ML for particle physics in the precision era

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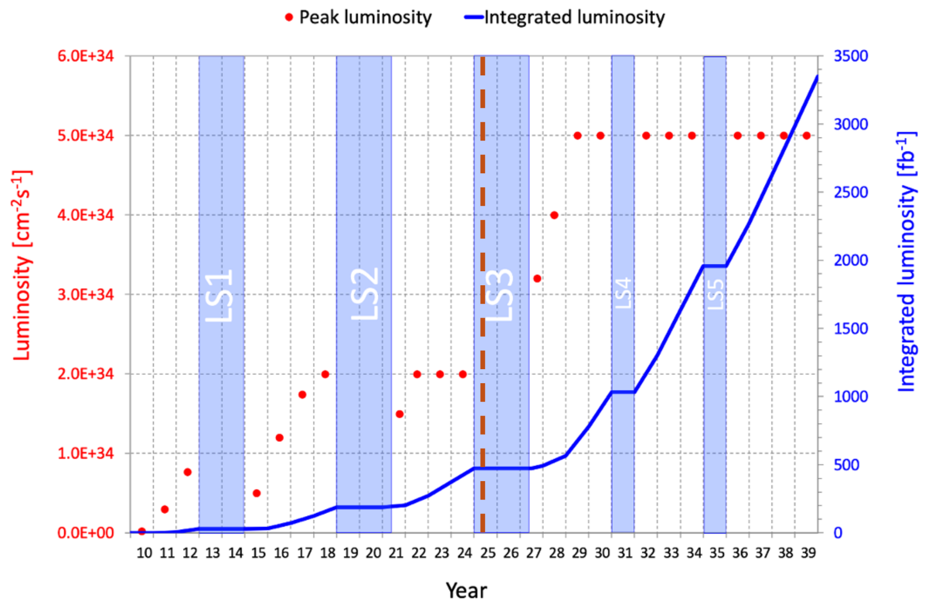
The challenge ahead

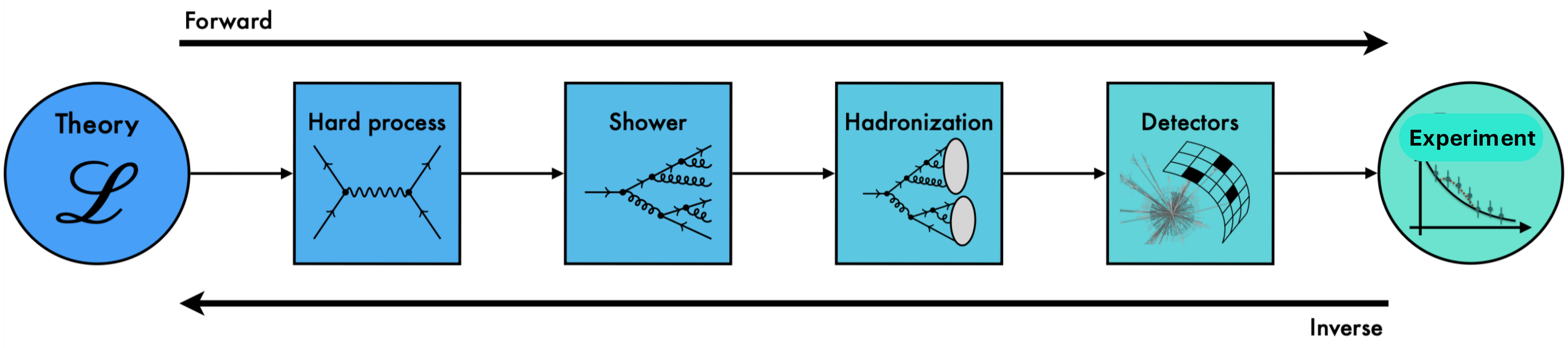
- general trend: larger-and-larger experiments collecting more-and-more data
- e.g. LHC: already enormous dataset will be further enlarged by a factor ~ 10
- costs for future experiments increasing



Fully exploit the available data!

- new analysis methods
- theory precision $\simeq$ experimental precision
- in particular: high-precision MC simulation

The particle physics workflow



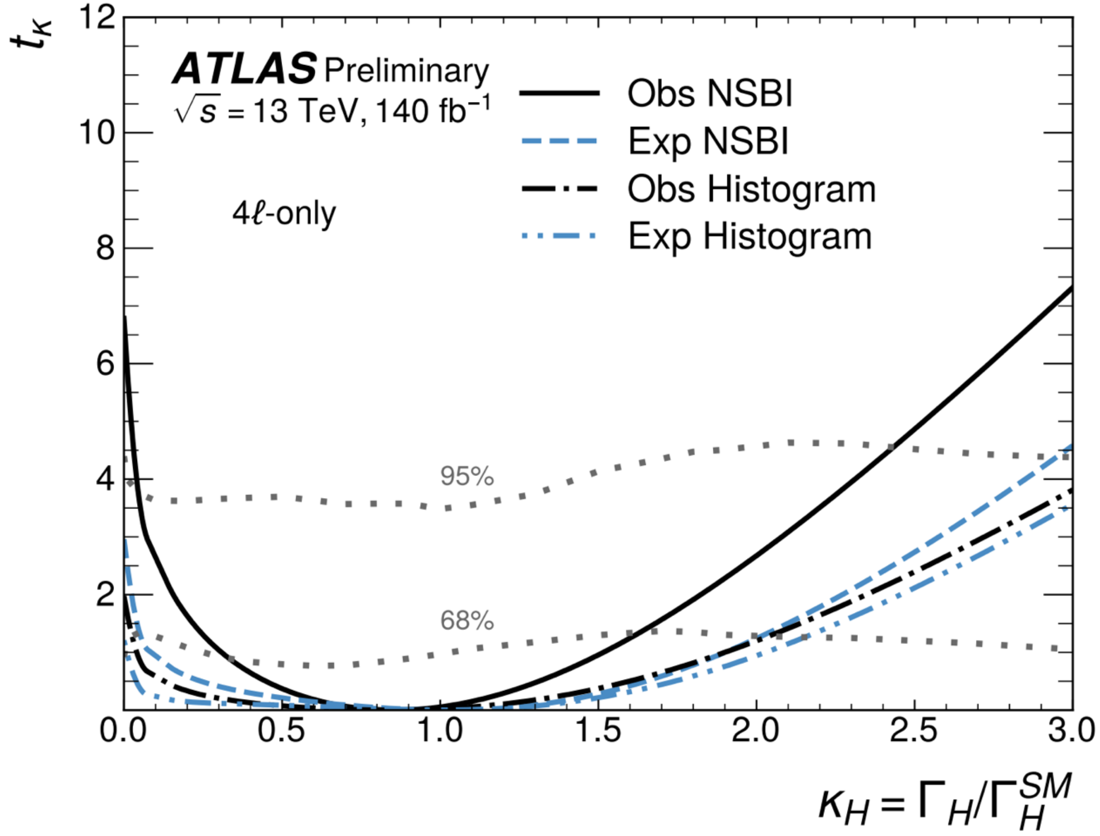
ML can help with each of these steps by increasing

- accuracy/performance
- speed

Example: 1st experimental SBI analysis

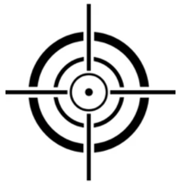
[ATLAS-CONF-2024-016]

- goal: measure off-shell signal strength in $H \to ZZ$ channel
- simulation-based inference (SBI) allows to exploit full kinematic information
- significant improvement in comparison to histogram approach



➡ What is needed to apply ML successfully?

