New Physics Learning Machine (NPLM) at work

Gaia Grosso[1,2]

[1]University and INFN of Padova, [2]CERN

In this talk

- **What is NPLM and how does it work?**

  Complete analysis strategy to test the data for departures from a Reference model (from data to a p-value for discovery, taking care of *systematic uncertainties* in the process).

  - Main concepts

    "Learning New Physics from a Machine" (d'Agnolo, Wulzer, 2018 Phys. Rev. D)

  - Multivariate implementation

    "Learning Multivariate New Physics" (d'Agnolo, Grosso, Pierini, Wulzer, Zanetti, 2019 Eur. Phys. J. C)

  - Systematic uncertainties

    "Learning New Physics from an Imperfect Machine" (d'Agnolo, Grosso, Pierini, Wulzer, Zanetti, 2022 Eur. Phys. J. C)

→ intro in Andrea's talk

More details on the **ML implementation** here!

In this talk

- **What is NPLM *good for*?**

  Multivariate, unbinned analysis, towards signal model independence (released constraints, lower level information, simultaneously sensitive to multiple signal patterns).

  - Model-independent New Physics searches at collider experiments
  - Data quality monitor (DQM)
  - Generator validation

→ See Marco Letizia's talk tomorrow!

More about NPLM tomorrow:

- NPLM implementation using kernel methods

  "Learning New Physics efficiently with non parametric methods" 2204.02317 (Letizia, Grosso, Wulzer et al.)

→ See Marco Letizia's talk tomorrow!

NPLM - negligible uncertainties

New Physics Learning Machine (NPLM)

Main Concepts (negligible uncertainties)

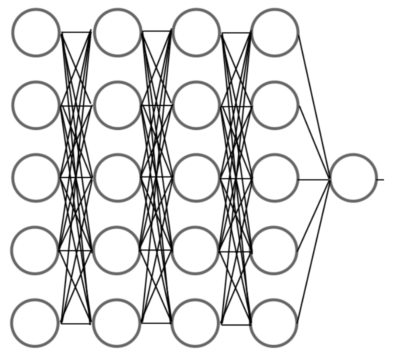
- Goal: performing a **log-likelihood-ratio hypothesis test**
  End-to-end strategy, from the data to a p-value for the discovery (frequentistic approach)

$$t(\mathcal{D}) = \max_{\mathbf{w}} \left[2 \log \frac{\mathcal{L}(\mathcal{D} \mid \mathrm{H}_{\mathbf{w}})}{\mathcal{L}(\mathcal{D} \mid \mathrm{R}_{\mathbf{0}})} \right]$$

$\mathrm{R}_{\mathbf{0}}$: null hypothesis
$\mathrm{H}_{\mathbf{w}}$: alternative hypothesis

- Exploiting a Neural Network (NN) to **parametrize** the data distribution in terms of a Reference distribution ($\mathrm{R}_{\mathbf{0}}$)

$$n(x \mid \mathrm{T}) \approx n(x \mid \mathrm{H}_{\hat{\mathbf{w}}}) = n(x \mid \mathrm{R}_0)\, e^{f(x,\hat{\mathbf{w}})}$$

True (T) data distribution	Data distribution learnt by the NN	Reference distribution	
Unknown	Alternative hypothesis	Null hypothesis (SM)	 NN model

- **Signal-model-independent**: reduced assumptions on the signal hypothesis

"Learning New Physics from a Machine" Phys. Rev. D

New Physics Learning Machine (NPLM)

Main Concepts (negligible uncertainties)

Maximum Likelihood from minimal loss:

Test statistic

$$\bar{t}(\mathcal{D}) = 2\max_{\mathbf{w}}\log\left[\frac{\mathcal{L}(\mathcal{D}\,|\,\mathrm{H}_{\mathbf{w}})}{\mathcal{L}(\mathcal{D}\,|\,\mathrm{R}_{\mathbf{0}})}\right] = -2\min_{\mathbf{w}}\{\bar{L}[f(\cdot;\,\mathbf{w})]\}$$

Loss function

$$\bar{L}\,[f(x;\,\mathbf{w})] = -\sum_{x\in\mathcal{D}}[\,f(x;\,\mathbf{w})] + \sum_{x\in\mathcal{R}} w_x\left[e^{f(x;\,\mathbf{w})} - 1\right]$$

w: trainable parameters on the NN model

D: data sample

R: reference sample (built according to the R_0 hypothesis); could be weighted (w)

Assumptions:

- $N_R \gg N_D$ the statistical fluctuations of the reference sample are negligible.
- the weights of the reference sample (w) are such that the reference sample is normalised to match the data sample luminosity $\sum_{x\in R} w_x = N(R_0)$

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New Physics Learning Machine (NPLM)

Main Concepts (negligible uncertainties)

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$$\bar{t}(\mathcal{D}) = 2 \max_{\mathbf{w}} \log \left[\frac{\mathcal{L}(\mathcal{D} \mid \mathrm{H}_{\mathbf{w}})}{\mathcal{L}(\mathcal{D} \mid \mathrm{R_0})} \right] = -2 \min_{\mathbf{w}} \{ \bar{L}[f(\cdot;\ \mathbf{w})] \}$$

Loss function

$$\bar{L}\,[f(x;\ \mathbf{w})] = -\sum_{x \in \mathcal{D}} [\,f(x;\ \mathbf{w})] + \sum_{x \in \mathcal{R}} w_x \left[e^{f(x;\mathbf{w})} - 1 \right]$$

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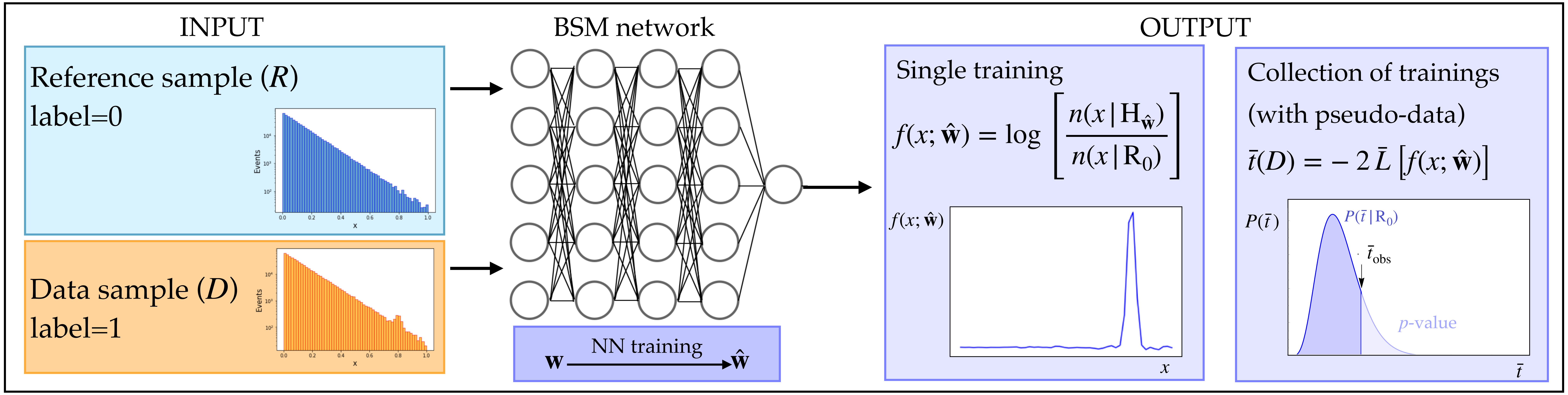
Unbinned training samples!



"Learning New Physics from a Machine" Phys. Rev. D

New Physics Learning Machine (NPLM)

Dealing with multivariate problems (negligible uncertainties)

Asymptotic formula for the $\bar{t}$ distribution under R_0:

Wilks-Wald theorem:

Θ_0: set of parameters describing H_0

Θ_1: set of parameters describing H_1

If $H_0 \subseteq H_1$, then under the H_0 hypothesis the test statistic

$$t(\mathcal{D}) = 2\,\log\frac{\mathcal{L}(\mathcal{D}\,|\,H_{\mathbf{w}})}{\mathcal{L}(\mathcal{D}\,|\,R_{\mathbf{0}})}$$

asymptotically follows a χ^2_{df} distribution with $df = |\Theta_1| - |\Theta_0|$

→ If the Wilks' theorem hold, the target distribution for $\bar{t}$ under the R_0 hypothesis is a χ^2_{df} with $df = |\mathbf{w}|$.

Due to the **finite size** of the training samples, the **sparsity** of the data (especially in multivariate problems) and the **approximation** errors, the distribution of $\bar{t}(D)$ under R_0 does not follow the target $\chi^2_{|\mathbf{w}|}$ by default.

→ a **(NN) MODEL REGULARIZATION** procedure can solve this problem!

"Learning Multivariate New Physics" Eur. Phys. J. C

New Physics Learning Machine (NPLM)

Dealing with multivariate problems (negligible uncertainties)

NN Model regularization:

Weight clipping parameter:
Upper boundary to the magnitude that each trainable parameter can assume during the training.

→

For a chosen NN architecture, tuning the weight clipping allows to recover a good agreement of the empirical distribution of $\bar{t}$ under R_0 with the **target** $\chi^2_{|\mathbf{w}|}$ distribution.

Example:
NN model: 5-7-7-1,
$|\mathbf{w}| = 106$

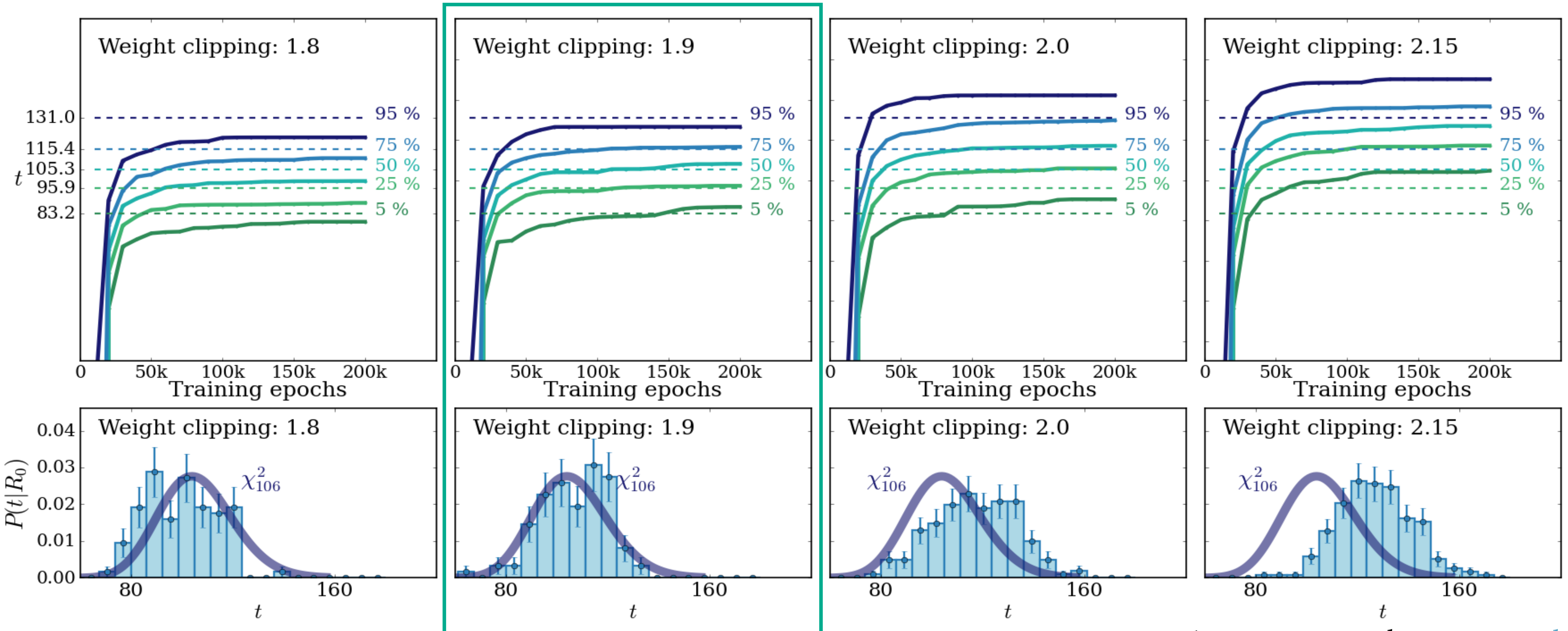
Legend:

