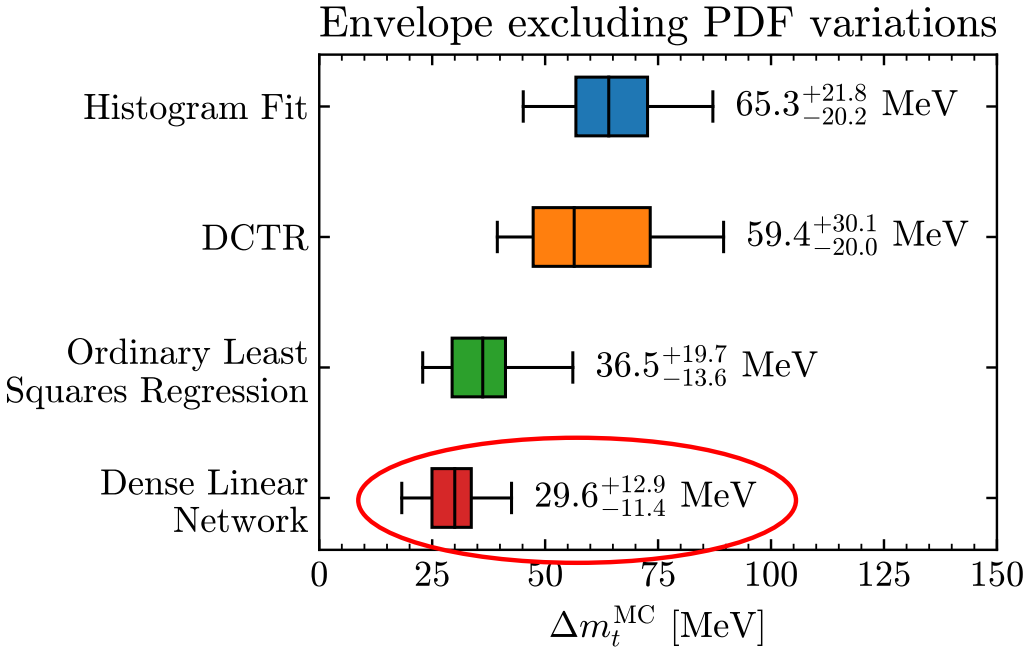
We can! Do regression on an ensemble of events without a binned histogram.

Regression on Event Ensembles



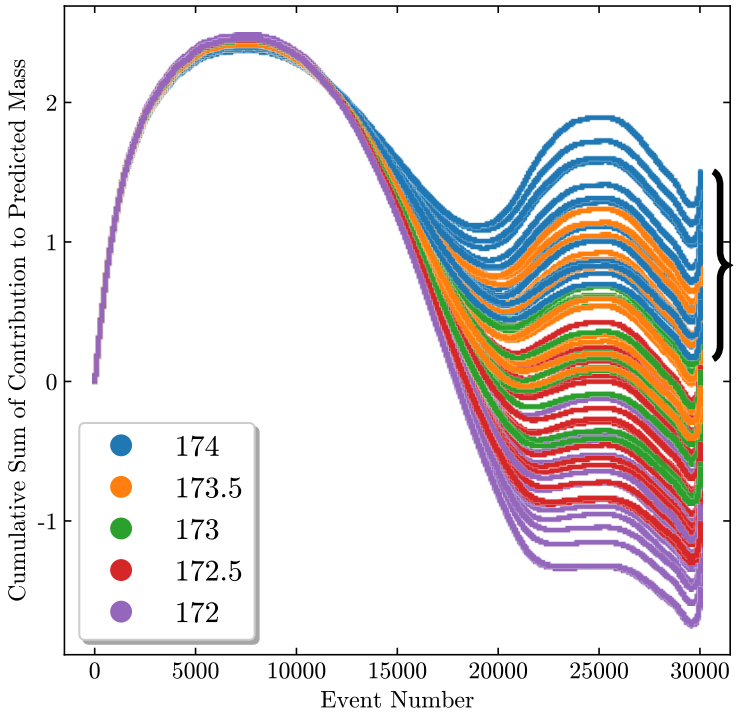
Regression on Event Ensembles

- Improves by a factor of ~ 2
- Modifications don't help, including:
  - Different inputs
  - Different network structures
  - Other tuning parameters as additional outputs
  - Ordinary Least Squares regression



Understanding the Improvement

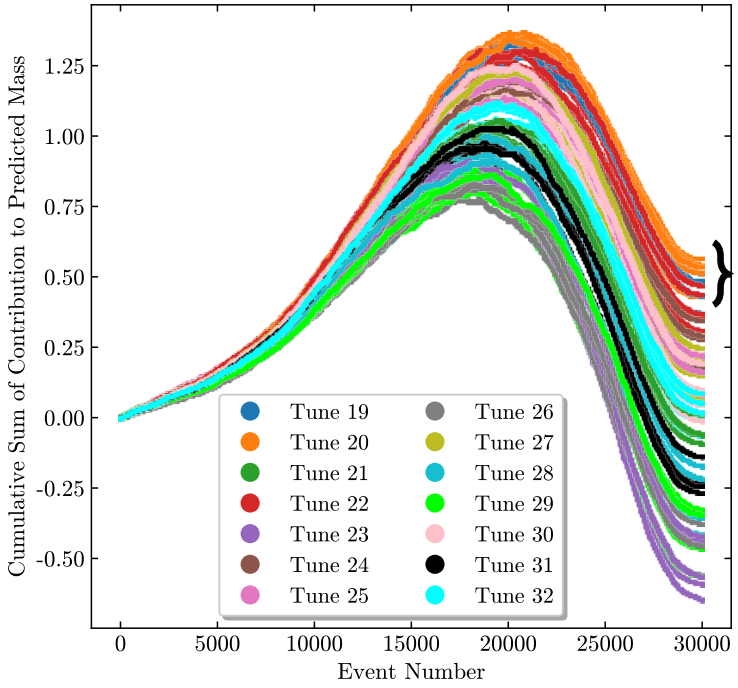
M_{3J} contribution:



Mass controls M_{3J}

14 lines of each color (one for each tune)

M_{2J} contribution:

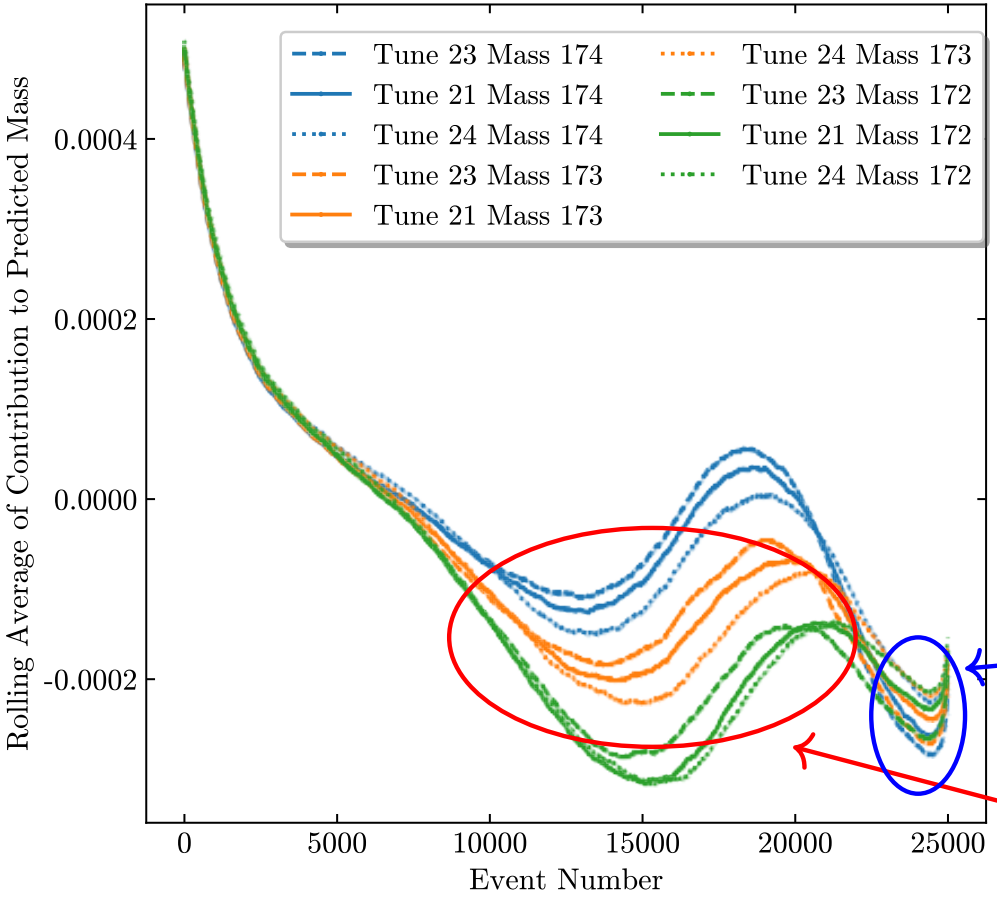


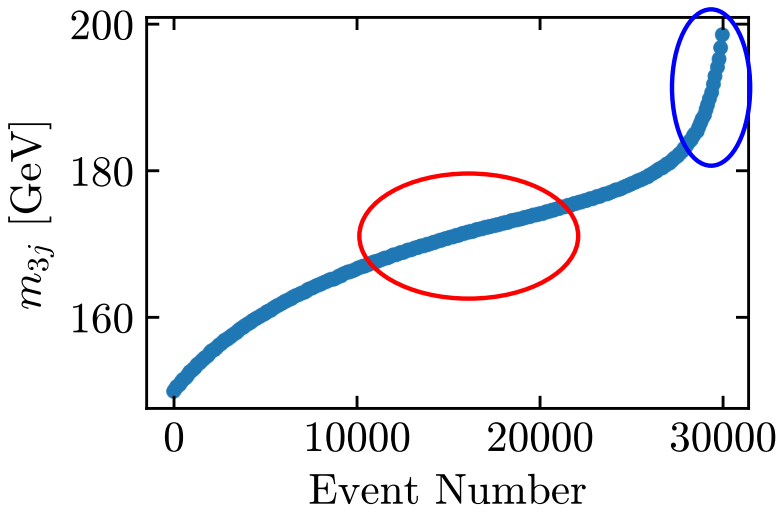
Tune controls M_{2J}

5 lines of each color (one for each mass)