ML for particle physics



accuracy

speed

uncertainties

interpretability

ML for particle physics


accuracy


speed


uncertainties


interpretability

→


physics knowledge

ML for particle physics

- accuracy
- speed
- uncertainties
- interpretability

physics knowledge

ML for particle physics


accuracy

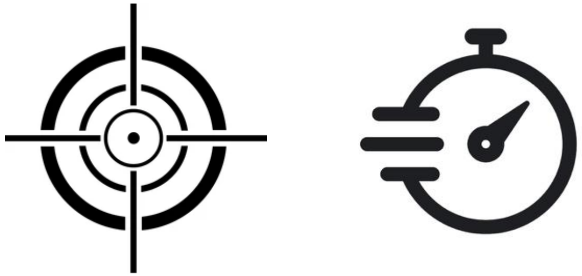

speed


uncertainties


interpretability

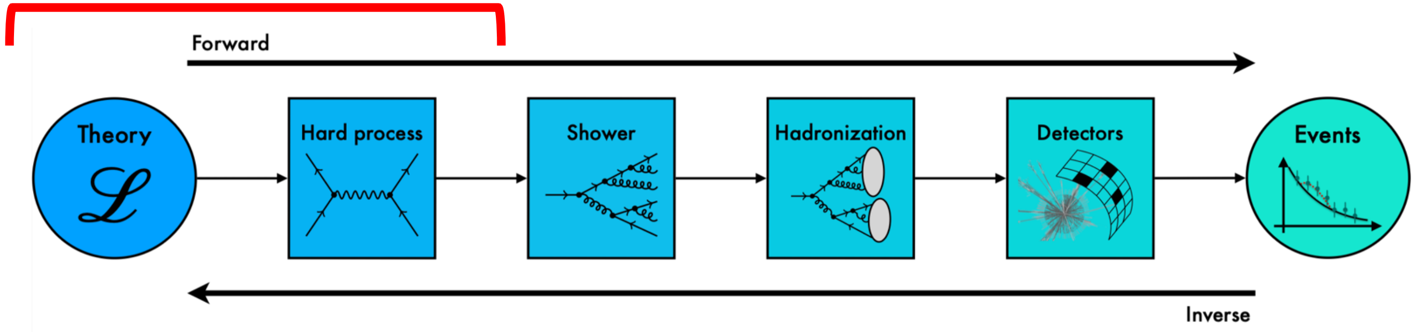

physics knowledge

Key to all these aspects: finding good representations of the data



Accuracy & speed

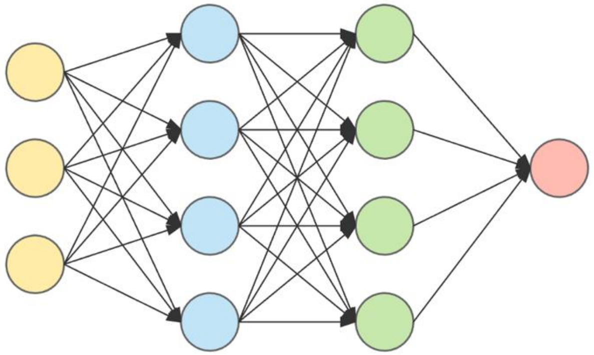
fast higher-order amplitude surrogates



Amplitude surrogates

- evaluating analytic expressions for amplitudes $|\mathcal{M}|^2$ can be very expensive due to
  - higher-order corrections
  - large final-state multiplicities