Percentiles of the empirical $\bar{t}$ distribution under R_0

Percentiles of the target $\chi^2_{|\mathbf{w}|}$

Empirical $\bar{t}$ distribution under R_0

Target $\chi^2_{|\mathbf{w}|}$

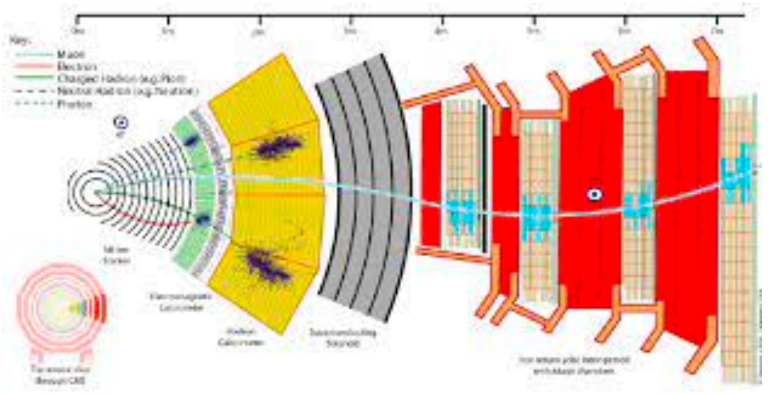


"Learning Multivariate New Physics" Eur. Phys. J. C

DQM

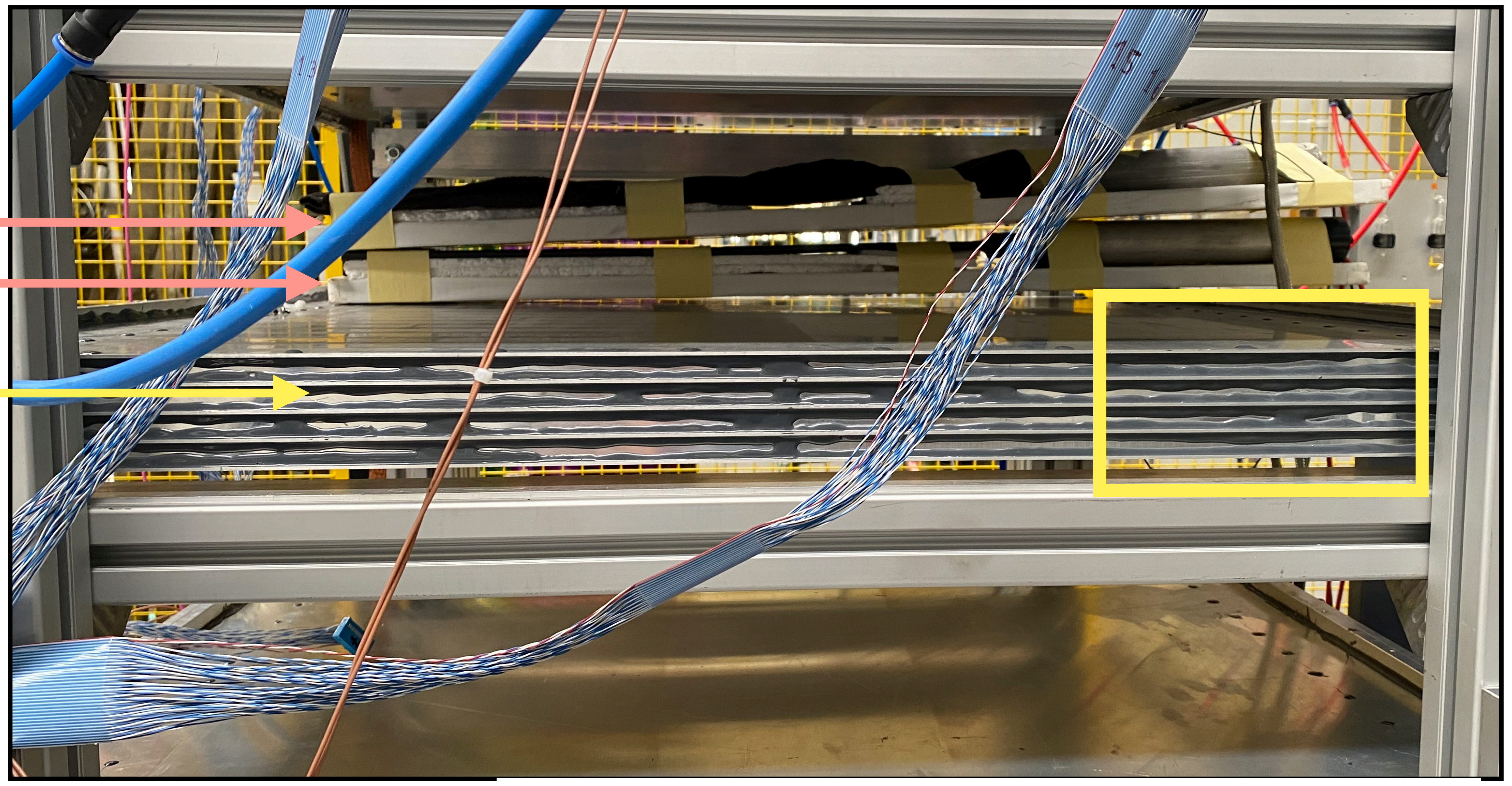
*n*D DQM

Online monitoring of a DT chamber:



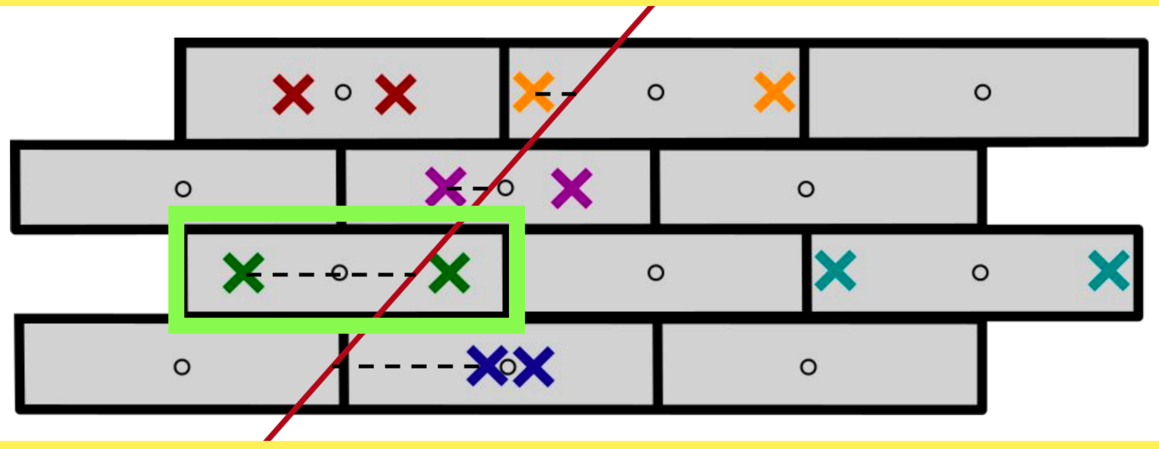
Setup (Legnaro INFN national laboratory):

- 2 scintillators as signal trigger
- 1 drift tube chamber: 4 layers 16 wires each (16x4=64 wires)
- Source of signals: cosmic muons (triggered rate ~3 MHz)
- **Event**: muon track reconstructed interpolating 3/4 hits (one per layer)

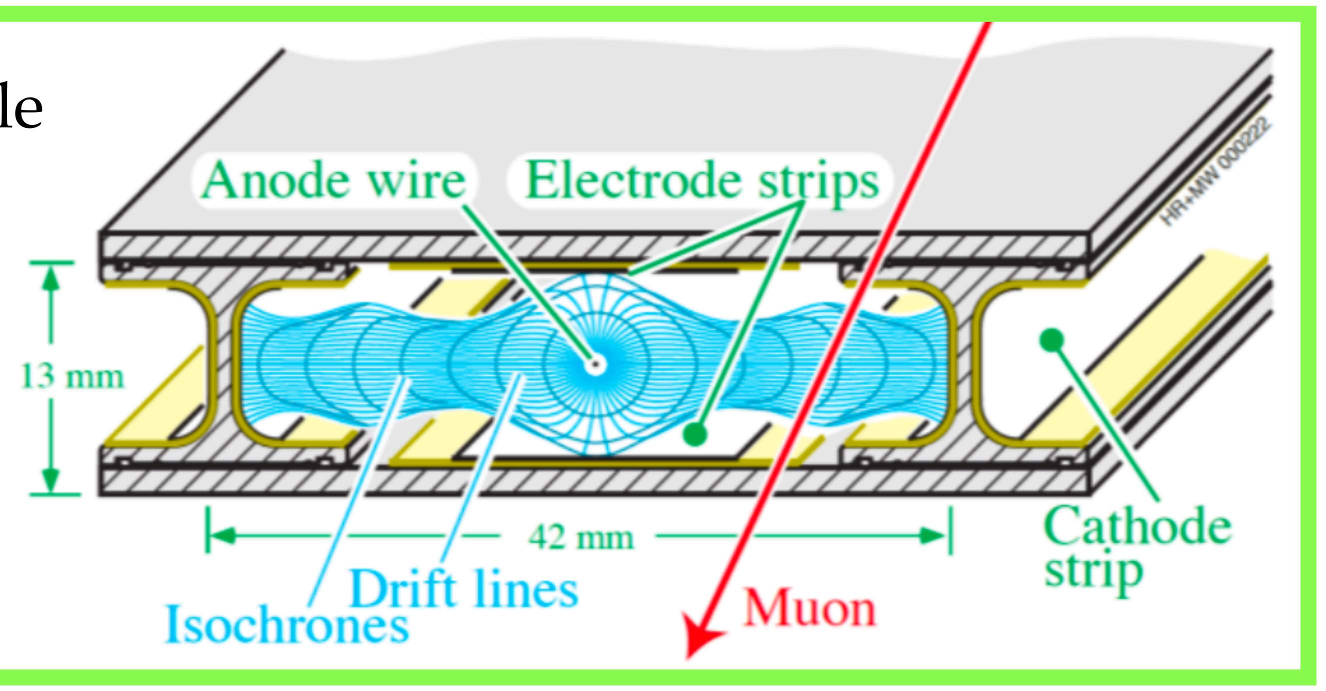


Observables (6D problem):

- 4 drift times [$t_{\text{drift, 1}}, t_{\text{drift, 2}}, t_{\text{drift, 3}}, t_{\text{drift, 4}}$]: time for the ionised electrons to reach the wire from the interaction point ($v_{\text{drift}} =$ cm/s) .
- θ: reconstructed track angle
- N_{hits}: average number of hits per time window ("orbit")



Sketch of a single chamber



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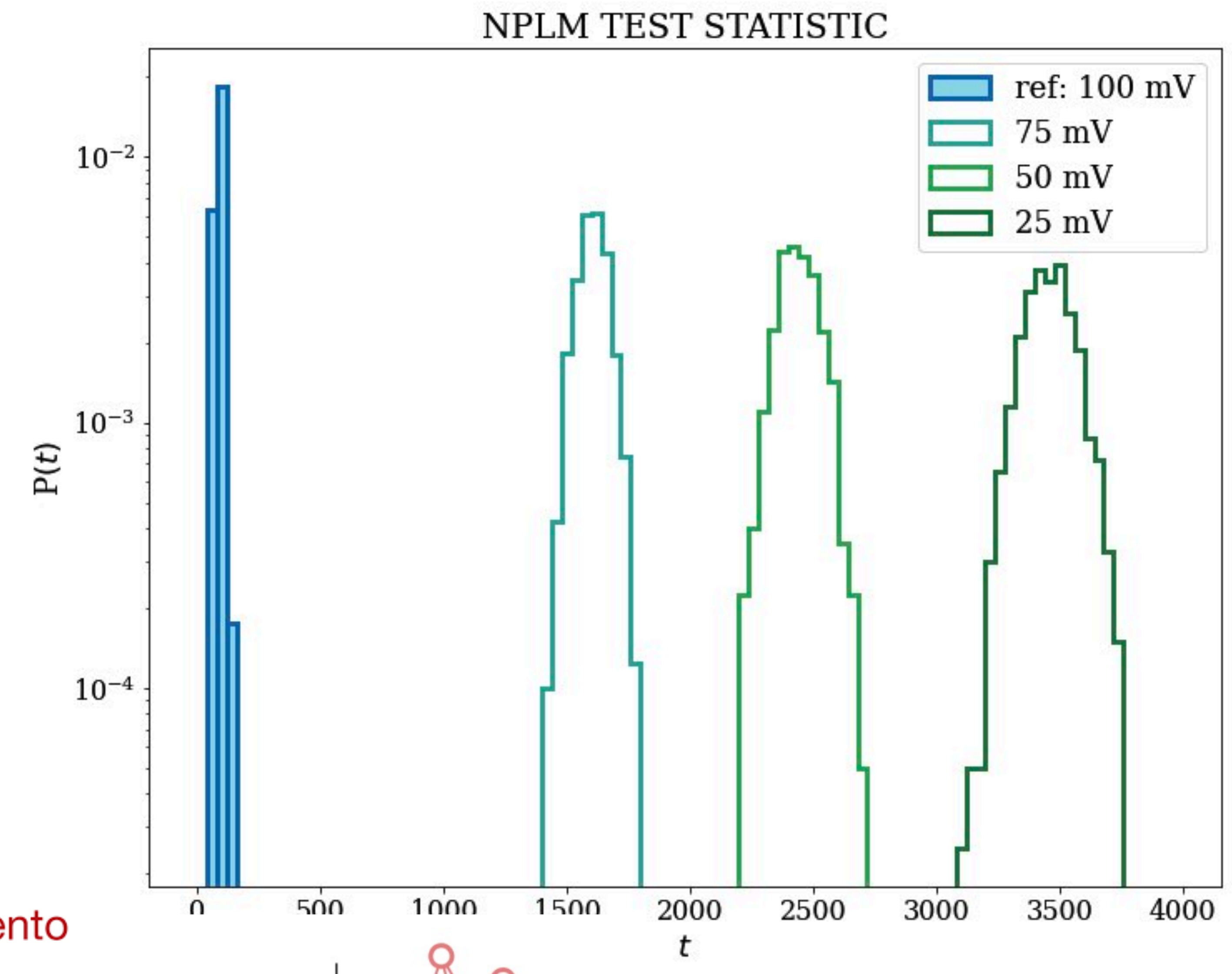
nD DQM

Online monitoring of a DT chamber:

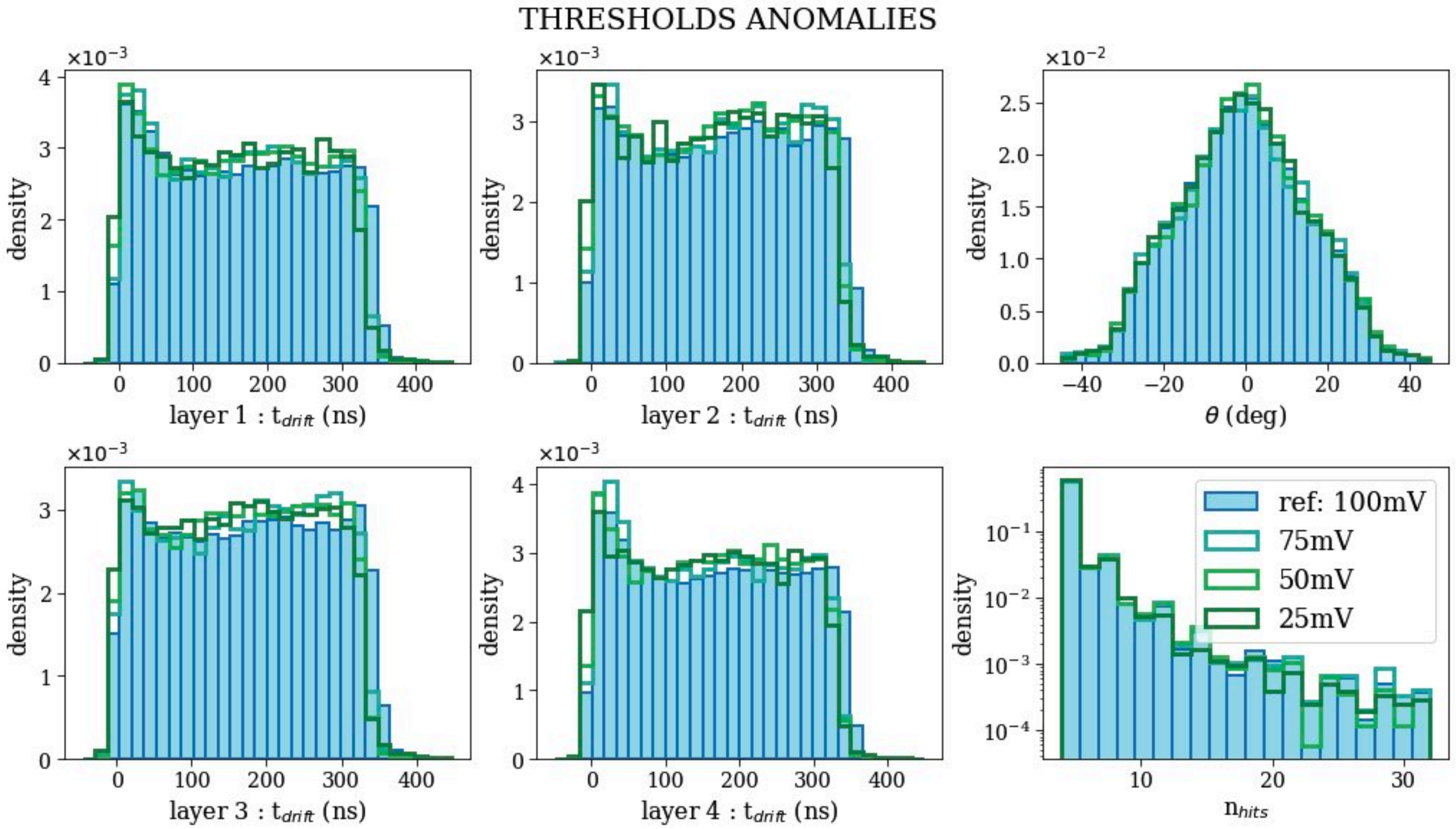
- **Reference sample:** long run in optimal conditions
- **Anomalous samples**: short runs acquired in presence of a controlled anomaly in the value of the **threshold tension** of the DT chamber

- Result of the test statistics

  Complete separation of the distributions!