A Closer Look at M_{3J}

M_{3J} contribution:



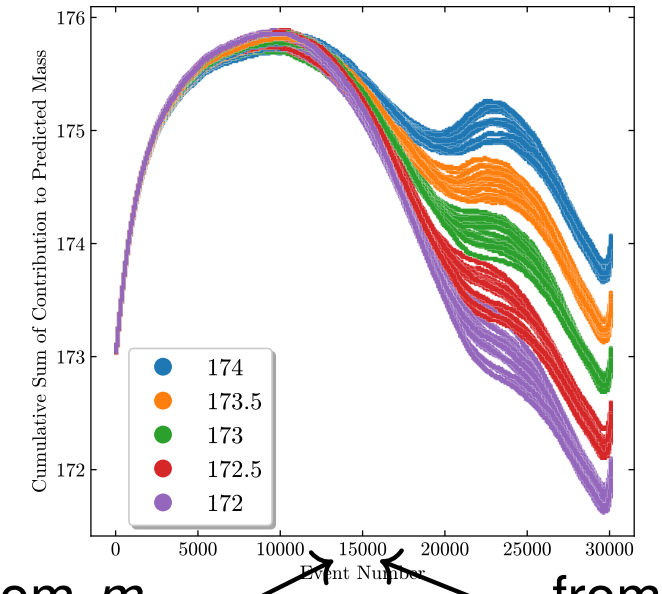


Correct for tunes away from peak

Learn the mass from the peak

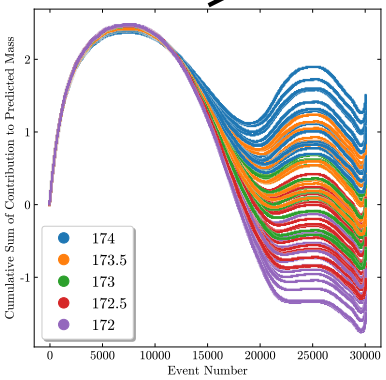
Understanding the Improvement

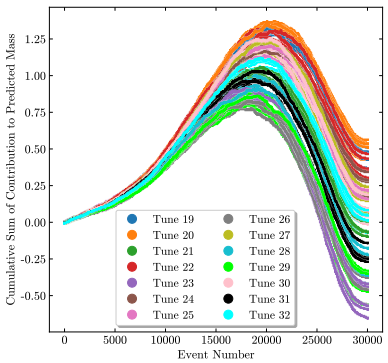
The full network can use tails to correct for differences in tune:

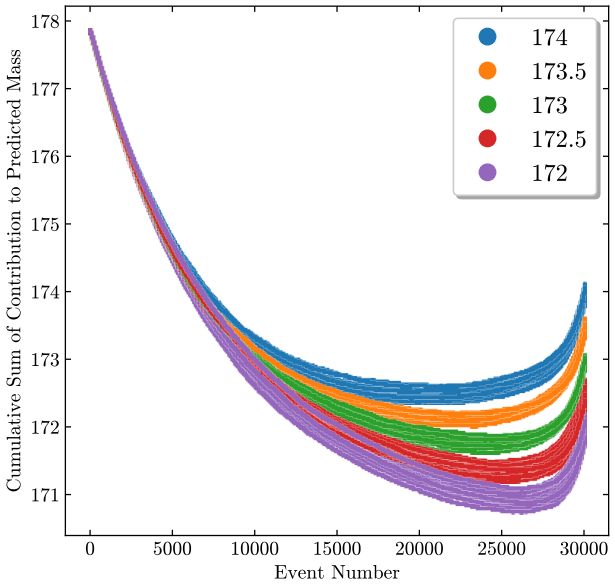


from m_{3J}

from m_{2J}



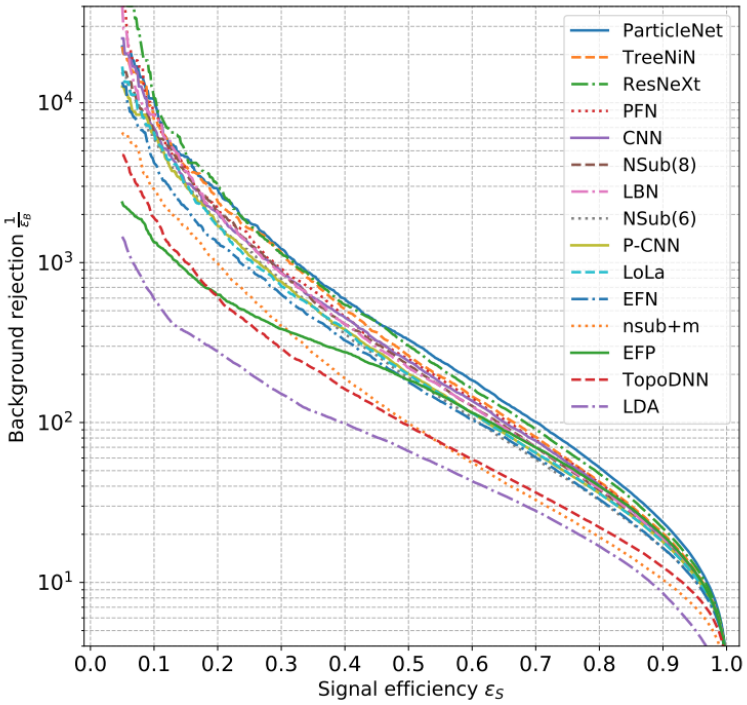




$$m_{3J}^{Avg}, m_{2J}^{Avg}$$

Can Modern ML Help?