$$|\mathcal{M}|^2 \approx$$

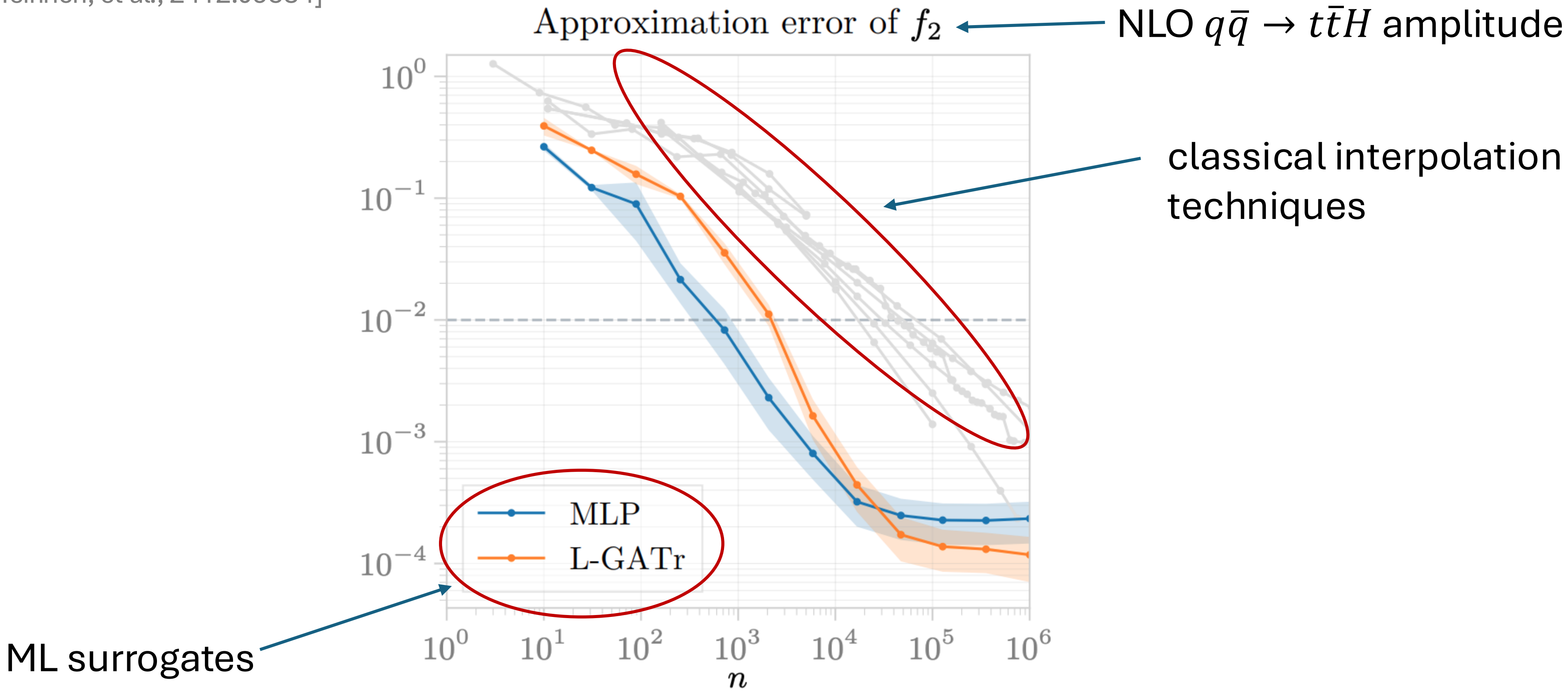


- idea:
  - generate small training sample using full analytic expression
  - train a NN to approximate $|\mathcal{M}|^2$
  - generate events using NN surrogate → fast to evaluate

→ fast high-precision event generation

Comparison to classical interpolation

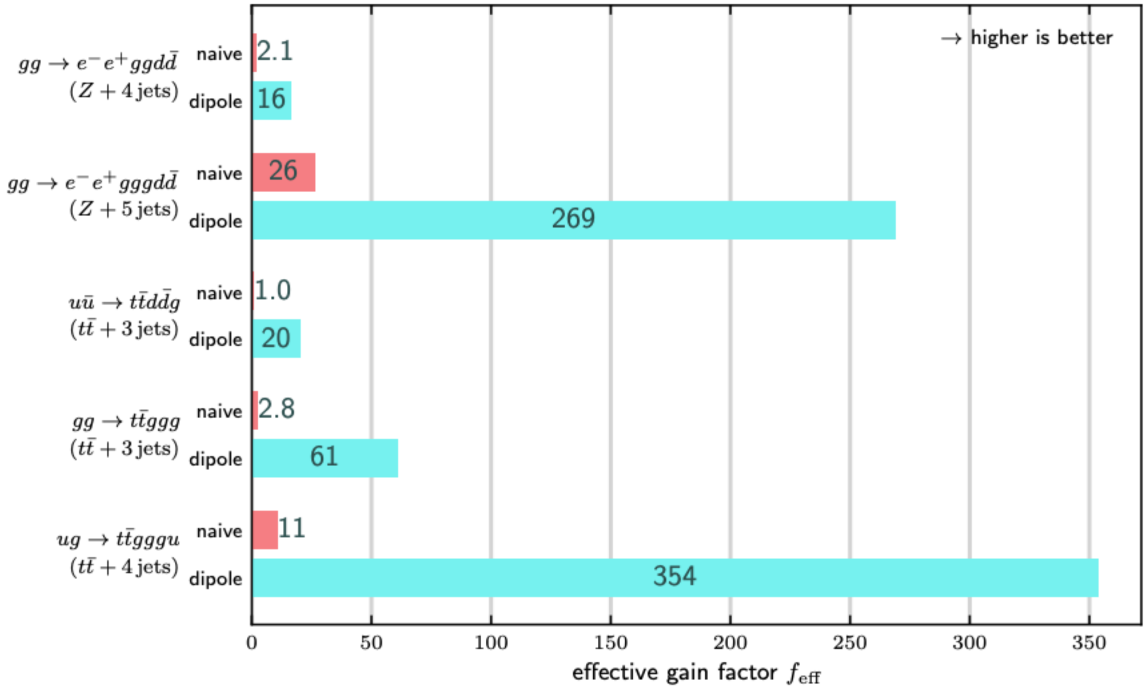
[Bresó, Heinrich, et al., 2412.09534]



➡ ML surrogates outperform classical interpolation techniques

Speed comparison

[Janßen et al.,2301.13562]



	SHERPA default			with dipole-model surrogate				
Process	t_{ME}[ms]	t_{PS}[ms]	ϵ_{full}	t_{surr}[ms]	x_{max}	$\epsilon_{\text{1st,surr}}$	$\epsilon_{\text{2nd,surr}}$	f_{eff}
$gg \to e^- e^+ g g d \bar{d}$	54	0.40	1.411 %	0.14	2.6	1.418 %	39 %	16
$gg \to e^- e^+ g g g d \bar{d}$	16 216	5.70	0.076 %	0.20	3.6	0.085 %	29 %	269

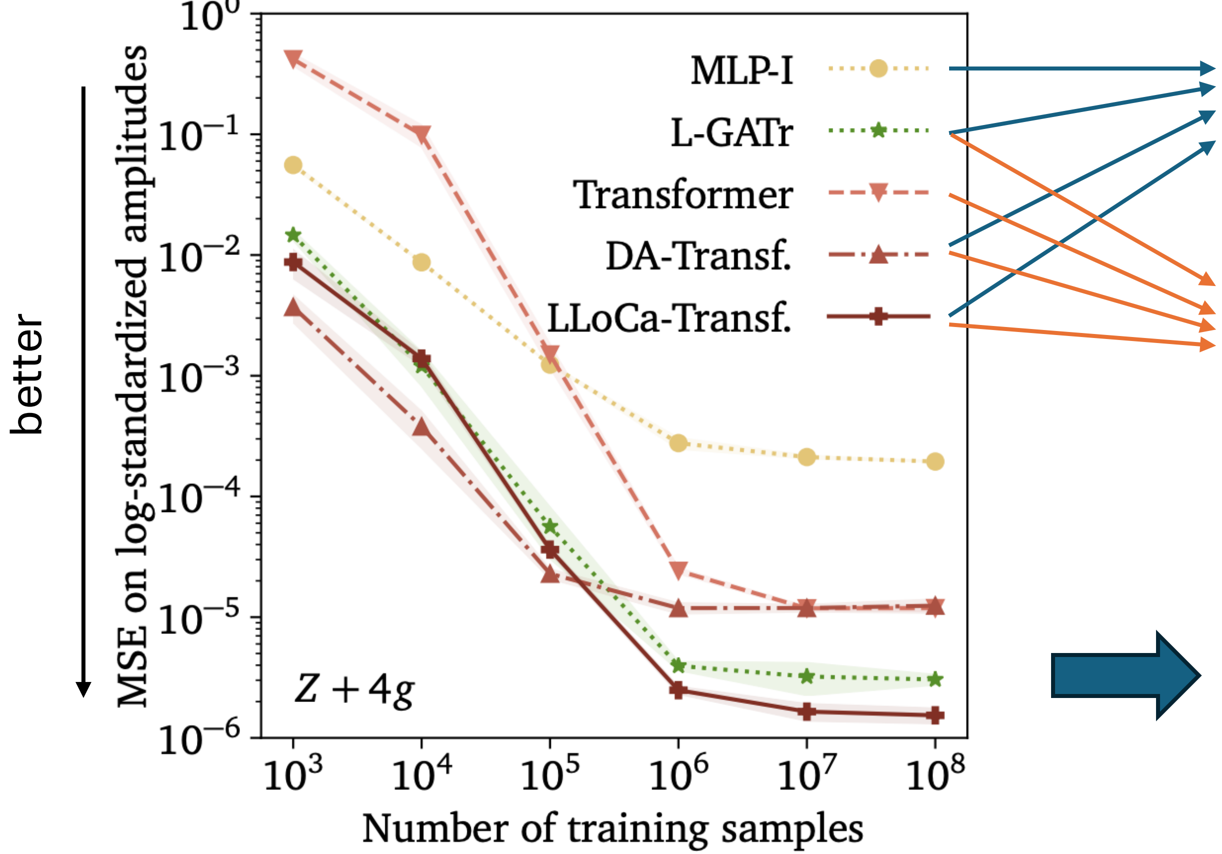
$$f_{\text{eff}} = \frac{T_{\text{standard}}}{T_{\text{surrogate}}}$$