NPLM with Falkon
M = 50, $\sigma = 4.84$, $\lambda = 10^{-7}$
N(D) = 5000
$N_{\text{ref}} = 200\,000$
Execution time: ~ 1.5 s



Distribution of the observables at different values of the threshold tension

→ more about this in Marco's talk tomorrow!

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NPLM - systematic uncertainties

New Physics Learning Machine (NPLM)

Including systematic uncertainties

Test statistic

$$t(\mathcal{D},\,\mathcal{A}) = 2\log\left[\frac{\max\limits_{\mathbf{w},\,\boldsymbol{\nu}} \mathcal{L}(\mathrm{H}_{\mathbf{w},\,\boldsymbol{\nu}}|\mathcal{D},\,\mathcal{A})}{\max\limits_{\boldsymbol{\nu}} \mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D},\,\mathcal{A})}\right] = 2\log\left[\frac{\max\limits_{\mathbf{w},\,\boldsymbol{\nu}} \mathcal{L}(\mathrm{H}_{\mathbf{w},\,\boldsymbol{\nu}}|\mathcal{D})\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\max\limits_{\boldsymbol{\nu}} \mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D})\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}\right]$$

$\mathbf{w}$: trainable parameters on the NN model

$\boldsymbol{\nu}$: set of nuisance parameters modelling the uncertainties effects

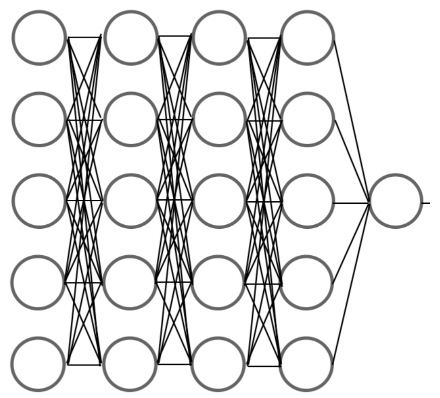
$\mathcal{D}$: data sample

$\mathcal{A}$: auxiliary sample (used to constrain $\boldsymbol{\nu}$)

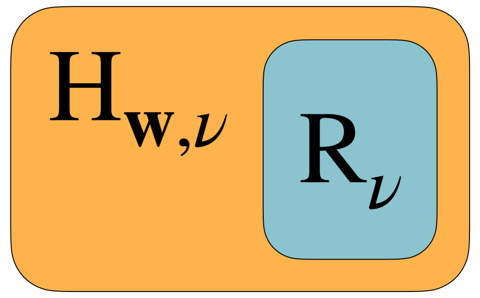
New parametrization

$$n(x\,|\,\mathrm{T}) \approx n(x\,|\,\mathrm{H}_{\hat{\mathbf{w}},\,\hat{\nu}}) = n(x\,|\,\mathrm{R}_0)\,\frac{n(x\,|\,\mathrm{R}_{\hat{\nu}})}{n(x\,|\,\mathrm{R}_0)}\,e^{f(x;\,\hat{\mathbf{w}})}$$

$n(x\,|\,\mathrm{T})$	$n(x\,|\,\mathrm{H}_{\hat{\mathbf{w}},\,\hat{\nu}})$	$n(x\,|\,\mathrm{R}_0)$	$\frac{n(x\,|\,\mathrm{R}_{\hat{\nu}})}{n(x\,|\,\mathrm{R}_0)}$	$f(x;\,\hat{\mathbf{w}})$
True (T) data distribution	Data distribution learnt by the NN	Reference distribution	New term containing the dependence on ν	NN model
Unknown	Alternative hypothesis	Null hypothesis	$r(x;\nu)$	



Note:
This parametrization choice guarantees $\mathrm{R}_\nu \subseteq \mathrm{H}_{\mathbf{w},\nu}$
($\mathrm{R}_\nu = \mathrm{H}_{\mathbf{w},\nu}$ for $f(\,\cdot\,;\,\mathbf{w}) \equiv 0$)



"Learning New Physics from an Imperfect Machine" Eur. Phys. J. C

New Physics Learning Machine (NPLM)

Including systematic uncertainties

$$t(\mathcal{D},\mathcal{A}) = \tau(\mathcal{D},\mathcal{A}) - \Delta(\mathcal{D},\mathcal{A})$$

τ term

$$\tau(\mathcal{D},\mathcal{A}) = 2\,\max_{\mathbf{w},\boldsymbol{\nu}} \log\left[\frac{\mathcal{L}(\mathrm{H}_{\mathbf{w},\boldsymbol{\nu}}|\mathcal{D})}{\mathcal{L}(\mathrm{R}_{\mathbf{0}}|\mathcal{D})}\cdot\frac{\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\mathcal{L}(\mathbf{0}|\mathcal{A})}\right]$$

Δ term

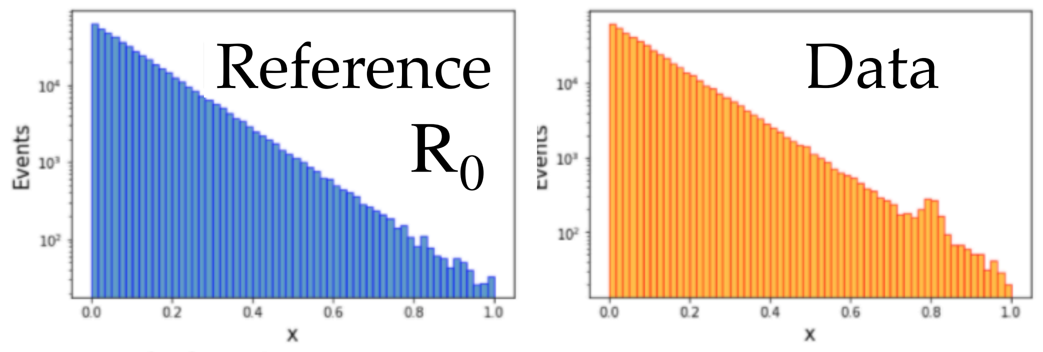
$$\Delta(\mathcal{D},\mathcal{A}) = 2\,\max_{\boldsymbol{\nu}} \log\left[\frac{\mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D})}{\mathcal{L}(\mathrm{R}_{\mathbf{0}}|\mathcal{D})}\cdot\frac{\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\mathcal{L}(\mathbf{0}|\mathcal{A})}\right]$$

Maximum likelihood from minimal loss

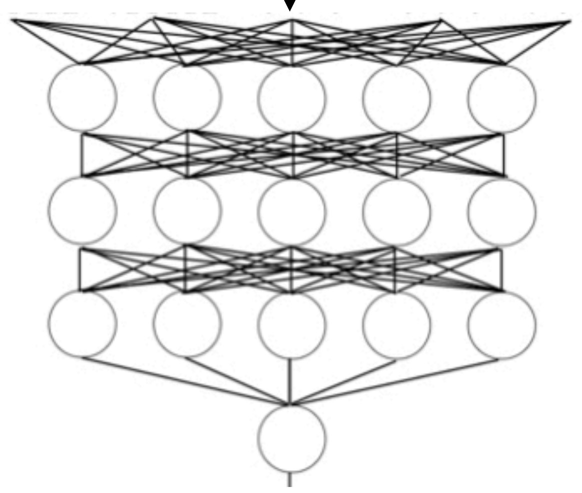
$$\tau(\mathcal{D},\mathcal{A}) = -2\,\min_{\mathbf{w},\boldsymbol{\nu}}\left\{L_\tau\left[f(\cdot;\mathbf{w}),\,\boldsymbol{\nu};\,\widehat{\delta}(\cdot)\right]\right\}$$

$$\Delta(\mathcal{D},\mathcal{A}) = -2\,\min_{\boldsymbol{\nu}}\left\{L_\Delta\left[\boldsymbol{\nu};\,\widehat{\delta}(\cdot)\right]\right\}$$

Training samples



$f(\cdot;\mathbf{w})$



$+$

$\boldsymbol{\nu};\,\widehat{\delta}(\cdot)$

$$\frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

$\boldsymbol{\nu};\,\widehat{\delta}(\cdot)$

$$\frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

New Physics Learning Machine (NPLM)

Including systematic uncertainties

$$t(\mathcal{D},\mathcal{A}) = \tau(\mathcal{D},\mathcal{A}) - \Delta(\mathcal{D},\mathcal{A})$$

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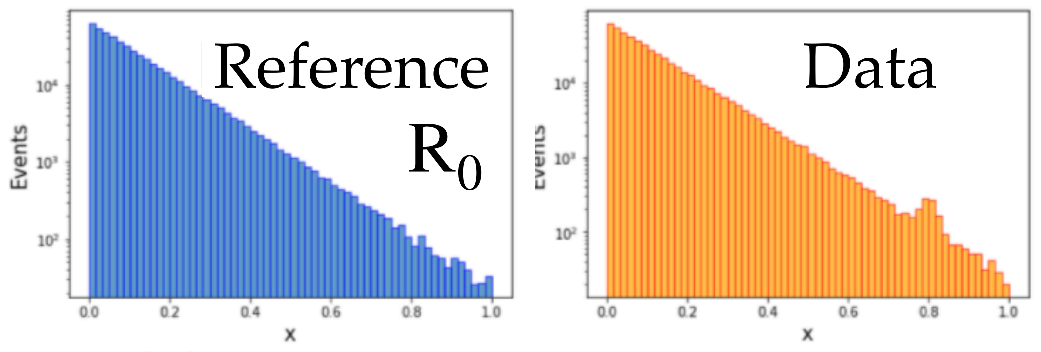
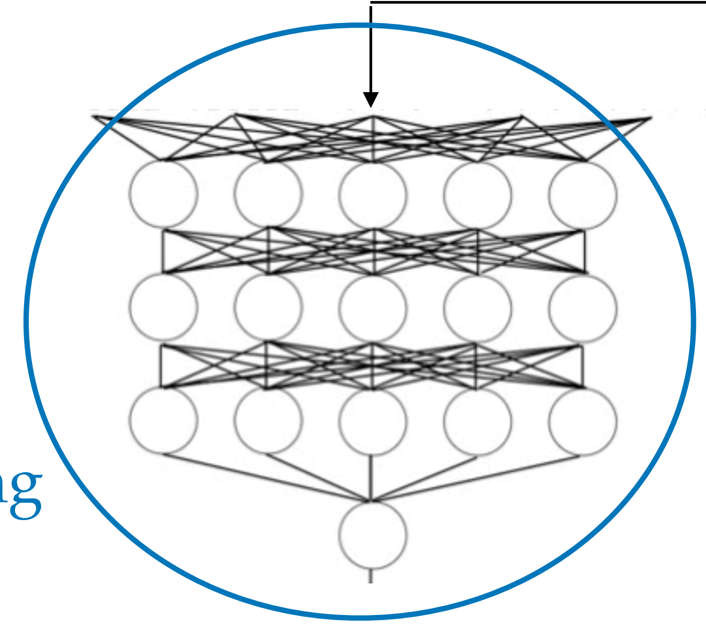
Training samples



$f(\cdot;\mathbf{w})$ $\quad$ $\boldsymbol{\nu};\ \widehat{\delta}(\cdot)$

NN model
Set up
↓
Weight clipping
tuning



$+$

$$\frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

$\boldsymbol{\nu};\ \widehat{\delta}(\cdot)$

$$\frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

New Physics Learning Machine (NPLM)

Including systematic uncertainties

$$t(\mathcal{D},\mathcal{A}) = \tau(\mathcal{D},\mathcal{A}) - \Delta(\mathcal{D},\mathcal{A})$$

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$$\tau(\mathcal{D},\mathcal{A}) = -2\,\min_{\mathbf{w},\boldsymbol{\nu}}\left\{L_\tau\Big[f(\cdot;\mathbf{w}),\,\boldsymbol{\nu};\,\widehat{\delta}(\cdot)\Big]\right\}$$

Δ term

$$\Delta(\mathcal{D},\mathcal{A}) = 2\,\max_{\boldsymbol{\nu}} \log\left[\frac{\mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D})}{\mathcal{L}(\mathrm{R}_{\mathbf{0}}|\mathcal{D})}\cdot\frac{\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\mathcal{L}(\mathbf{0}|\mathcal{A})}\right]$$

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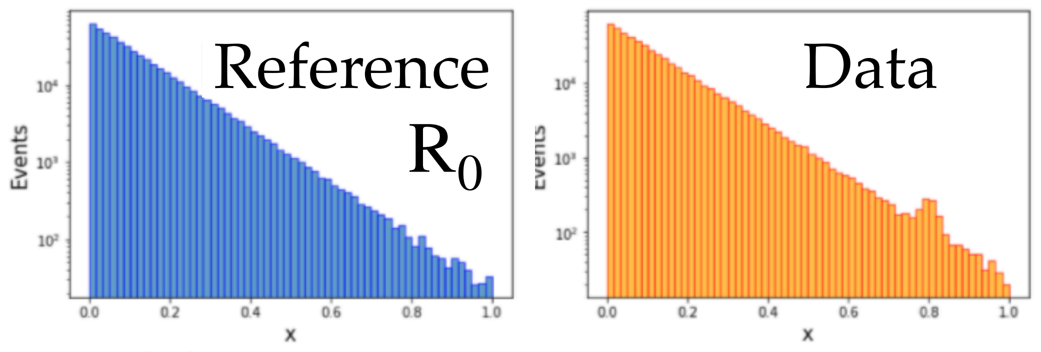
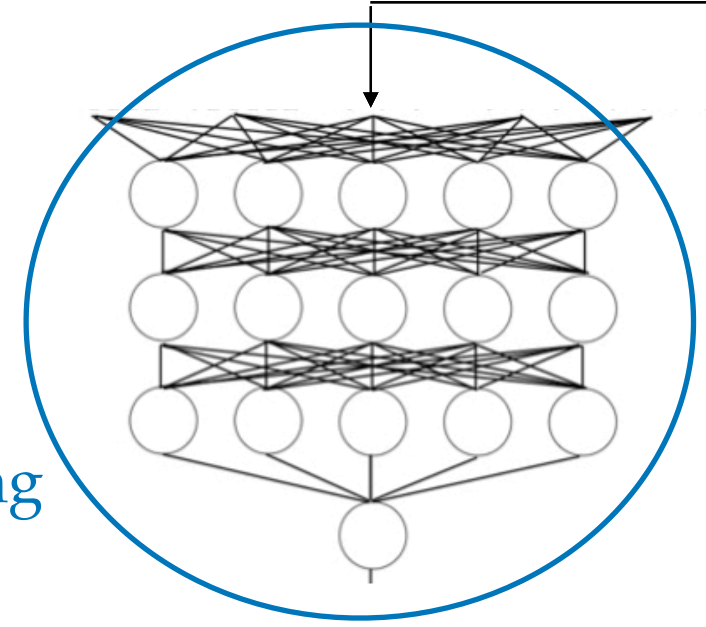
Maximum likelihood from minimal loss