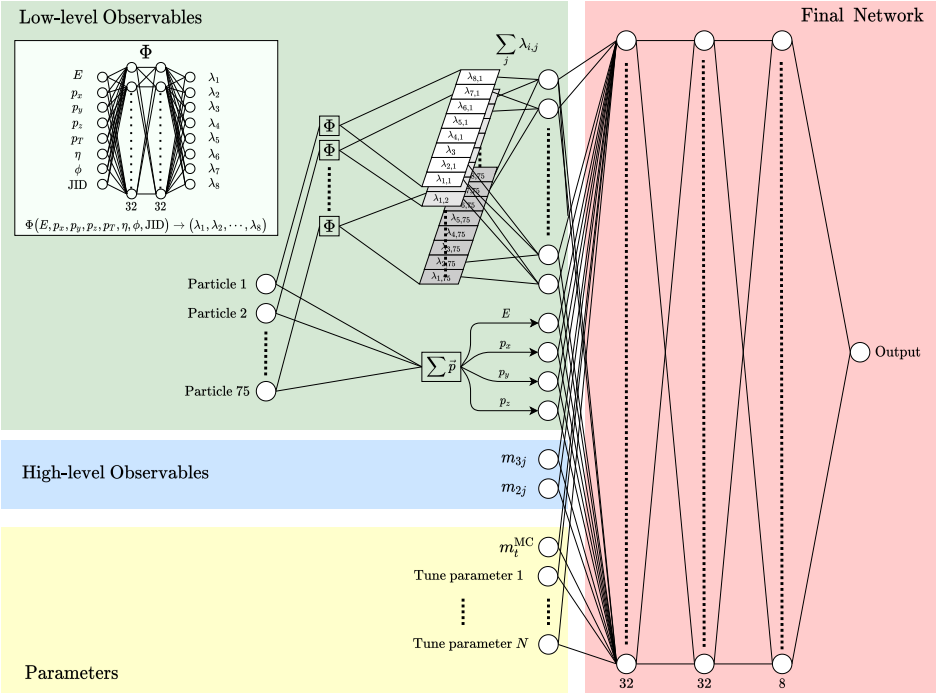
- Low level info helps for other applications such as top tagging
- Can't easily include low level info directly into regression
- Other options: reduce to Energy Flow Polynomials, DCTR



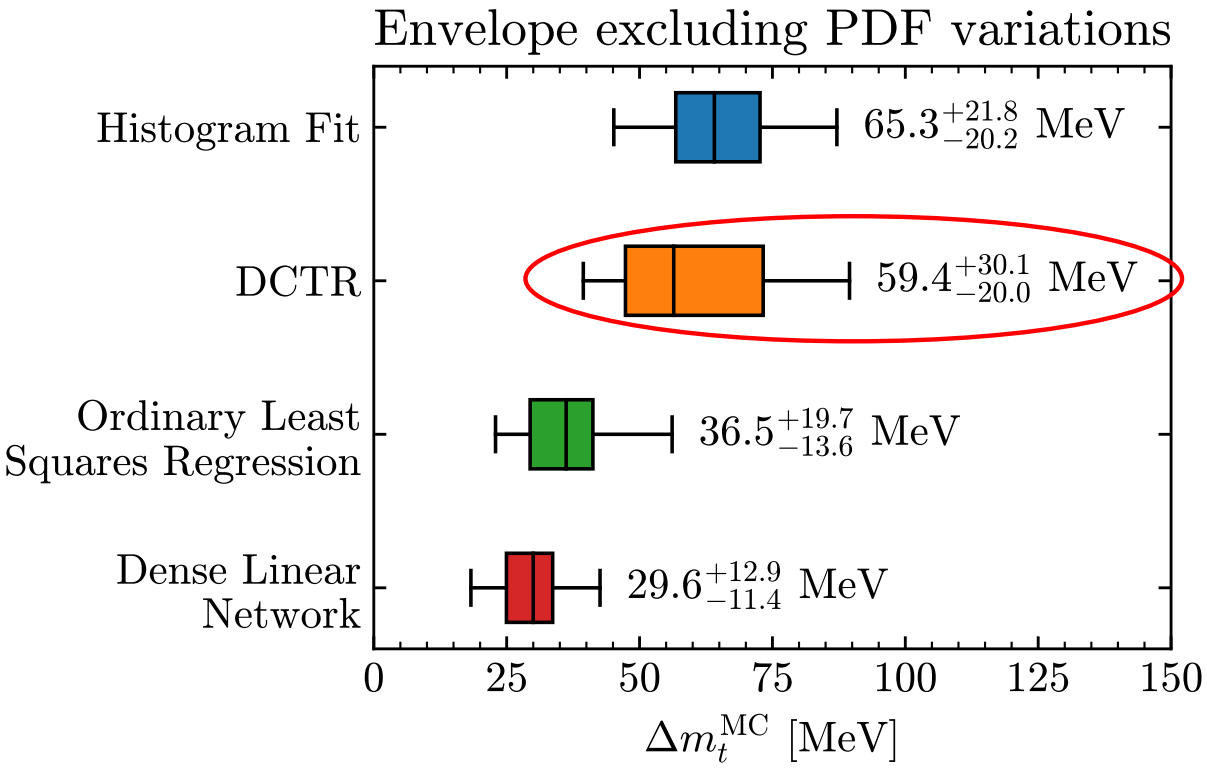
[Comparing ML Top Taggers Performance: Kasieczka et al, 1902.09914]