dipole vs naïve:
encode singularity structure of amplitudes

→ Large speed-ups possible!

Exploiting known symmetries

[2505.20280, Spinner et al.]



Lorentz invariance

permutation invariance ($g_i \leftrightarrow g_j$)

Enforcing symmetries drastically improves performance!

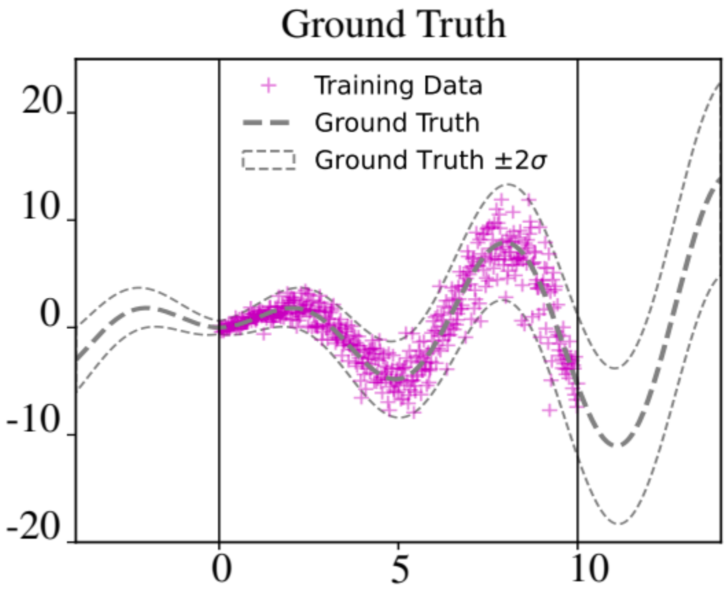
→ physic-informed data representations

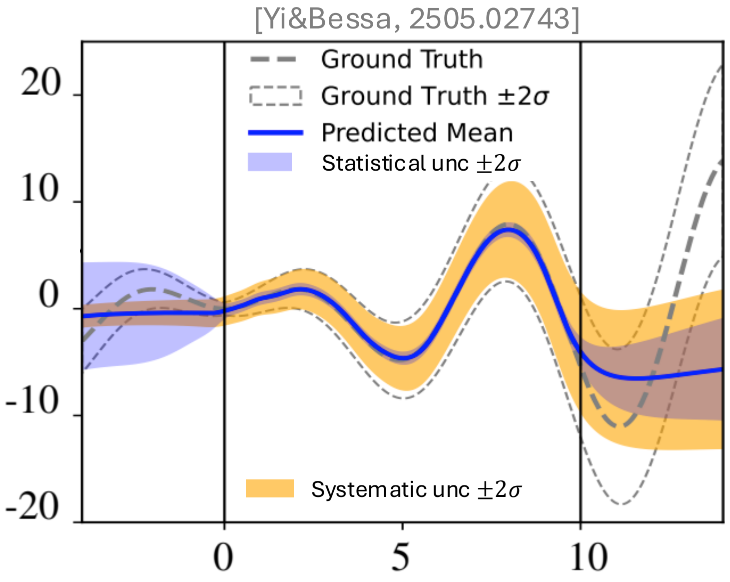
Uncertainties

"All models are wrong, but some — those that know when they can be trusted — are useful!"

George Box (adapted)

Regression with uncertainties





- statistical uncertainty ≙ lack of training data
- systematic uncertainty ≙ noise in the data, lack in model expressivity

➡ Can we the NNs encode a representation of their own uncertainties?

Probabilistic learning

NN parameters

Learn amplitude statistically

$$p(A|x) = \int \mathrm{d}\theta\; p(\theta|D_{\text{train}})\; p(A|x,\theta) \approx \int \mathrm{d}\theta\; q(\theta)\; p(A|x,\theta)$$

Then, we can calculate the mean prediction and uncertainties as

$$A_{\text{NN}}(x) = \int dA\, A\, p(A|x) = \int d\theta\, q(\theta)\, \bar{A}(x,\theta) \qquad \text{with} \qquad \bar{A}(x,\theta) = \int dA\, A\, p(A|x,\theta)$$

$$\sigma^2_{\text{syst}}(x) = \int d\theta\, q(\theta) \left[\overline{A^2}(x,\theta) - \bar{A}(x,\theta)^2\right]$$

→ vanishes for perfect data: $p(A|\theta) \to \delta(A - A_0)$

$$\sigma^2_{\text{stat}}(x) = \int d\theta\, q(\theta) \left[\bar{A}(x,\theta) - A_{\text{NN}}(x)\right]^2$$

→ vanishes for perfect training: $q(\theta) \to \delta(\theta - \theta_0)$

Modelling the systematic uncertainty

- log-likelihood loss:

true amplitudes

$$\mathcal{L} = - \sum_{x_i, A_i \in D_{\text{train}}} \log p(A_{\text{true}}(x_i)|x_i, \theta)$$

phase-space point

- assume Gaussian likelihood: $p(A|x) = \mathcal{N}(\overline{A}(x), \sigma_{\text{syst}}^2(x))$