Training samples



$f(\cdot;\mathbf{w})$

NN model
Set up
↓
Weight clipping
tuning



+

$\boldsymbol{\nu};\,\widehat{\delta}(\cdot)$

$$\frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

$\boldsymbol{\nu};\,\widehat{\delta}(\cdot)$

$$\frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

New!

r modelling

$$r(x;\boldsymbol{\nu}) \equiv \frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

New Physics Learning Machine (NPLM)

Including systematic uncertainties

r modelling

$$r(x;\boldsymbol{\nu}) \equiv \frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})}$$

Normalization uncertainties:
Analytic description

$$r(x;\boldsymbol{\nu}) \equiv \frac{n(x|\mathrm{R}_{\boldsymbol{\nu}})}{n(x|\mathrm{R}_{\mathbf{0}})} = \exp\left[\sum_{i=1}^{N_\nu} \nu_i\right]$$

Shape uncertainties:
Taylor's expansion around the nuisance central value

$$\hat{r}(x;\nu) = \exp\left[\hat{\delta}_1(x)\,\nu + \hat{\delta}_2(x)\,\nu^2 + \dots\right]$$

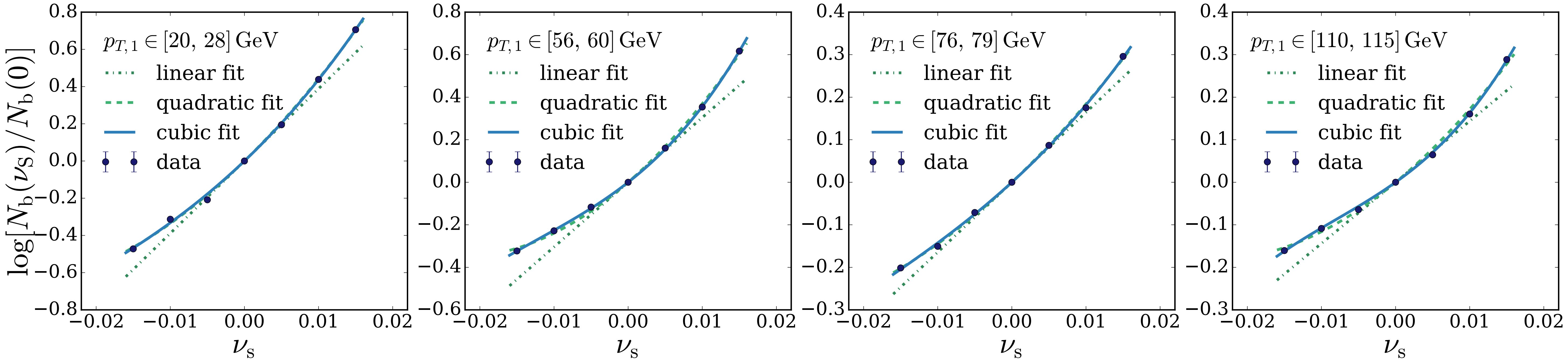
Including systematic uncertainties

Shape uncertainties: Learning the nuisance Taylor's expansion

Preliminary study

Preliminary binned analysis to determine the proper order for the Taylor's expansion

Electron-like regime



Taylor's expansion learning

Training a neural network model to learn each coefficient of the Taylor's expansion of $r(x;\nu) = \dfrac{n(x\,|\,R_\nu)}{n(x\,|\,R_0)}$

Input samples

ν_1	ν_2	...	ν_n
$S_0(\nu_1) \sim R_0$	$S_0(\nu_2) \sim R_0$	...	$S_0(\nu_n) \sim R_0$
$S_1(\nu_1) \sim R_{\nu_1}$	$S_1(\nu_2) \sim R_{\nu_2}$		$S_1(\nu_n) \sim R_{\nu_n}$

→ $\hat{\delta}_1$

→ $\hat{\delta}_2$

$$\hat{r}(x;\nu) = \exp\left[\hat{\delta}_1(x)\,\nu + \hat{\delta}_2(x)\,\nu^2\right]$$

Loss function*

$$L[\hat{\delta}(\cdot)] = \sum_{\nu_i}\left[\sum_{e\in S_0(\nu_i)} w_e c(x_e)^2 + \sum_{e\in S_1(\nu_i)} w_e\left[1 - c(x_e)\right]^2\right], \qquad c(x) = \frac{1}{1+\hat{r}(x;\nu)}$$

* *Parametrized classifiers for optimal EFT sensitivity* arXiv:2007.10356

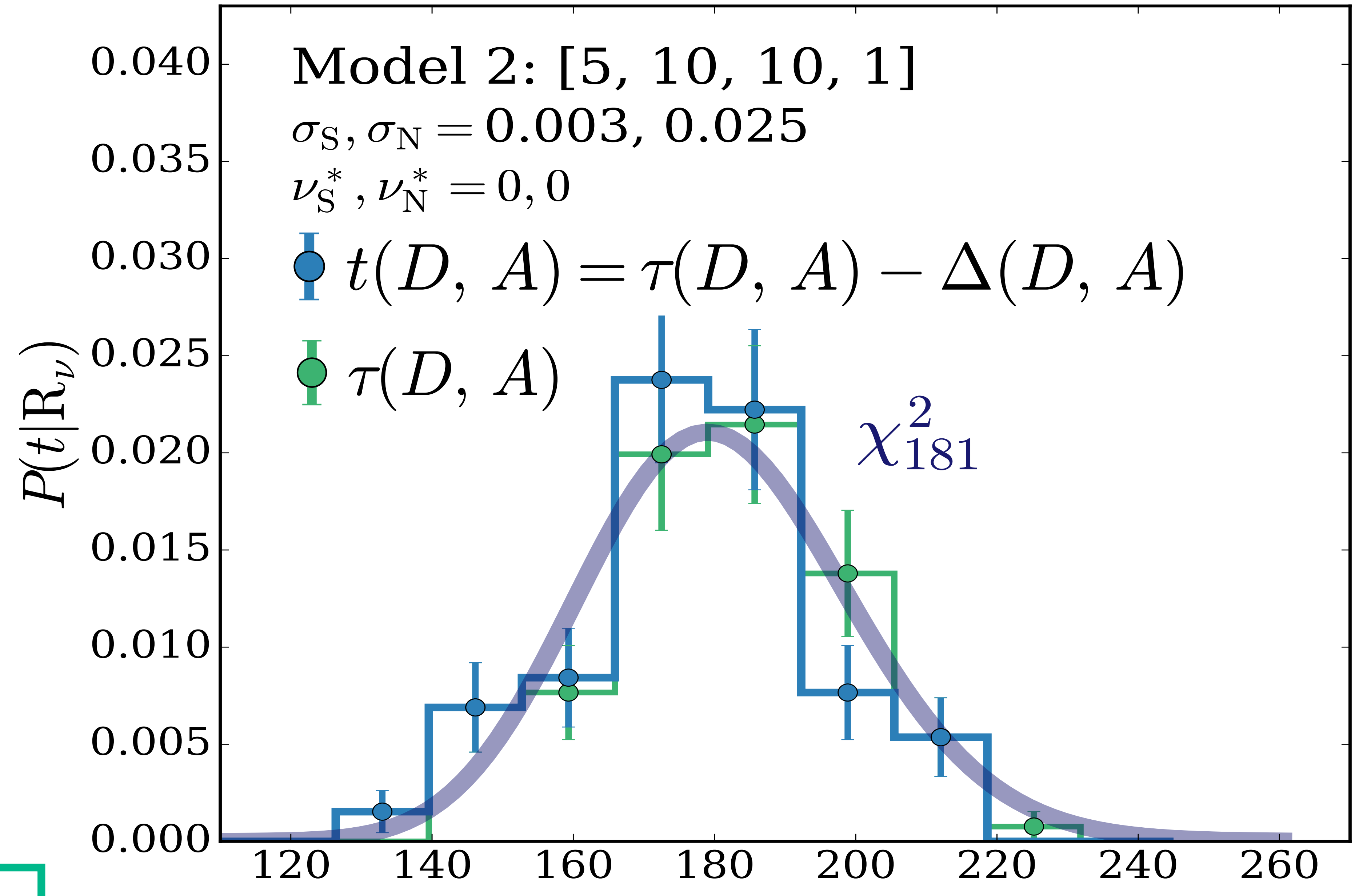
New Physics Learning Machine (NPLM)

Including systematic uncertainties

Validation of the $(\tau - \Delta)$ procedure

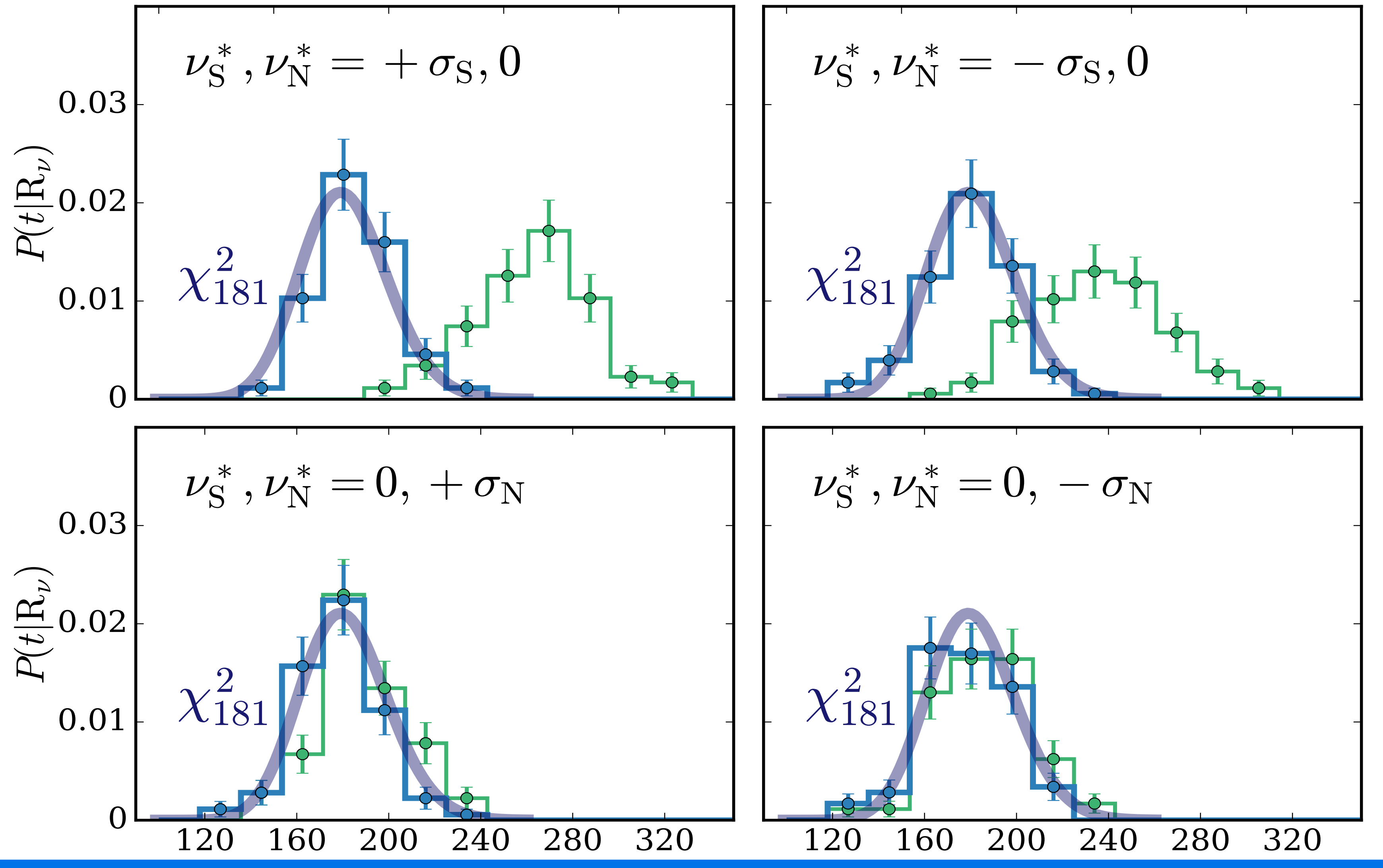
"Toy Data" : test the procedure on simulated toys following the Reference (SM) hypothesis with generation value for the nuisance parameters $\nu^* = \pm\sigma_\nu$:

$$\mathcal{D} \sim \mathrm{R}_{\boldsymbol{\nu}^*}, \quad \boldsymbol{\nu}^* = \pm\sigma_{\boldsymbol{\nu}}$$



The $\bar{t}$ distribution under the reference hypothesis $\mathrm{R}_{\boldsymbol{\nu}^*}$ is **compatible with the target** $\chi^2_{|\mathbf{w}|}$ for values of the true nuisance parameters within the uncertainty ($\boldsymbol{\nu}^* = \pm\sigma_{\boldsymbol{\nu}}$).

$\bar{t}$ is **independent** of the true value of the nuisance parameters!



We can build a *frequentistic* test statistic relying on the asymptotic $\chi^2_{|\mathbf{w}|}$.