A DCTR Study

- DCTR is a modern ML method [Andreassen, Nachman: 1907.08209]
- Relies on parameterized classifiers, which can take as input HLV, low level input, and parameters
- Works because loss of a classifier = likelihood ratio



DCTR Results



Summary

The degeneracy between mass and tune is a significant source of error in measuring m_t.
Three strategies for reducing this error: (1) Jet Grooming [1705.07135] (2) Regression on event ensembles (3) Modern ML DCTR method
Conclusions:

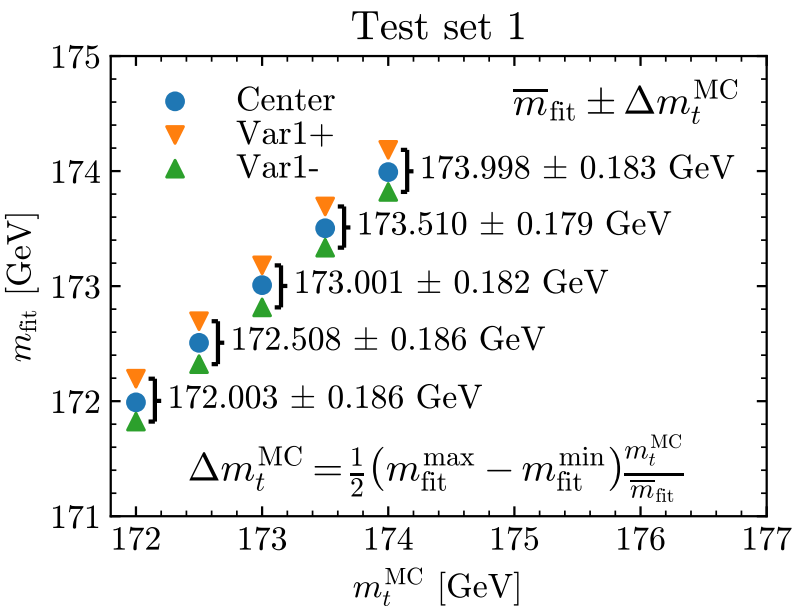
- **Regression on event ensembles reduces error by a factor of ~ 2 compared to groomed histograms**
- DCTR matches grooming but doesn't improve further
- Regression on event ensembles could potentially be useful for other measurements