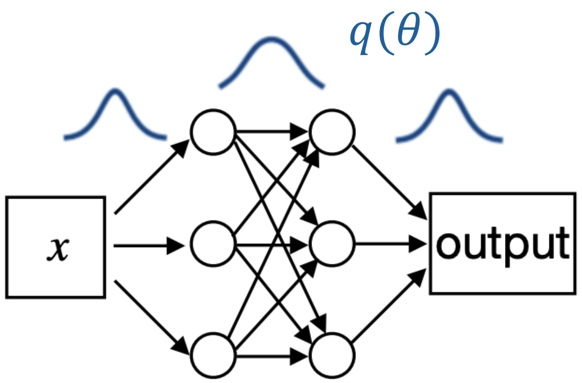
- NN learns both: $\overline{A}(x)$ and $\sigma_{\text{syst}}(x)$

$$\Rightarrow \text{heteroskedastic loss: } \mathcal{L} = \sum_i \left[\frac{\left(\overline{A}(x_i) - A_{\text{true}}(x_i)\right)^2}{2\sigma_{\text{syst}}^2(x_i)} + \log\left(\sigma_{\text{syst}}(x_i)\right) \right]$$

- if needed: replace by Gaussian mixture model

Modelling the statistical uncertainty

- variational approximation: $p(\theta|D_{\text{train}}) \simeq q(\theta)$
- promote each NN parameter to Gaussian distribution
- train by minimizing KL divergence:



$$\mathrm{KL}[q(\theta), p(\theta|D_{\text{train}})] = \int \mathrm{d}\theta\; q(\theta) \log \frac{q(\theta)}{p(\theta|D_{\text{train}})}$$

Bayes' theorem →

$$= \int \mathrm{d}\theta\; q(\theta) \log \frac{q(\theta) p(D_{\text{train}})}{p(\theta) p(D_{\text{train}}|\theta)}$$

$$= \underbrace{\mathrm{KL}[q(\theta), p(\theta)]}_{\text{prior}} - \underbrace{\int \mathrm{d}\theta\; q(\theta) \log p(D_{\text{train}}|\theta)}_{\text{log likelihood}} + \;\ldots$$

Alternative: repulsive ensembles

- can describe NN training via ODE or continuity equation:

$$\frac{\mathrm{d}\theta}{\mathrm{d}t} = v(\theta, t) \qquad \text{or} \qquad \frac{\partial \rho(\theta, t)}{\partial t} = -\nabla_\theta \left[v(\theta, t)\rho(\theta, t) \right]$$

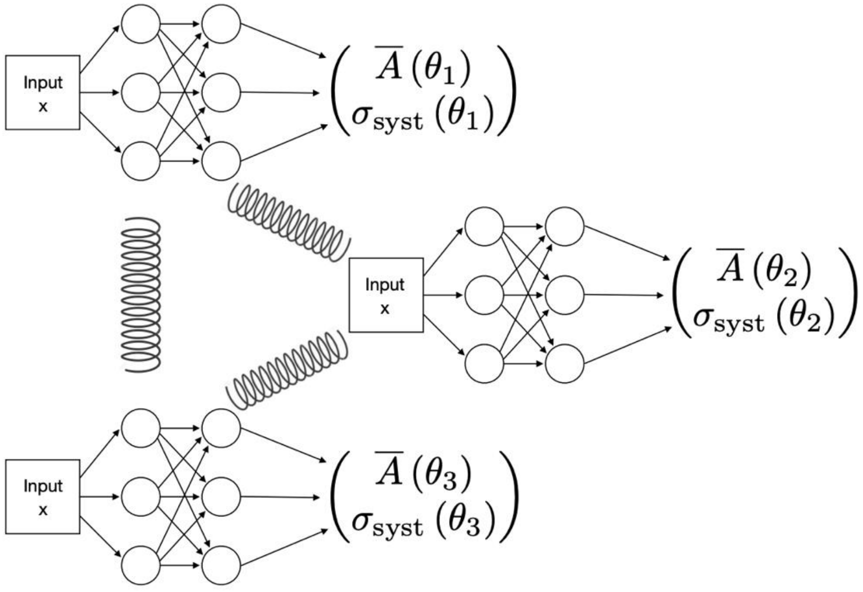
- choose $v(\theta, t) = -\nabla_\theta \log \frac{\rho(\theta, t)}{\pi(\theta)}$ → solution: $\rho(\theta) = \pi(\theta) \equiv p(\theta | D_{\text{train}})$

- estimate density via NN ensemble: $\rho(\theta^t) \approx \frac{1}{n} \sum_{i=1}^{n} k(\theta^t, \theta_i^t)$

kernel

- NN parameter update rule

$$\frac{d\theta}{dt} = -\nabla_\theta \left[\log \left(\frac{1}{n} \sum_i k(\theta, \theta_i) \right) - \log p(\theta | x) \right]$$

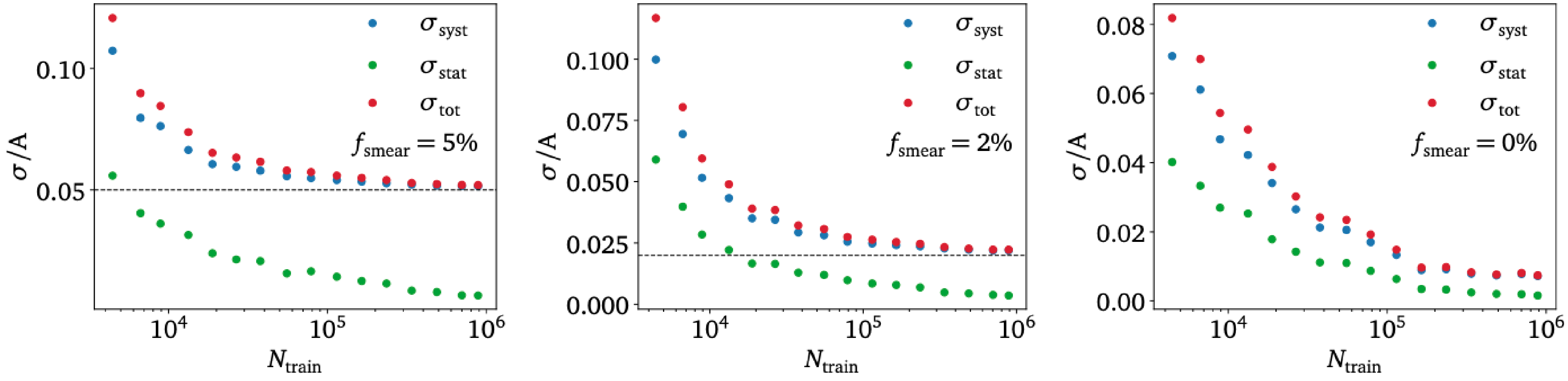


➡ NN ensemble with repulsive force ensuring $\theta \sim p(\theta | D_{\text{train}})$

Behavior of uncertainties

[HB et al.,2412.12069]