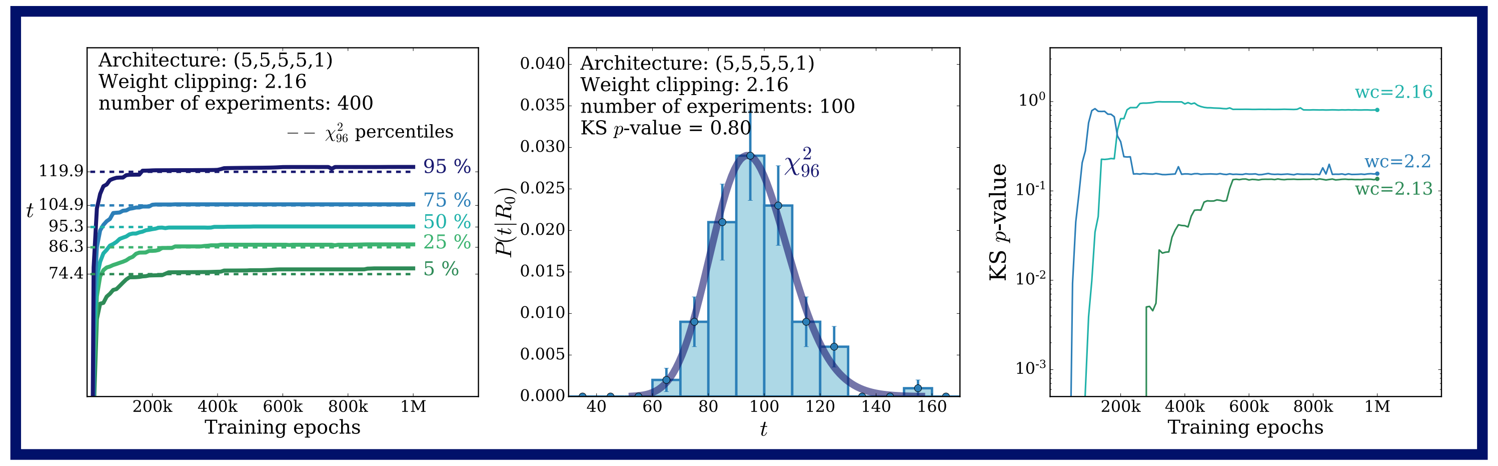
New Physics Learning Machine (NPLM)

Including systematic uncertainties

Final procedure in steps:

1. **NN MODEL SELECTION**:

   weight clipping tuning → target $\chi^2_{|\mathbf{w}|}$;



2. **NUISANCE TAYLOR'S EXPANSION LEARNING**:

   modelling $\hat{r}(x;\nu) = \exp\left[\hat{\delta}_1(x)\,\nu + \hat{\delta}_2(x)\,\nu^2 + \dots\right]$;

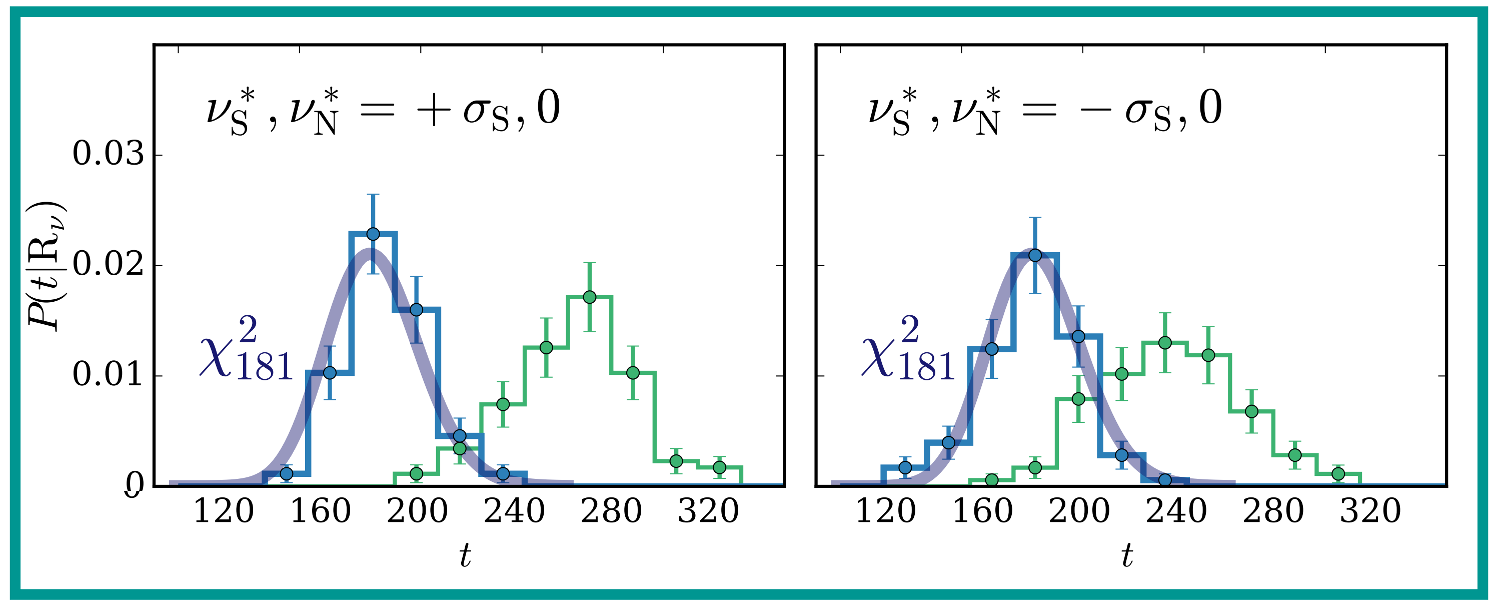
$$\hat{r}(x;\nu) = \exp\left[\hat{\delta}_1(x)\,\nu + \hat{\delta}_2(x)\,\nu^2 + \dots\right]$$

NN 1 NN2 ...

3. **VALIDATION**:

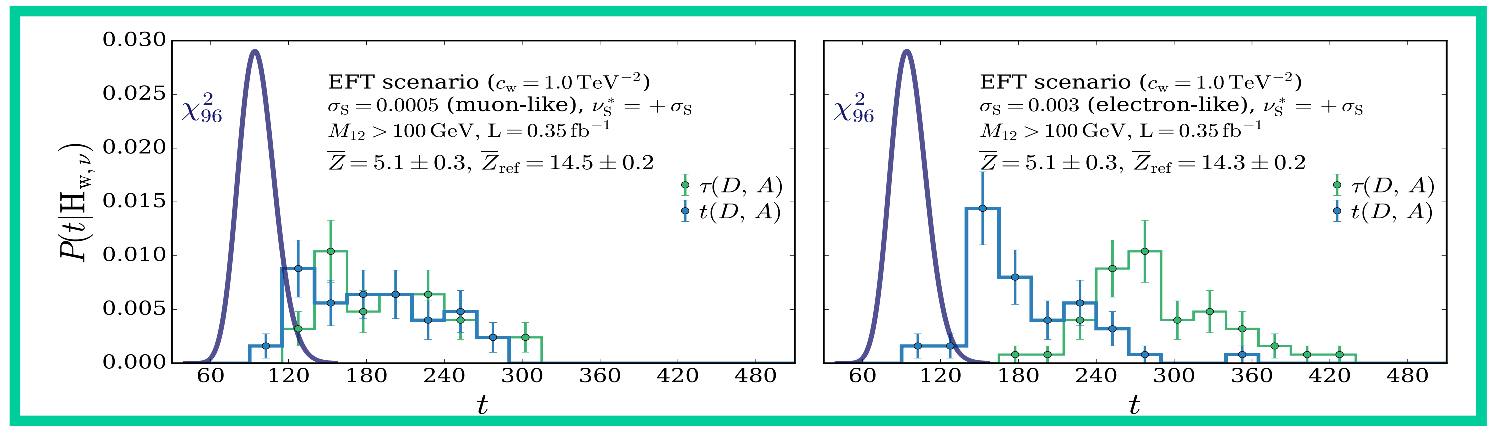
$$\mathcal{D} \sim \mathrm{R}_{\boldsymbol{\nu}^*}, \quad \boldsymbol{\nu}^* = \pm\sigma_{\boldsymbol{\nu}}$$

   Verifying that the target $\chi^2_{|\mathbf{w}|}$ is always recovered;



4. **TESTING THE DATA**:

   running the procedure on real data.



Search for New Physics at LHC

Easy task: 1D analysis

Mass spectrum (toy model)

Signal reconstruction with the NN:

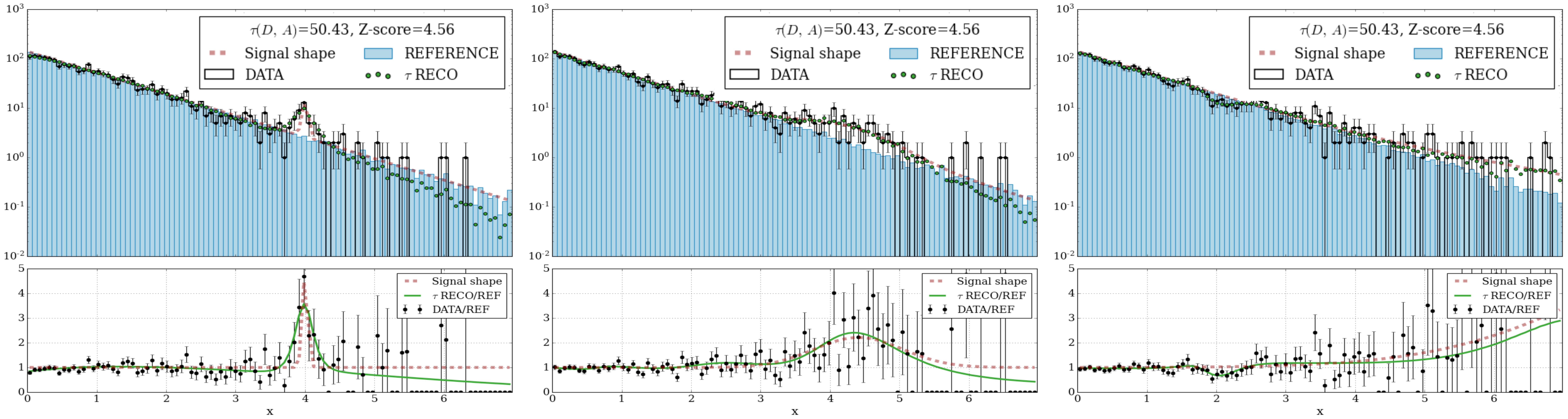
Architecture: [1-4-1] (13 dof), weigh clipping 9, N_{bkg}=2000

τ reconstruction: $n(x\,|\,H_{\hat{\mathbf{w}},\hat{\nu}}) = n(x\,|\,R_0)\,\dfrac{n(x\,|\,R_{\hat{\nu}})}{n(x\,|\,R_0)}\,e^{f(x;\,\hat{\mathbf{w}})}$

Δ reconstruction: $n(x\,|\,R_{\hat{\nu}})$

Sensitivity to multiple signals at the same time

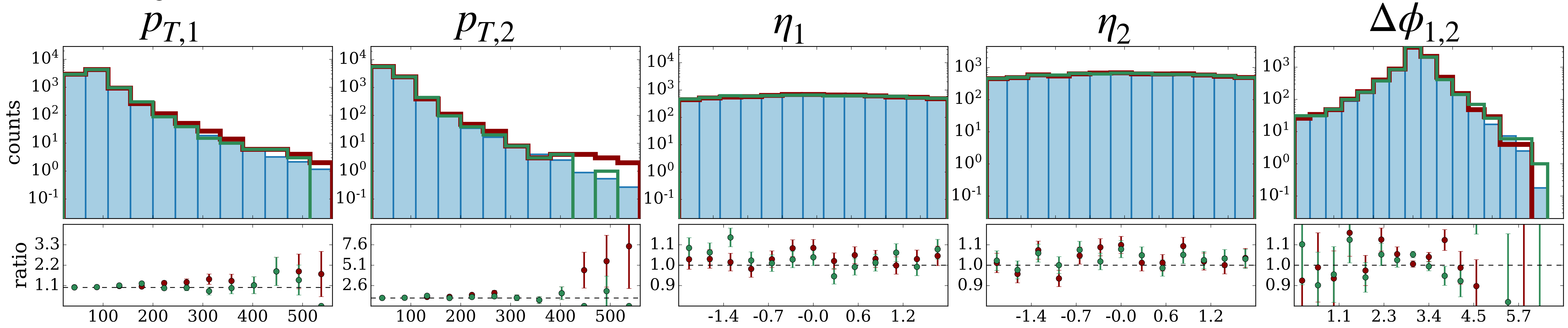
Narrow resonance **Broad resonance** **Excess in the tail**



Harder task: *n*D analysis

Two body final state (5D)

5D analysis — Input: set of variables fully describing the kinematic of the final state



Simulated samples (Madgraph+Phytia+Delphes)
Dataset available on Zenodo

Uncertainties on the Reference hypothesis (SM):

- Global normalization effect: $\sigma_N = 2.5\,\%$
- Momentum scale effect:

$$p_{T\,1,2}^{(b,e)} = \exp\left[\nu_s \sigma_s^{(b,e)} / \sigma_s^{(b)}\right] p_{T\,1,2}^{(b,e)}$$

(b) barrel region $|\eta| < 1.2$, (e) endcaps region $|\eta| \geq 1.2$

- Muon-like regime: $\sigma_S^{(b)} = 0.05\,\%$, $\sigma_S^{(e)} = 0.15\,\%$
- Electron-like regime: $\sigma_S^{(b)} = 0.3\,\%$, $\sigma_S^{(e)} = 0.9\,\%$
- Tau-like regime: $\sigma_S^{(b)} = \sigma_S^{(e)} = 3\,\%$