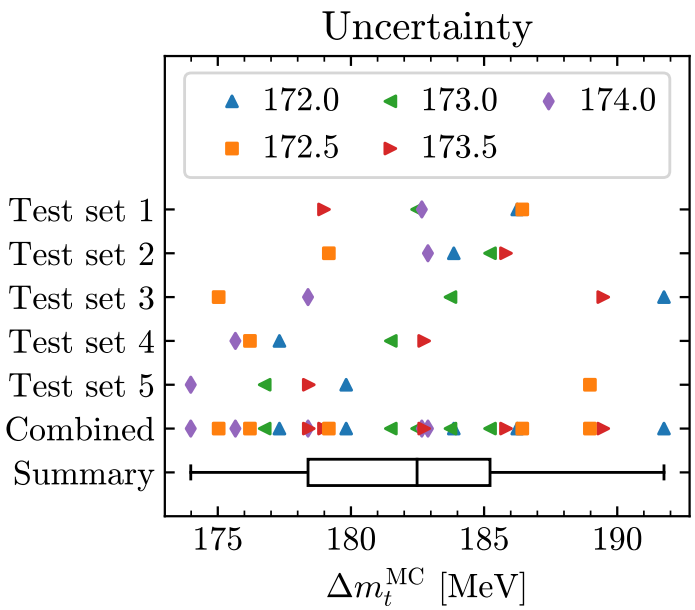
Back Up Slides

Defining the Error

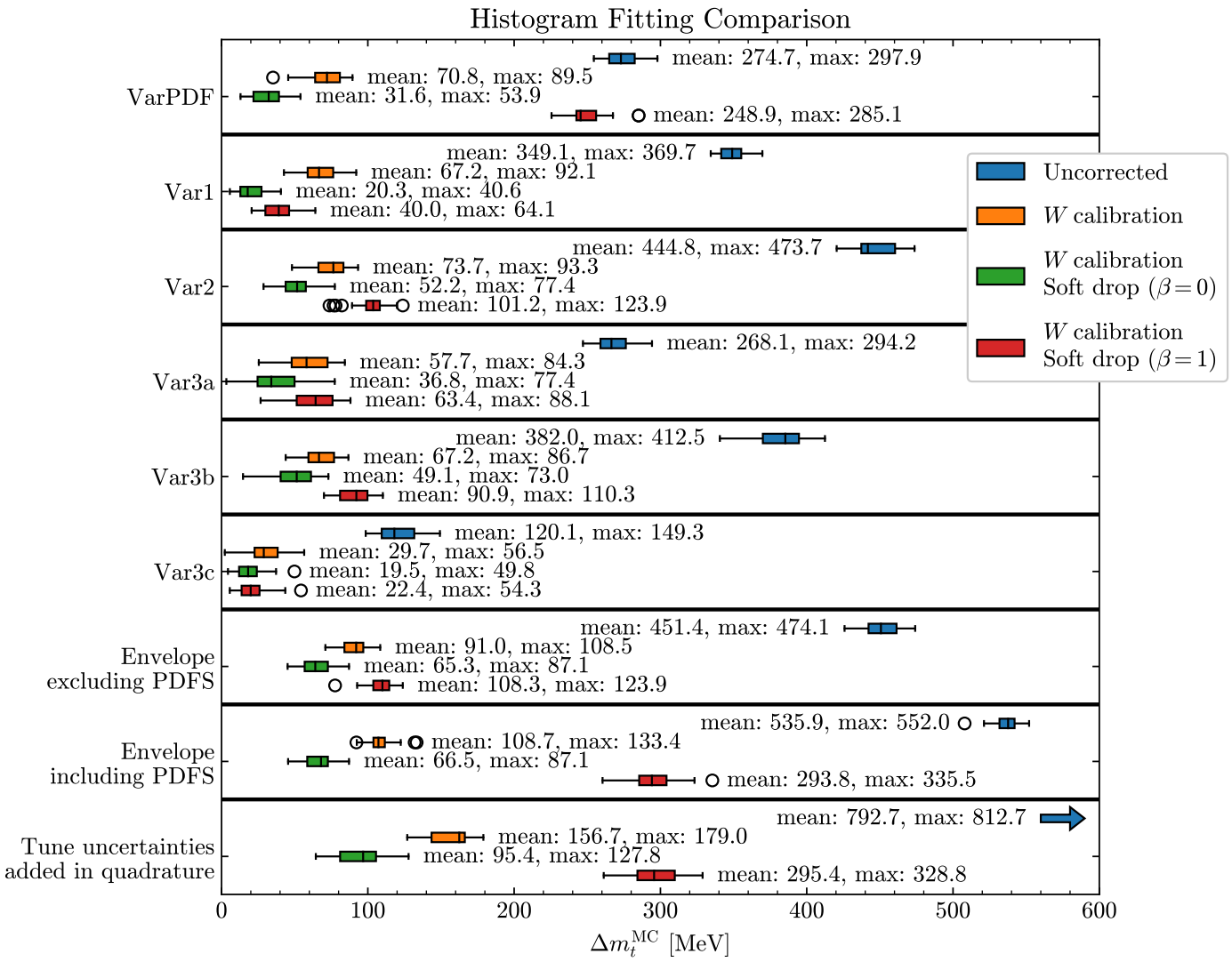
For a set of tunes with fixed input mass, the error is defined to be

$$\Delta m_t^{MC} = \frac{1}{2}\left(m_{\text{fit}}^{\max} - m_{\text{fit}}^{\min}\right)\frac{m_t^{MC}}{\bar{m}_t^{\text{fit}}}.$$