$A_{\text{train}} \sim \mathcal{N}(A_{\text{true}}, \sigma^2_{\text{train}})$
$\sigma_{\text{train}} = f_{\text{smear}} A_{\text{true}}$



test: apply Gaussian noise to $gg \to \gamma\gamma g$ amplitudes

- statistical unc. decreases with more training data
- systematic unc. converges to level of applied noise

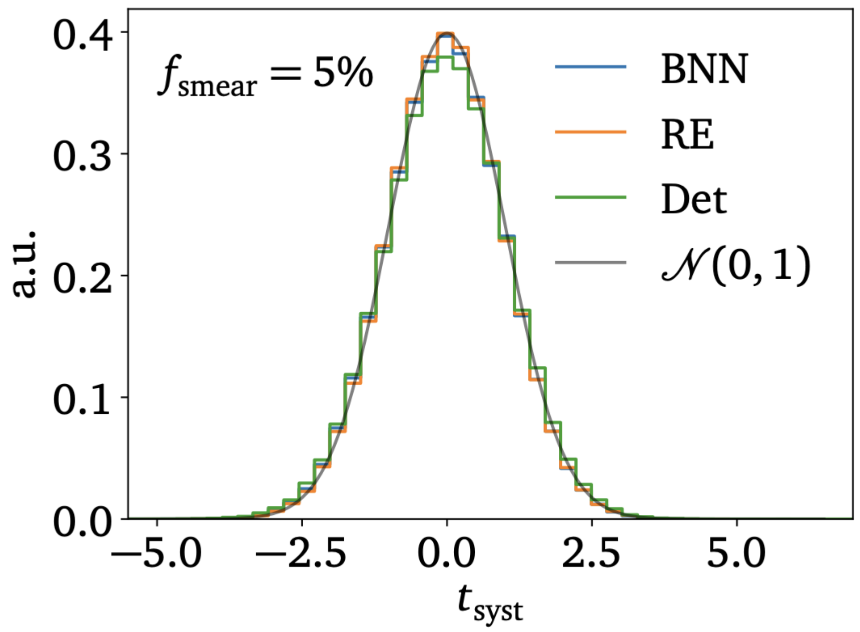
→ reliable uncertainty estimate

Are these uncertainties calibrated?

- statistical uncertainties play minor role for amplitude regression
- define systematic pull:

$$t_{\text{syst}} = \frac{\langle A \rangle(x) - A_{\text{train}}(x)}{\sigma_{\text{syst}}(x)}$$

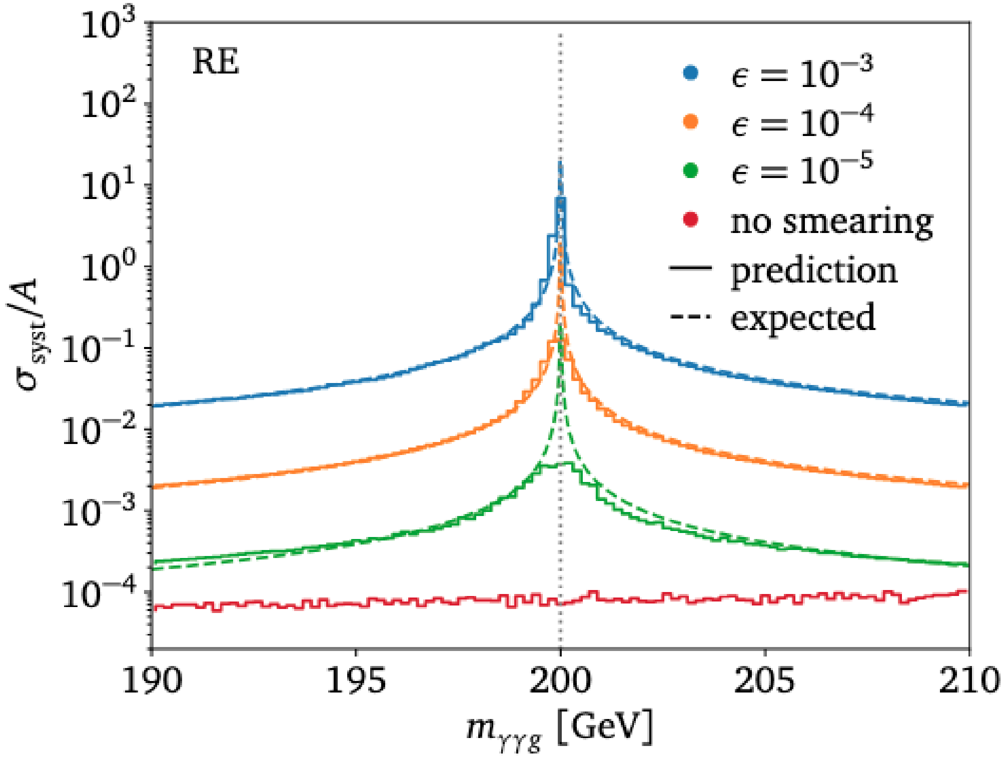
- if calibrated, t_{syst} distribution should follow $\mathcal{N}(0,1)$



Almost perfectly calibration → reliable uncertainty estimate

Localized noise

[HB et al., 2509.00155]



$$A_{\rm train}(x) = \mathcal{N}\left(A_{\rm true}(x), \frac{\epsilon\, m_{\rm thresh}}{|m_{\gamma\gamma g}(x) - m_{\rm thresh}|} A_{\rm true}(x)\right)$$

- emulates numerical noise close to threshold
- well captured by systematic uncertainties
- NN effectively finds the mean prediction
- uncertainties still well calibrated

Same techniques also applicable to all kind of other regression problems!

Controlling generative ML

[HB et al., 2509.08048]

training dataset — true distribution: $D_{\text{true}}^{n_{\text{train}}} \sim p_{\text{true}}(x)$

⟺

generated dataset — learned distribution: $D_{\text{gen}}^{n_{\text{gen}}} \sim p_{\text{gen}}(x) \overset{?}{\sim} p_{\text{true}}(x)$

How can we quantify the performance of the generative NN?