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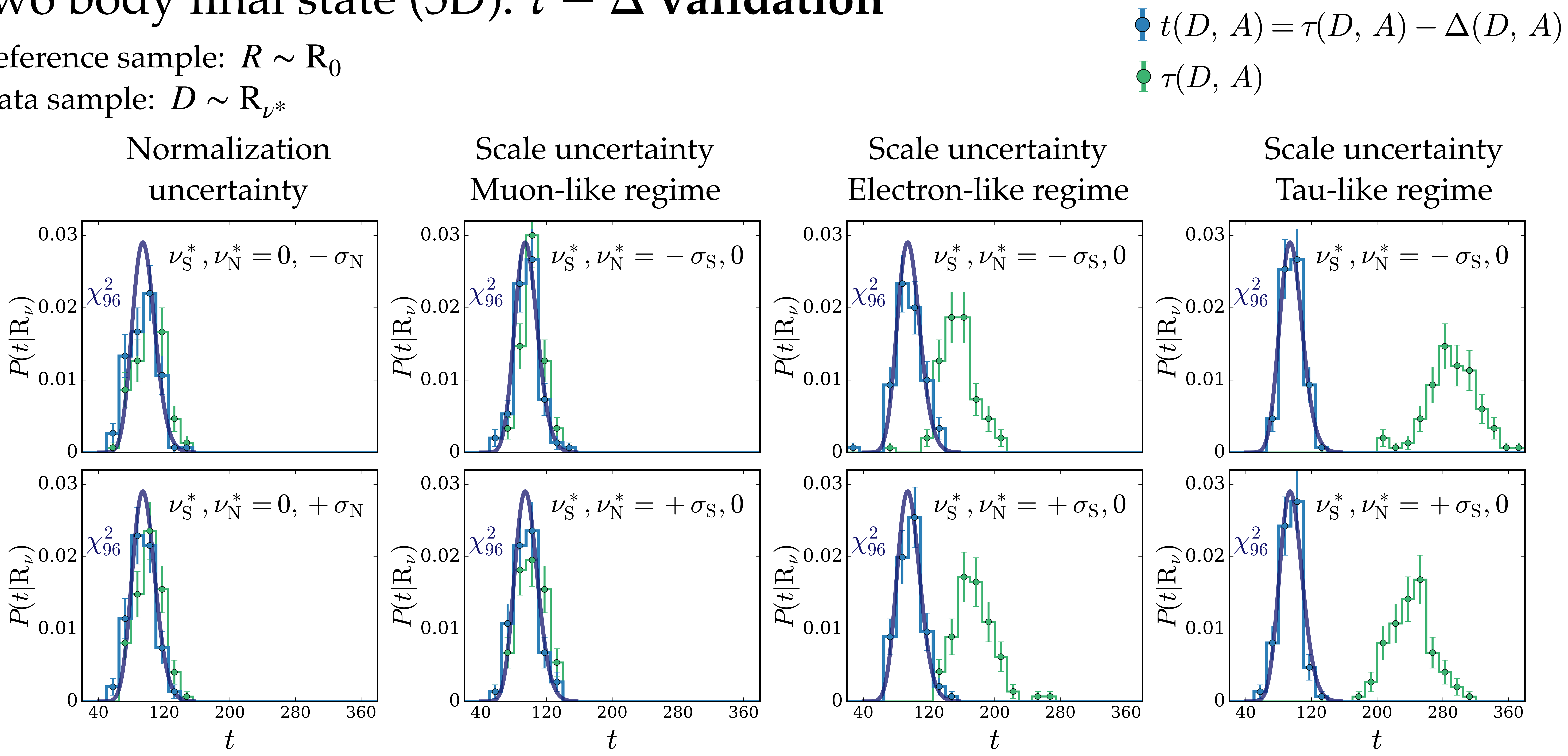
Harder task: *n*D analysis

Two body final state (5D): $\tau - \Delta$ validation

Reference sample: $R \sim \mathrm{R}_0$

Data sample: $D \sim \mathrm{R}_{\nu^*}$

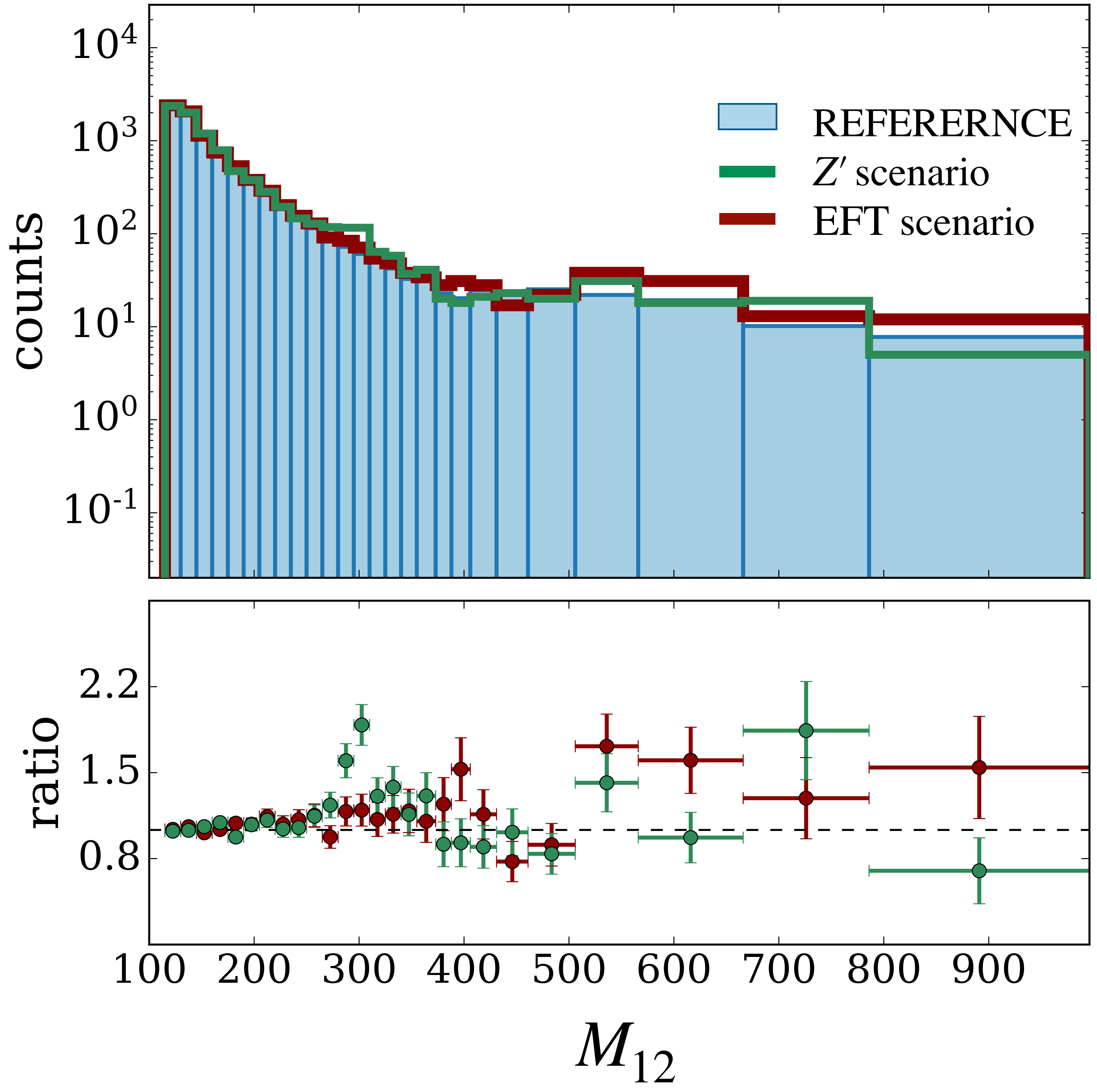


DNN [5-5-5-5-1], #trainable parameters = 96, weight clipping = 2.16

Harder task: *n*D analysis

Two body final state (5D): sensitivity to NP scenarios

Example:
Tau-like regime



Resonance in the two-body invariant mass

- ***Z′* scenario:** new vector boson with the same SM coupling as the Z boson and mass of 300 GeV.
    - Muon-like, electron-like regimes:
      $M_{12} > 100\,\mathrm{GeV}, L = 0.35\,\mathrm{fb}^{-1}, \mathrm{N(S)} = 120$
    - Tau-like regime:
      $M_{12} > 120\,\mathrm{GeV}, L = 1.1\,\mathrm{fb}^{-1}, \mathrm{N(S)} = 210$

Non resonant excess in the tail of the two-body invariant mass

- **EFT scenario:** dimension-6 4-fermions-contact operator:

$$\frac{c_W}{\Lambda} J^{a}_{L\mu} J^{\mu}_{La}.$$

    - Muon-like, electron-like regimes:
      $M_{12} > 100\,\mathrm{GeV}, L = 0.35\,\mathrm{fb}^{-1}, c_W = 1.0\,\mathrm{TeV}^{-2}$
    - Tau-like regime:
      $M_{12} > 120\,\mathrm{GeV}, L = 1.1\,\mathrm{fb}^{-1}, c_W = 0.25\,\mathrm{TeV}^{-2}$

NOTE:
M_{12} is **not** given as an input to the algorithm!

Harder task: *n*D analysis

Two body final state (5D): sensitivity to NP scenarios

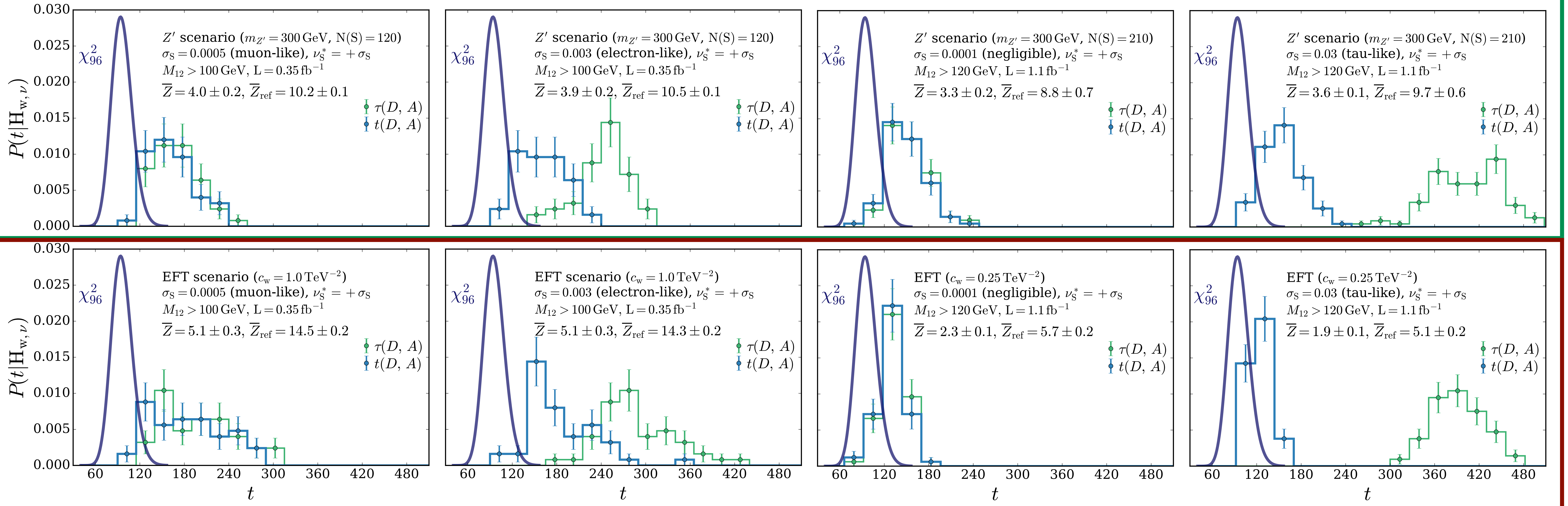
Muon-like regime | Electron-like regime | Negligible systematic uncertainties | Tau-like regime

Z' scenario

$\nu_S^* = +\sigma_S$

EFT scenario

$\nu_S^* = +\sigma_S$



$t(D, A) = \tau(D, A) - \Delta(D, A)$

$\tau(D, A)$

Z-score: $Z = \Phi^{-1}\left[1 - p\right]$

$\overline{Z}$: Z-score from the median of the empirical $t(D, A)$ distribution

Harder task: nD analysis

Two bodies final state (5D)

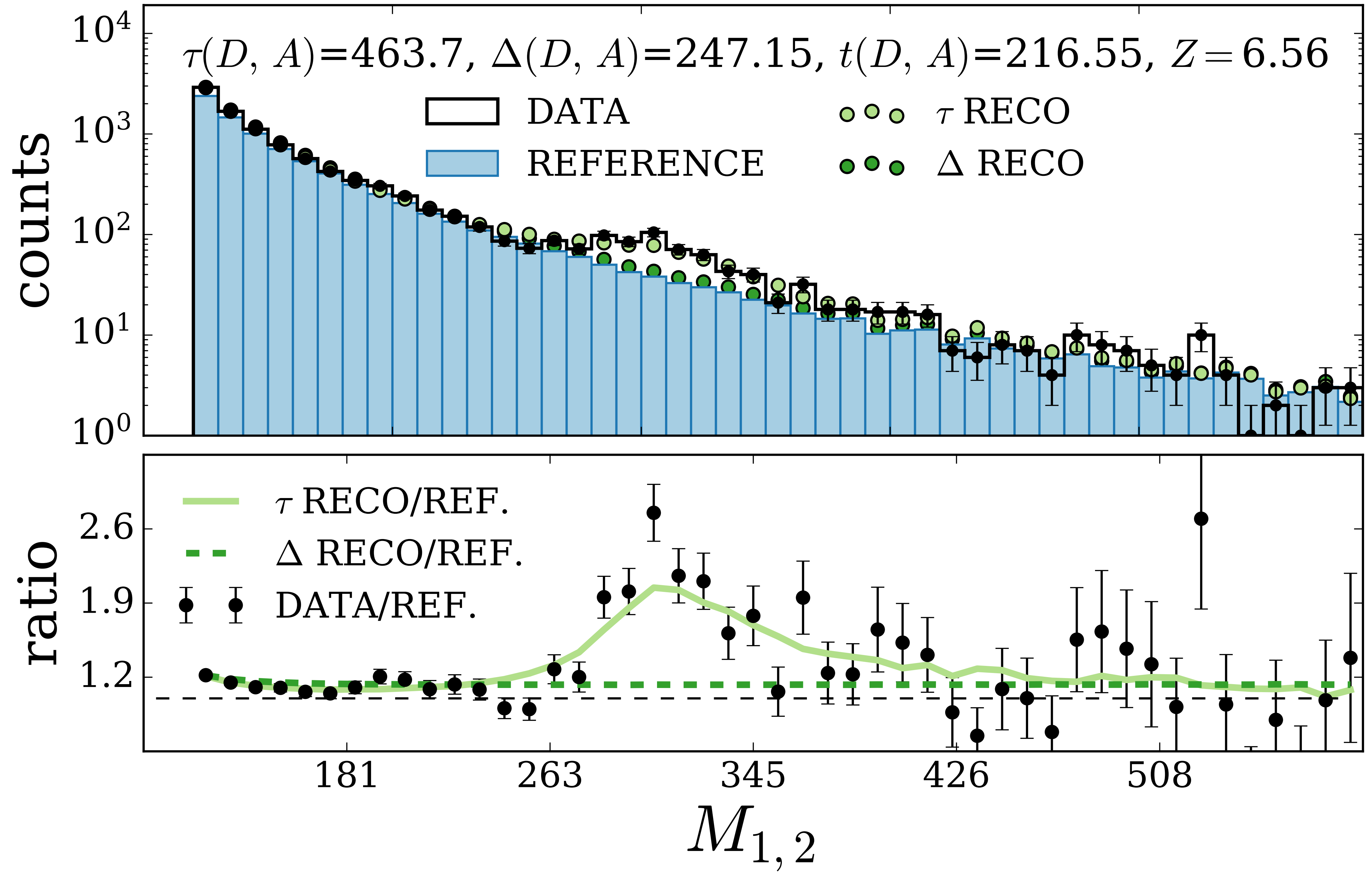
Signal reconstruction with the NN:

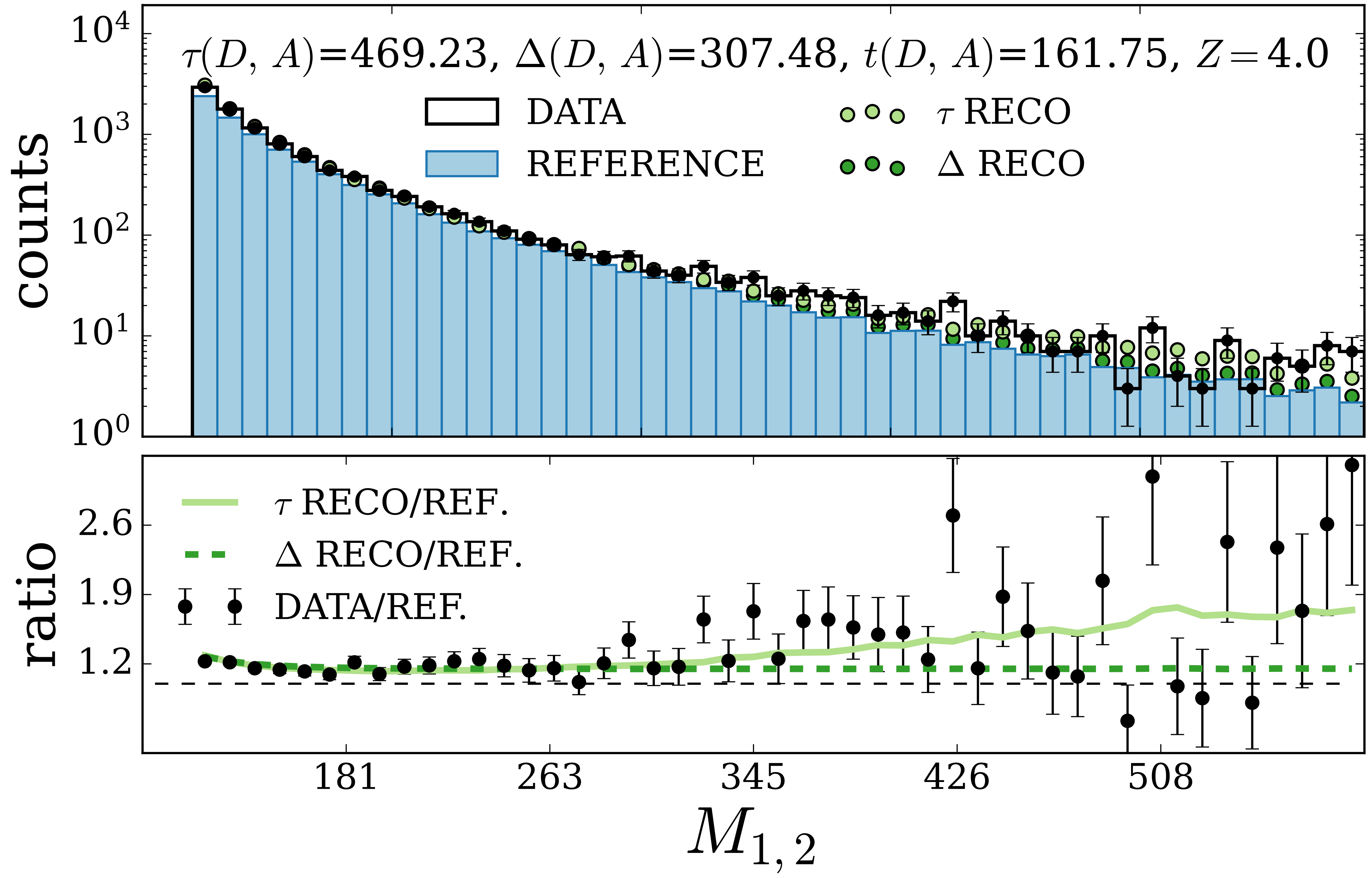
Architecture: [5-5-5-5–1] (96 dof), weigh clipping 2.15, L = 240 fb^{-1}

τ reconstruction: $n(x\,|\,\mathrm{H}_{\hat{\mathbf{w}},\hat{\nu}}) = n(x\,|\,\mathrm{R}_0)\,\dfrac{n(x\,|\,\mathrm{R}_{\hat{\nu}})}{n(x\,|\,\mathrm{R}_0)}\,e^{f(x;\,\hat{\mathbf{w}})}$

Δ reconstruction: $n(x\,|\,\mathrm{R}_{\hat{\nu}})$

NOTE:
M_{12} is **not** given as an input to the algorithm!





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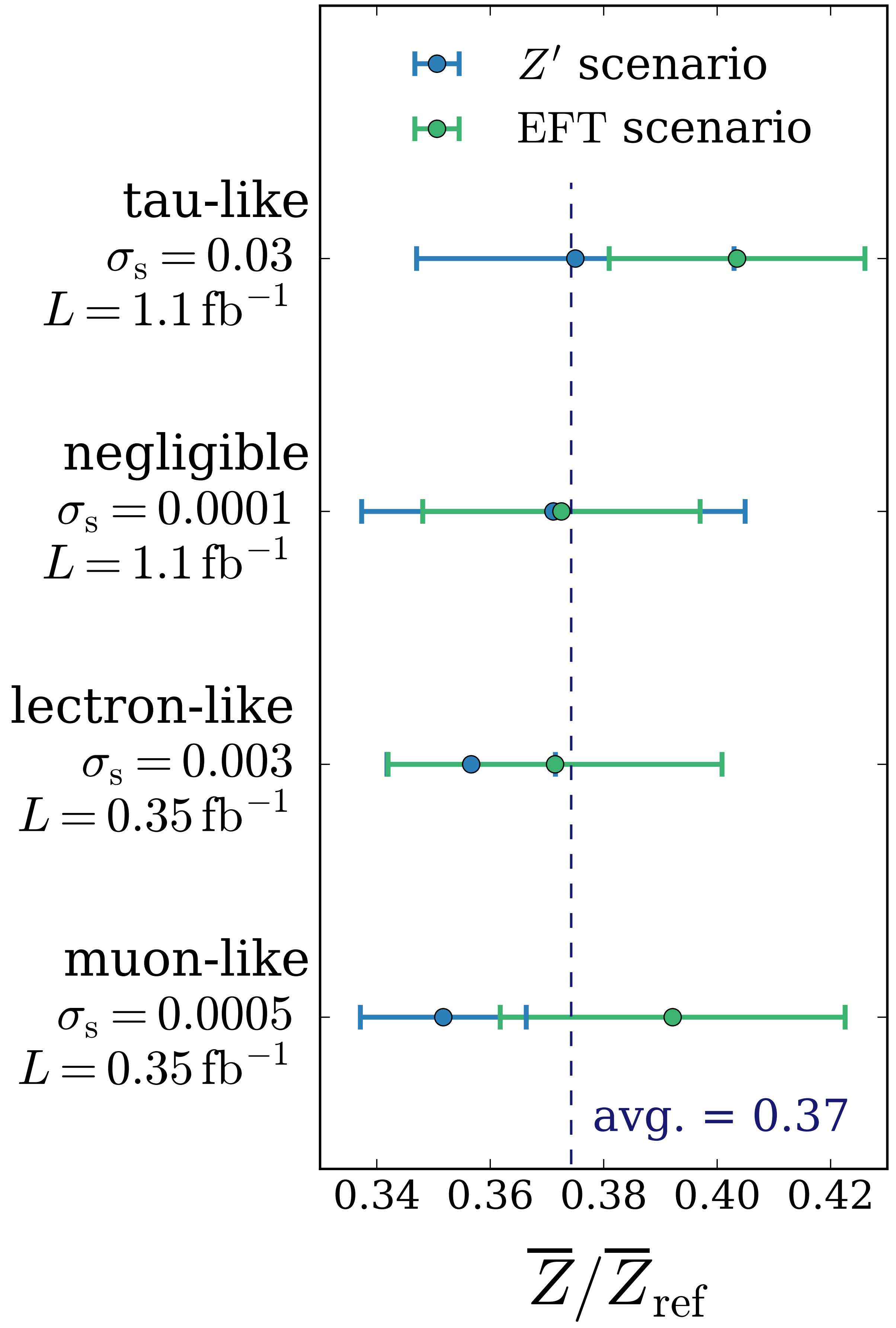
Two-body final state at the LHC

Sensitivity to New Physics scenarios

Summary of the results:

- Comparable performances in the resonant and non-resonant scenarios:
  - NPLM is simultaneously sensitive to any source of New Physics;
- Comparable performances at different systematic uncertainties regimes:
  - NPLM is robust against the presence of systematic uncertainties;
  - the presence of systematic uncertainties affects NPLM in the same measure as any other hypothesis test;
- No information about the New Physics signal has been provided to the algorithm at any step of its implementation:
  - The performances of NPLM are lower than any model-dependent strategy by construction ($\overline{Z}/\overline{Z}_{\text{ref}} = 0.37$);



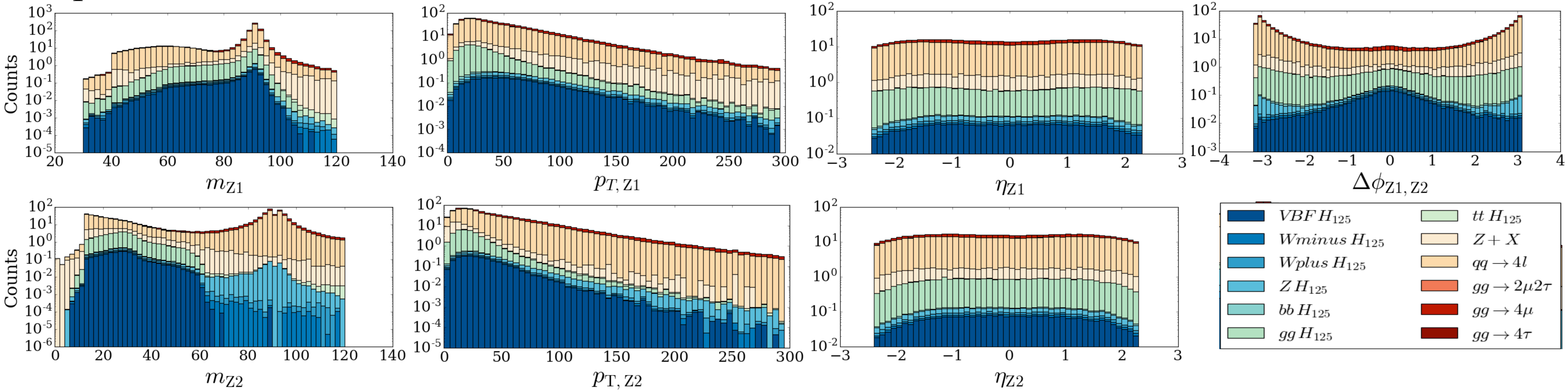
Z-score: $Z = \Phi^{-1}\left[1 - p\right]$

- $\overline{Z}$: Z-score from NPLM
- $\overline{Z}_{\text{ref}}$: Z-score from a model-dependent (optimized) test statistics

Harder task: nD analysis

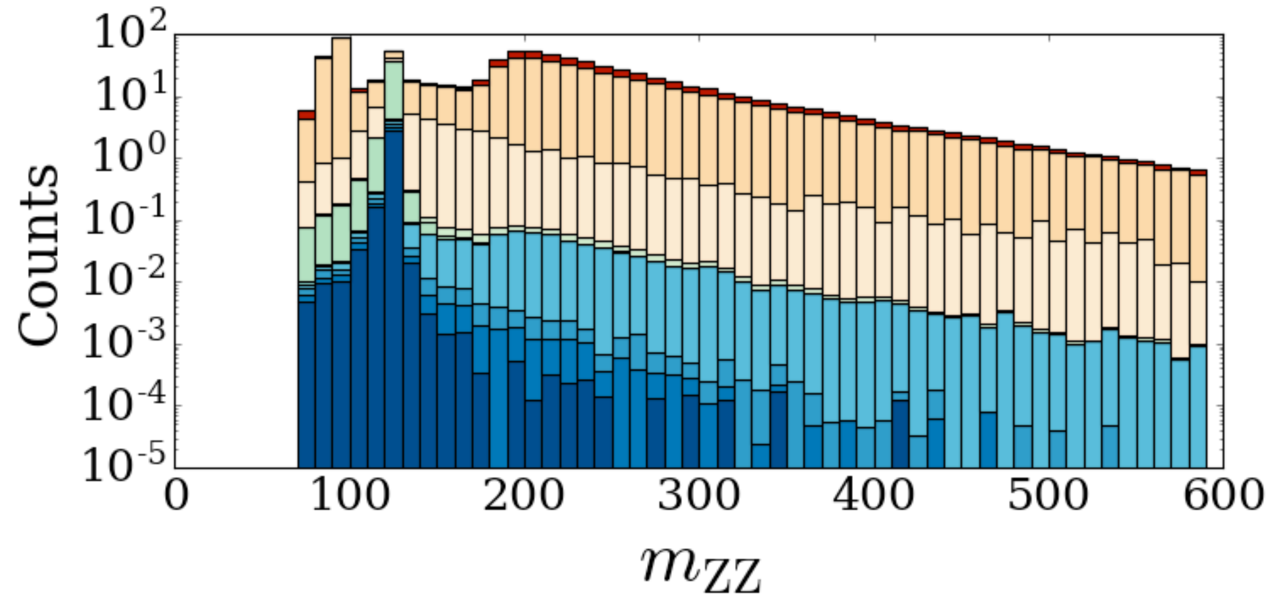
ZZ to 4 muons final state (7D)

Input variables:



Signal benchmarks:

- Higgs boson (as an exercise)



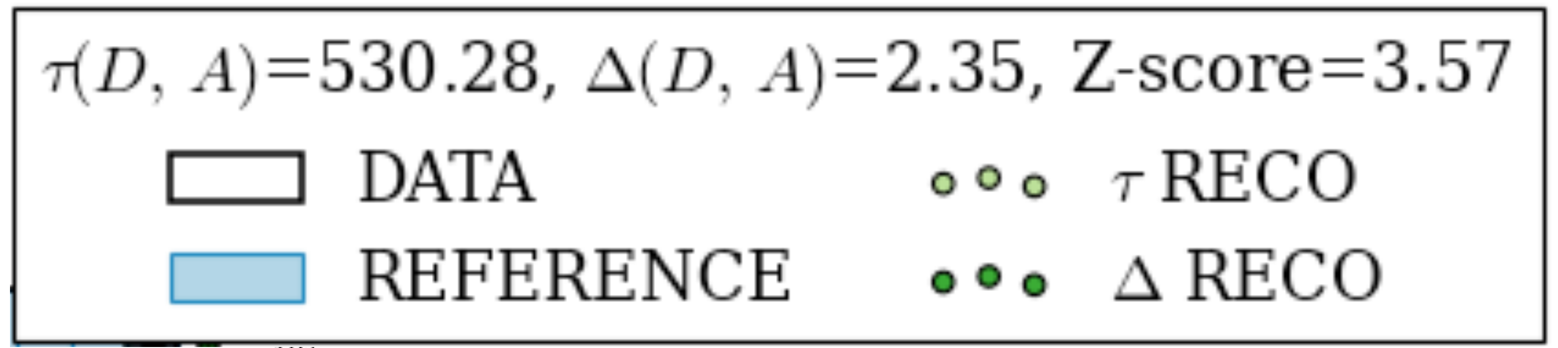
NOTE:
m_{ZZ} is **not** given as an input to the algorithm!