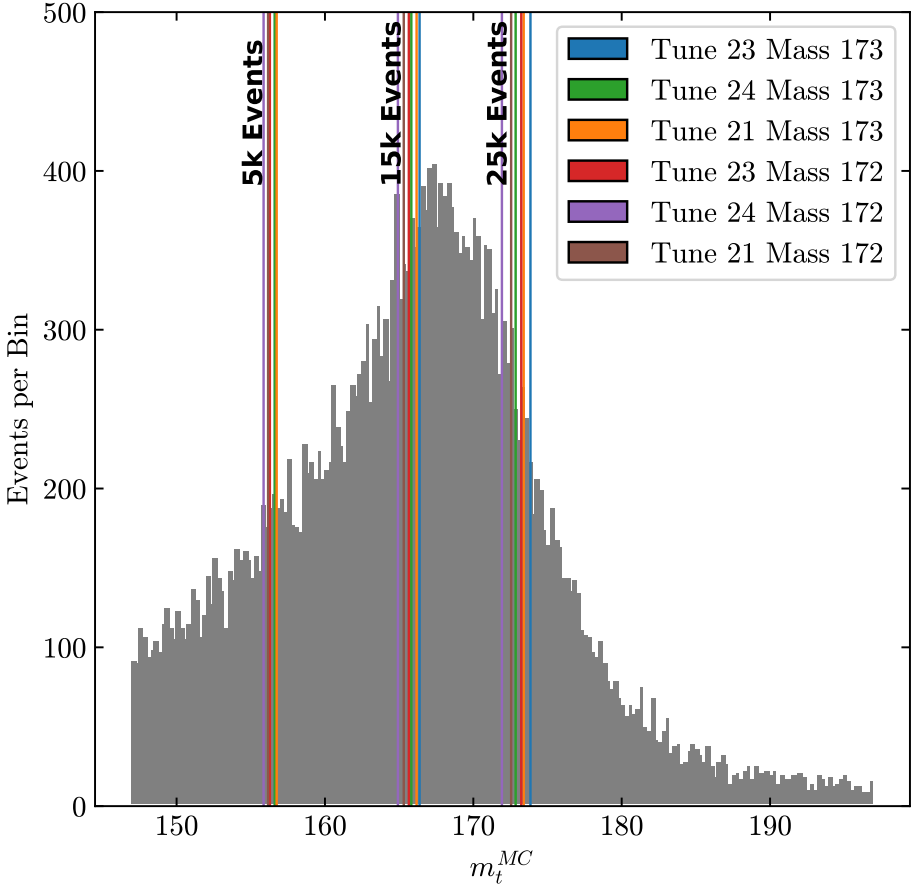




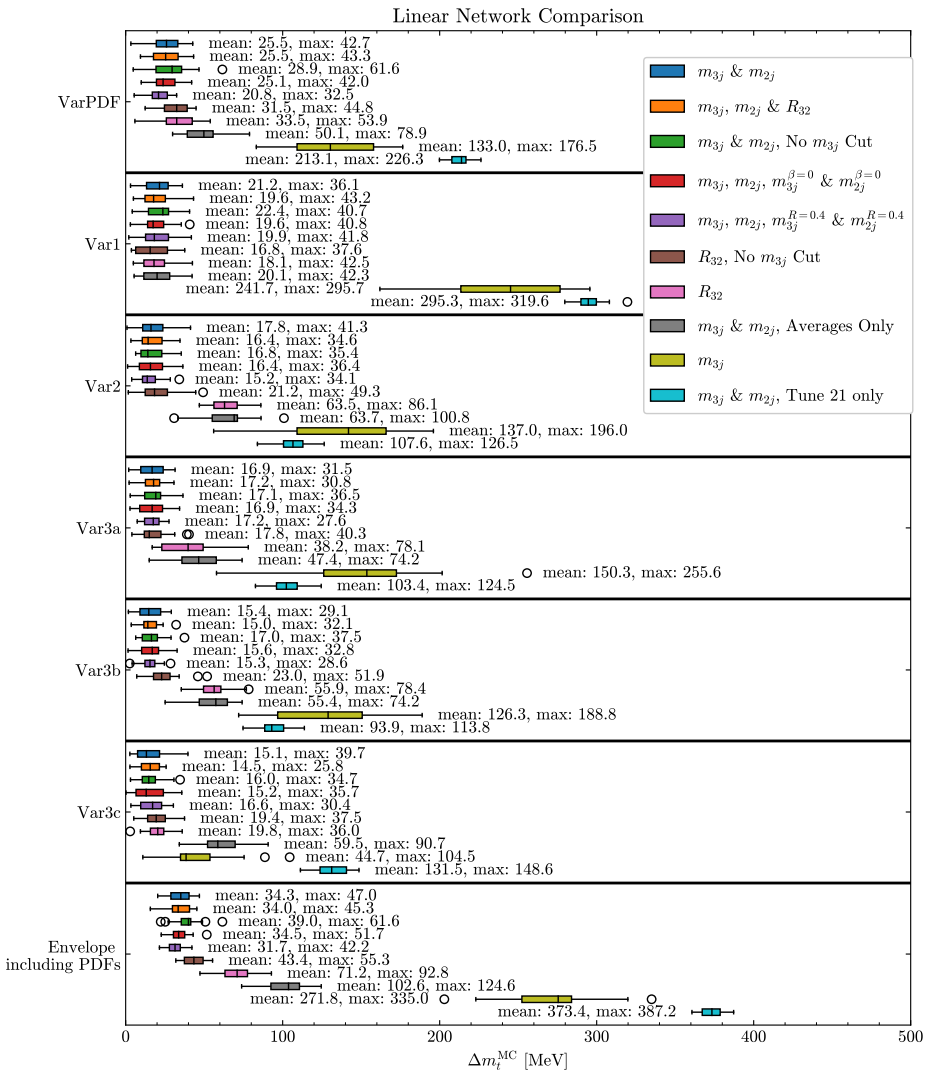
Histogram Full Results



Event Histograms



Linear Network Full Results



DCTR in Practice

Two Steps:

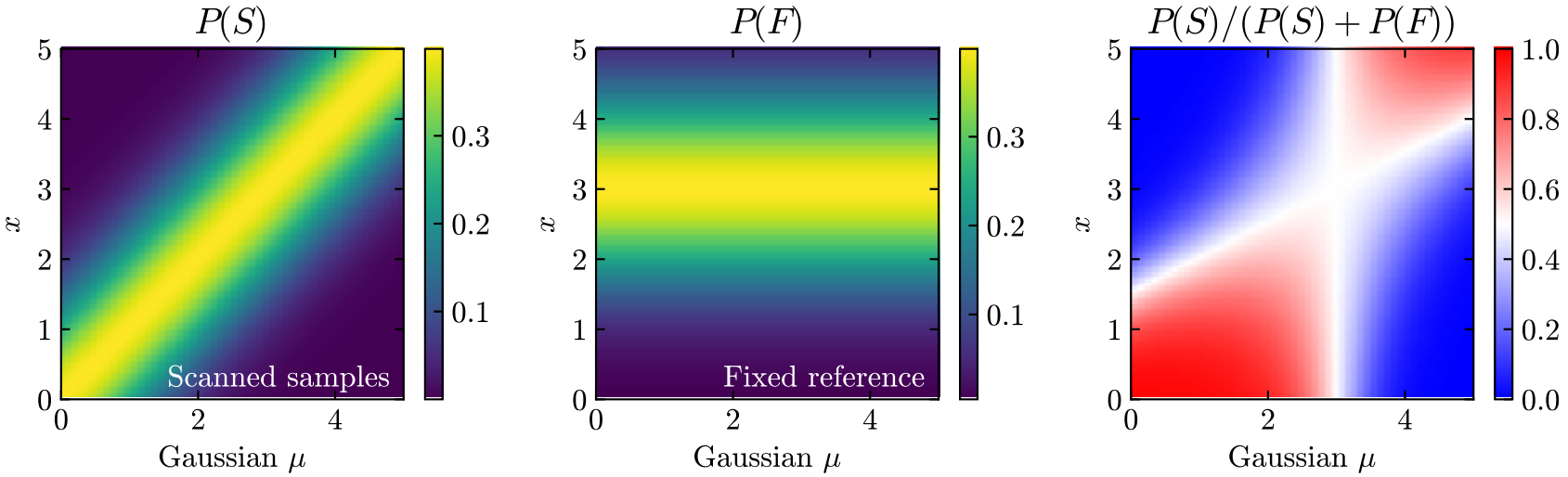
1. Train a parameterized classifier to learn the likelihood ratio
2. Evaluate classifier for an unknown sample and a reference sample, trying multiple input parameters for the unknown sample.

   Likelihood is maximized at true parameters used to generate the unknown sample

DCTR Gaussian Example: Training Step

- 2 Training Samples:
  1. Samples S from Gaussian with mean μ random, label μ
  2. Samples U from Gaussian with mean μ fixed, random label
- Output of Classifier gives ratio of probability densities:

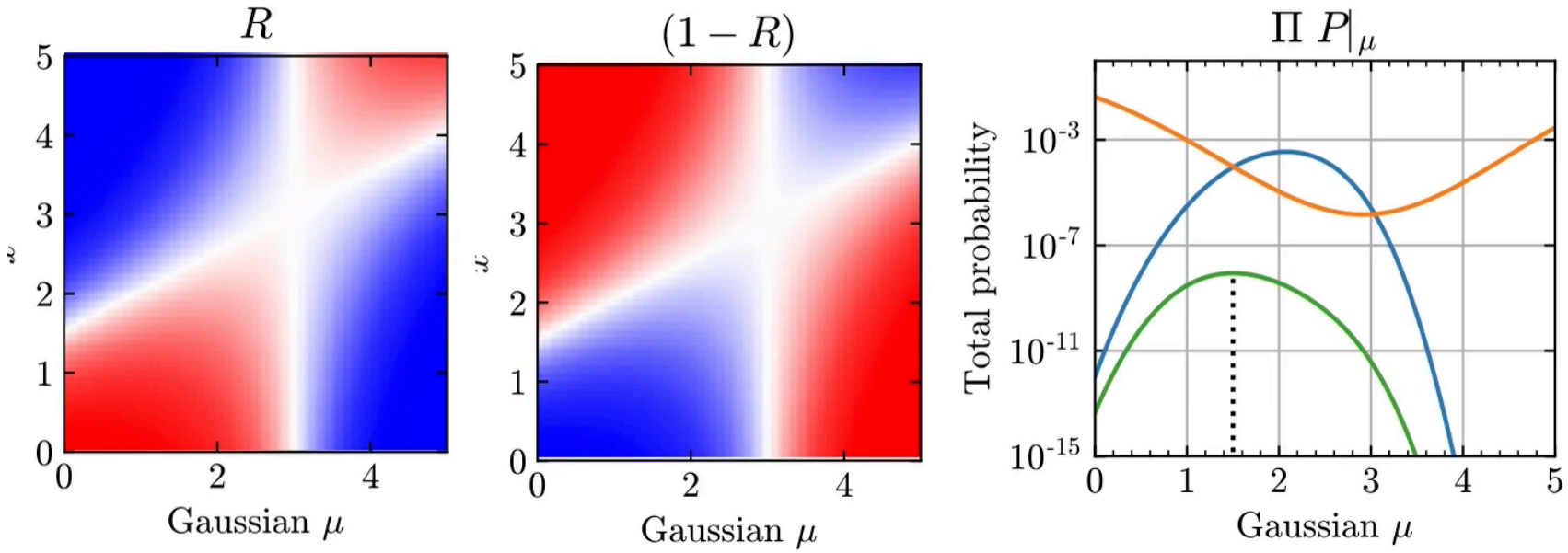
$$R(\mu, x) = \frac{P(S(\mu, x))}{P(S(\mu, x)) + P(U(\mu, x))}$$



More DCTR Results: Evaluation Step

To infer most probable parameter, maximize $C(\mu)$:

$$C(\mu) = \prod_{x \in T} R(\mu, x) \prod_{x \in F} (1 - R(\mu, x))$$



In Example: Reference $\mu = 3$, New $\mu = 1.5$