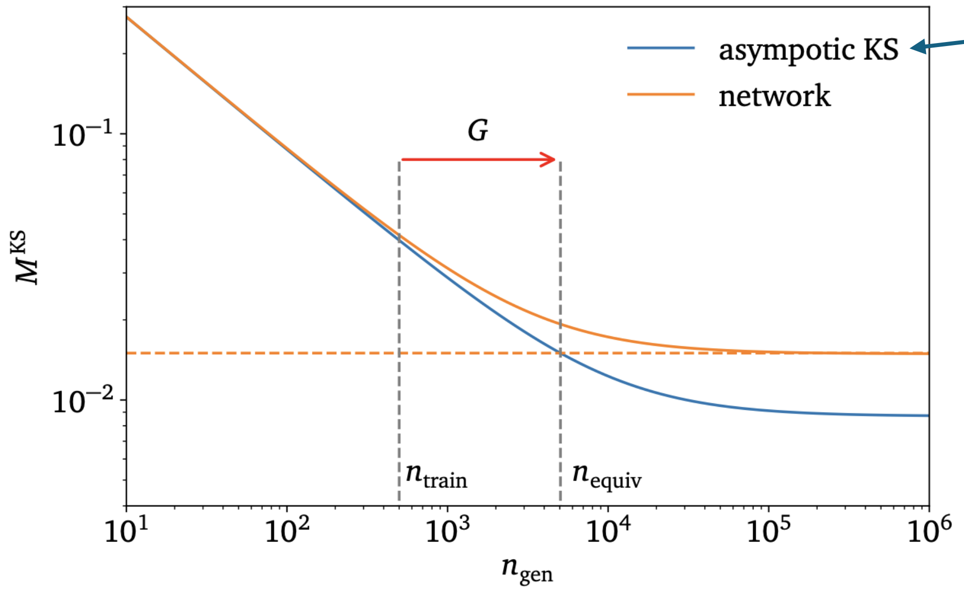
→ determine n_{equiv} such that $M\left(D_{\text{true}}^{n_{\text{equiv}}}, p_{\text{true}}(x)\right) \equiv M\left(D_{\text{gen}}^{n_{\text{gen}}}, p_{\text{true}}(x)\right)$ with $D_{\text{true}}^{n_{\text{equiv}}} \sim p_{\text{true}}(x)$

comparison metric (M)

⇒ amplification factor $G = \dfrac{n_{\text{equiv}}}{n_{\text{train}}}$

Controlling generative ML

one option for M: Kolmogorov-Smirnov test comparing D_{train} and D_{gen}



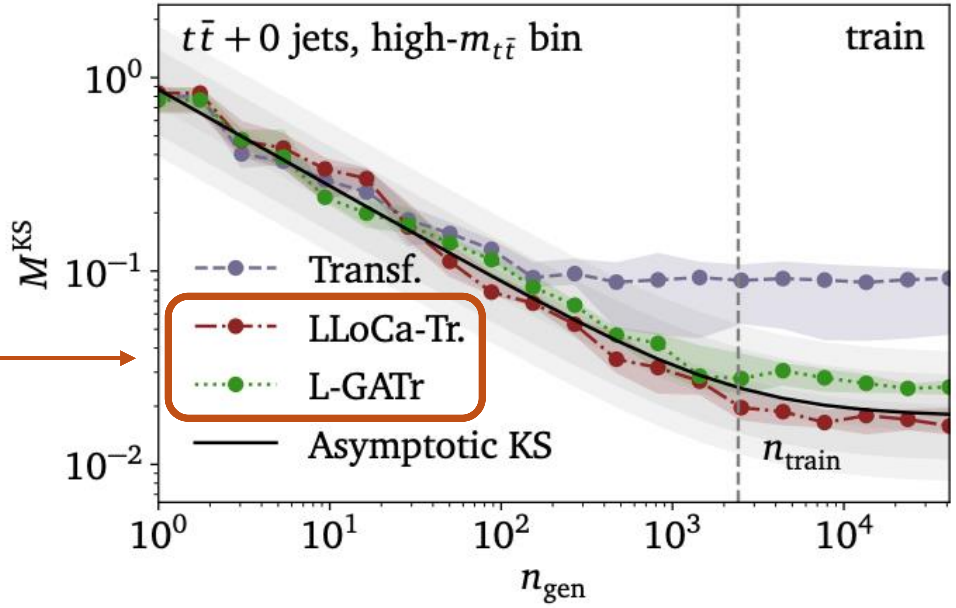
known asymptotic if $p_{\text{gen}} = p_{\text{true}}$

→ systematic approach to assess quality of generative NNs

Controlling generative ML

one option for M: Kolmogorov-Smirnov test comparing D_{train} and D_{gen}

Lorentz-equivariant
&
permutation-invariant



systematic approach to assess quality of generative NNs

Interpretable ML

looking under the hood

Back to the formula – symbolic regression

- many ways to make ML interpretable

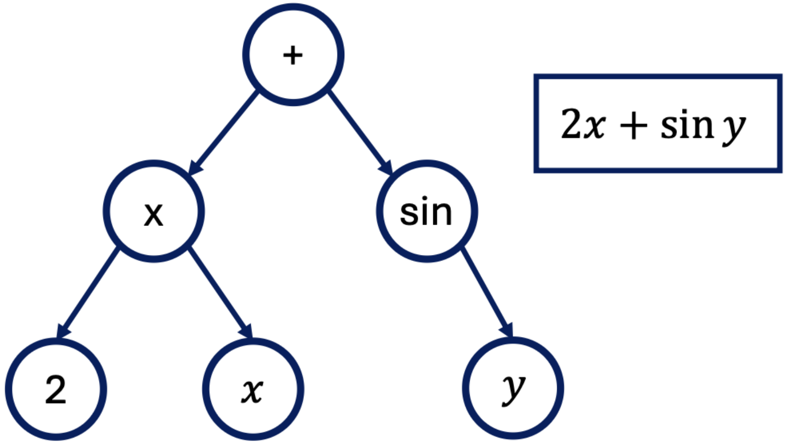
- goal: find most relevant representation/observables describing the data

→ maximal interpretability: analytic equation!

- construct them dynamically using symbolic regression
  [Schmidt&Lipson`09, Udrescu&Tegmark`19, Cranmer et al.`19,`20,`23]

- build upon genetic algorithm successively forming equation

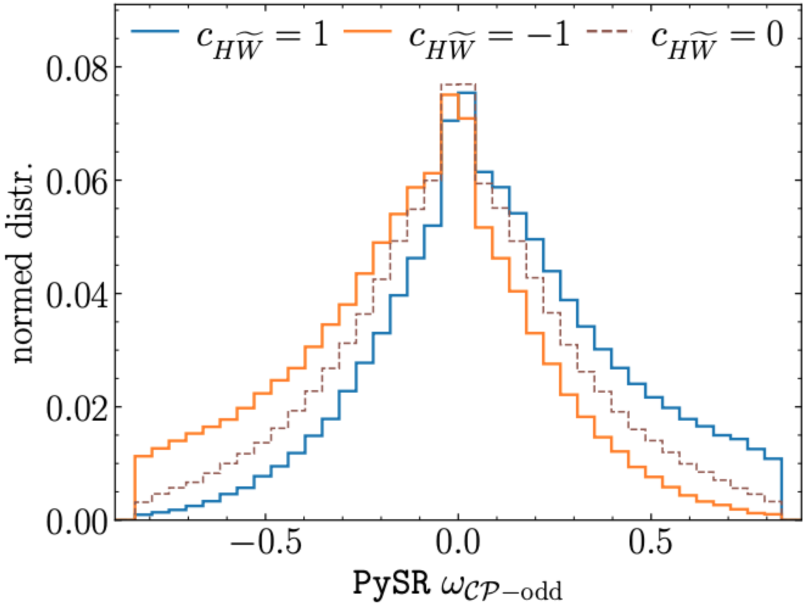
- interplay between goodness-of-fit and complexity of equation