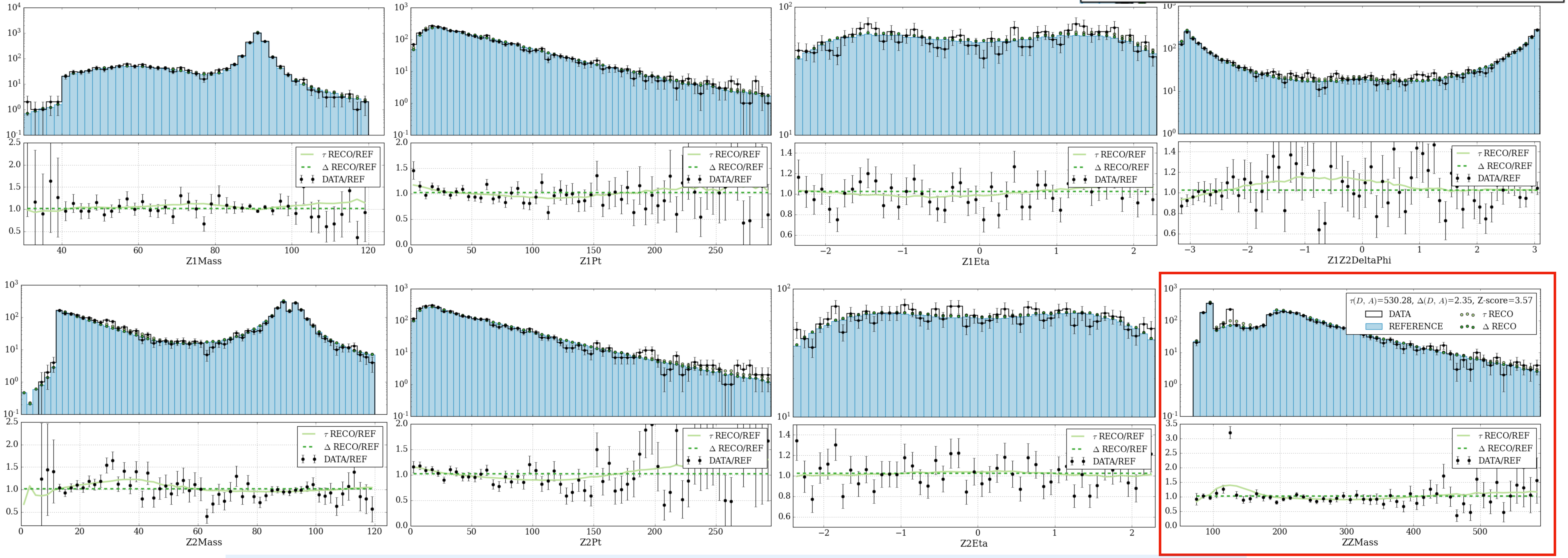
*n*D analysis

ZZ to 4 leptons final state (7D)

Signal reconstruction with the NN:

Architecture: [7-16-16-1] (417 dof), weigh clipping 1.75





Ongoing work for optmizing NPLM sensitivity in high dimensional problems

Conclusions

Outlook:

- NPLM for signal model independent New Physics searches:

Ready to be performed on a real analysis at the LHC!

✓ Heuristic method to setup **multivariate** analysis
✓ Strategy to account for **systematic uncertainties**

Limitations

- Accuracy of the Reference sample
- Accuracy of the systematic uncertainties modelling
- Training time
  (NN are slow, speed up with kernel methods!
  see Marco's talk tomorrow)

limits to the actual **luminosity** that we are allowed to inspect, but not an obstacle to the applicability of NPLM.

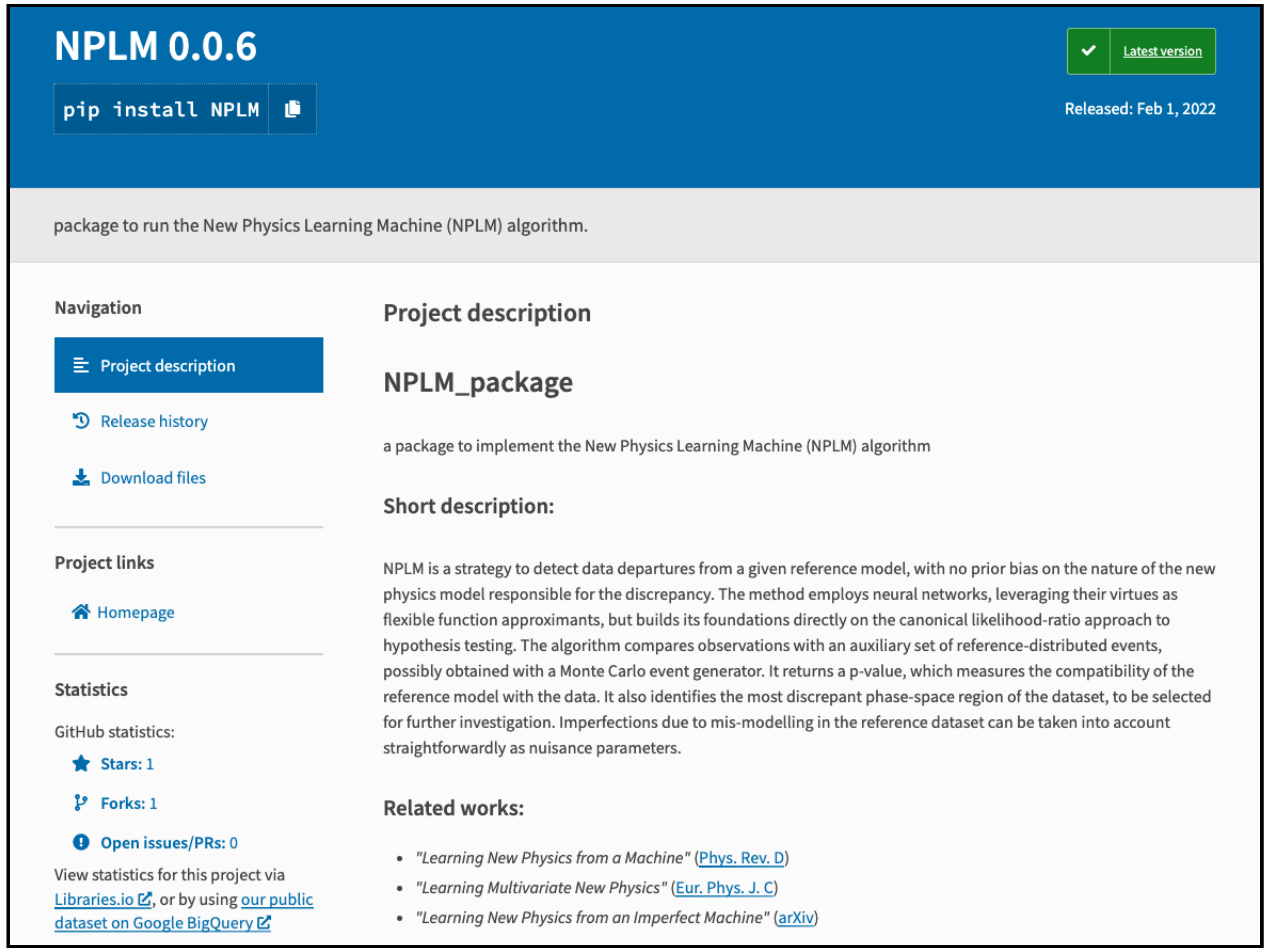
Ongoing work

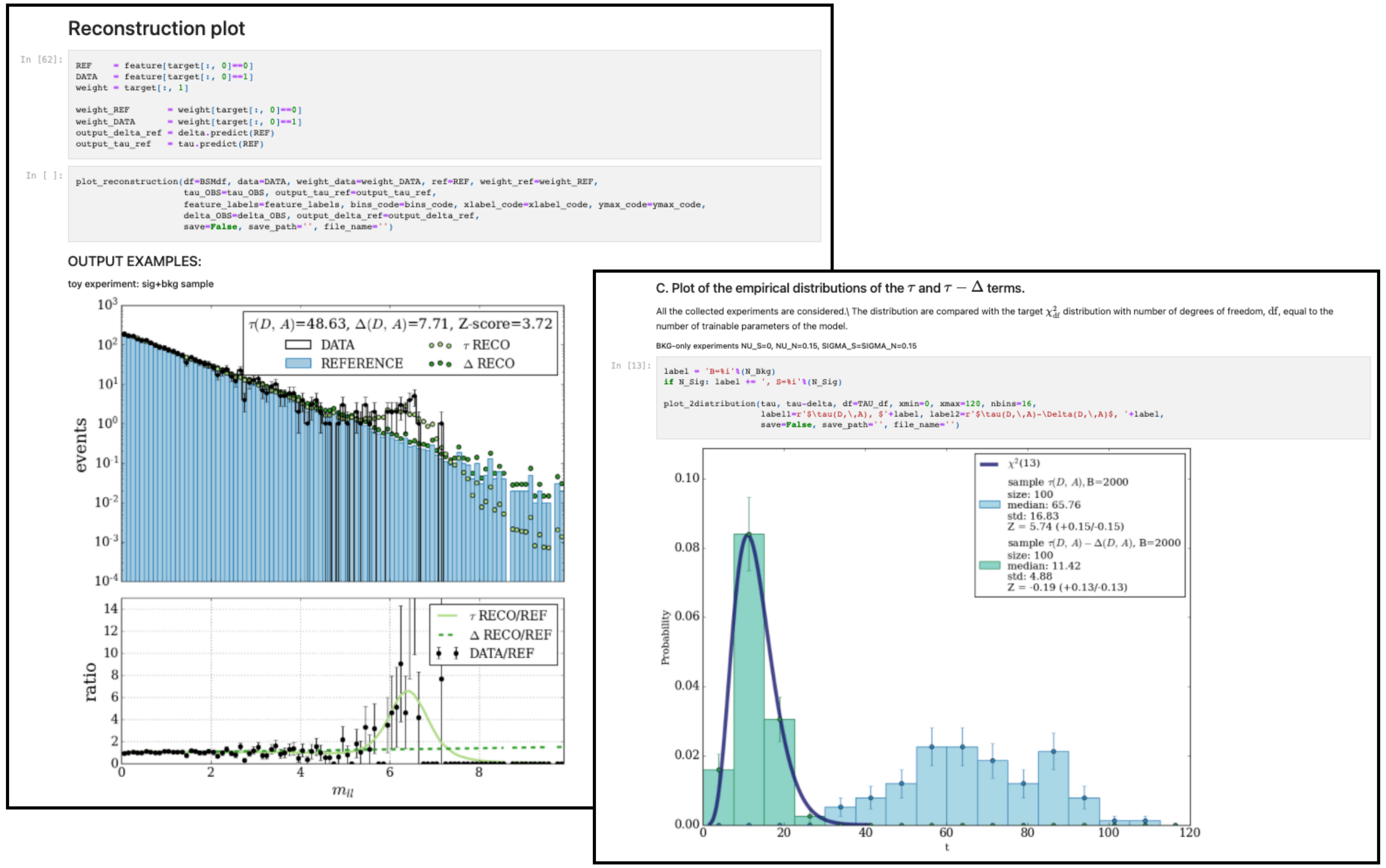
- Comparison to other techniques
- Exploring alternatives to the weight clipping as form of regularization
- How to choose the NN architecture?

Outlook:

Getting started with NPLM

- NPLM package: python-based package to run the NPLM analysis strategy
- Tutorial on 1D toy model for getting started





Back up

New Physics Learning Machine (NPLM)

Including systematic uncertainties

Maximum Likelihood from minimal loss:

Test statistic

$$t(\mathcal{D},\, \mathcal{A}) = 2\log\left[\frac{\max_{\mathbf{w},\,\boldsymbol{\nu}} \mathcal{L}(\mathrm{H}_{\mathbf{w},\,\boldsymbol{\nu}}|\mathcal{D},\, \mathcal{A})}{\max_{\boldsymbol{\nu}} \mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D},\, \mathcal{A})}\right] = 2\log\left[\frac{\max_{\mathbf{w},\,\nu} \mathcal{L}(\mathrm{H}_{\mathbf{w},\,\boldsymbol{\nu}}|\mathcal{D})\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\max_{\boldsymbol{\nu}} \mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D})\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}\right]$$

$$= \tau(\mathcal{D},\, \mathcal{A}) - \Delta(\mathcal{D},\, \mathcal{A})$$

$\mathbf{w}$: trainable parameters on the NN model

$\boldsymbol{\nu}$: set of nuisance parameters modelling the uncertainties effects

$\mathcal{D}$: data sample

$\mathcal{A}$: auxiliary sample (used to constrain $\boldsymbol{\nu}$)

Tau term:

$$\tau(\mathcal{D},\, \mathcal{A}) = 2\max_{\mathbf{w},\,\boldsymbol{\nu}}\log\left[\frac{\mathcal{L}(\mathrm{H}_{\mathbf{w}},\, \boldsymbol{\nu}|\mathcal{D})\,\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\mathcal{L}(\mathrm{R}_{\mathbf{0}}|\mathcal{D})\,\mathcal{L}(\mathbf{0}|\mathcal{A})}\right] = -2\min_{\mathbf{w},\boldsymbol{\nu}} L\left[f(x,\mathbf{w}),\boldsymbol{\nu};\widehat{\delta}(x)\right]$$

Contains the dependence on a NN model

Delta term:

$$\Delta(\mathcal{D},\, \mathcal{A}) = 2\max_{\boldsymbol{\nu}}\log\left[\frac{\mathcal{L}(\mathrm{R}_{\boldsymbol{\nu}}|\mathcal{D})\,\mathcal{L}(\boldsymbol{\nu}|\mathcal{A})}{\mathcal{L}(\mathrm{R}_{\mathbf{0}}|\mathcal{D})\,\mathcal{L}(\mathbf{0}|\mathcal{A})}\right] = -2\min_{\boldsymbol{\nu}} L\left[\boldsymbol{\nu};\widehat{\delta}(x)\right]$$

Built on the knowledge of the Reference model (purely SM term)

$$r(x;\nu) = \frac{n(x\,|\,\mathrm{R}_\nu)}{n(x\,|\,\mathrm{R}_0)}$$

Taylor's expansion learning:

$$\widehat{r}(x;\nu) = \exp\left[\widehat{\delta}_1(x)\,\nu + \widehat{\delta}_2(x)\,\nu^2 + \ldots\right]$$

NN 1 NN2 …

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New Physics Learning Machine (NPLM)

Including systematic uncertainties