Example: Higgs CP test for VBF

[HB et al., 2507.05858]

- consider dim-6 operator $\frac{c_{H\widetilde{W}}}{\Lambda^2} \Phi^\dagger \Phi \widetilde{W}^a_{\mu\nu} W^{a\mu\nu}$
- unambiguous CP test → CP-odd observables
- construct optimal reco-level CP-odd obs. by training a classifier on $c_{H\widetilde{W}} = \pm 1$ samples
- analytic equation → ensure learned observable is indeed CP-odd



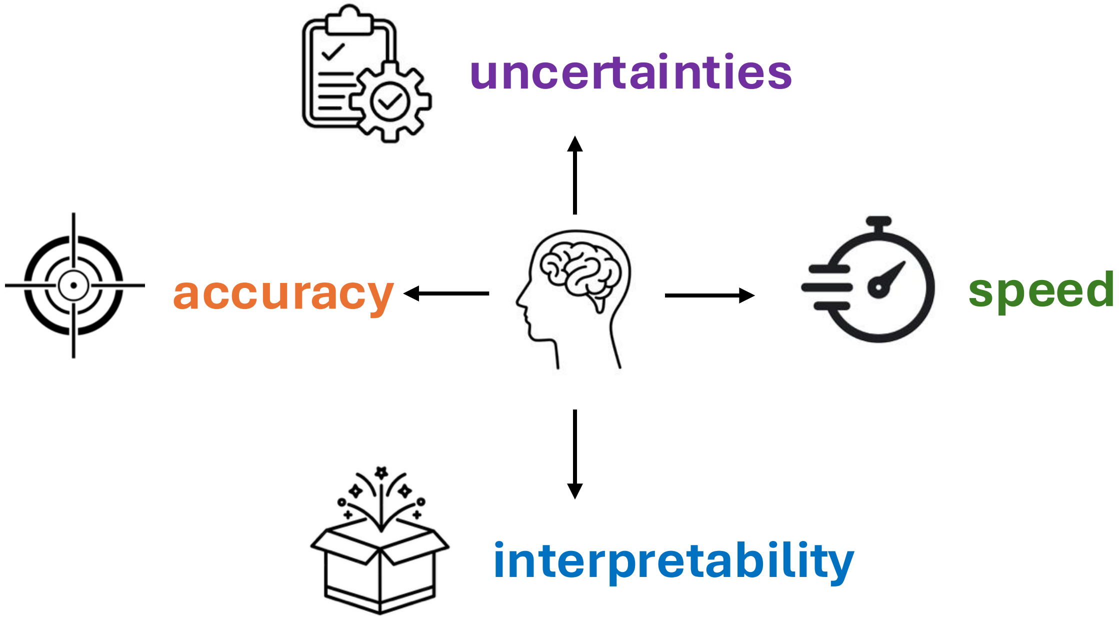
	$\sigma(c_{H\widetilde{W}} = 1$ vs. SM)
$p_{T,j_1} p_{T,j_2} \sin \Delta\phi_{jj}$	6.76
trained on $c_{H\widetilde{W}} = \pm 1$	
PySR	6.98
SymbolNet	7.07
BDT	6.71

$$d^{\text{PySR}} = \frac{1.8566 \sin \Delta\phi_{jj}}{\left| \frac{0.3080 x_{j_1} \log \Delta\eta_{jj} + \log \Delta\eta_{jj} \sinh(x_{j_2} - 2.5977) + 0.3080 \sinh x_h}{x_{j_1} \log \Delta\eta_{jj} + \sinh x_h} \right| + 0.6047}$$

with $x = p_T / m_h$

Conclusions

Conclusions



- particle physics is in the precision era
  → large amounts of multidimensional data
- ML methods excel in such an environment
- important requirements: uncertainties and interpretability
- key ingredient: representation learning based on particle theory

→ ML is an essential tool for the future of particle physics

Appendix

The goal of particle physics

→ Answer the big fundamental questions!

Nature of EWSB

Neutrino masses

.....

Dark matter

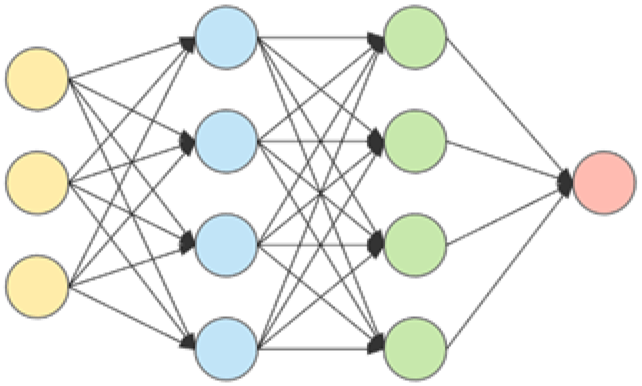
Baryon asymmetry

Naturalness

Can ML find answer these questions for us? **No!**

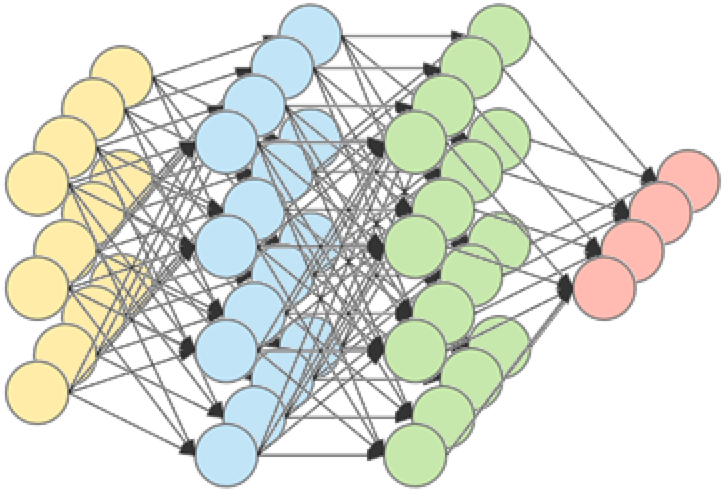
Can it help us with it? **Yes!**

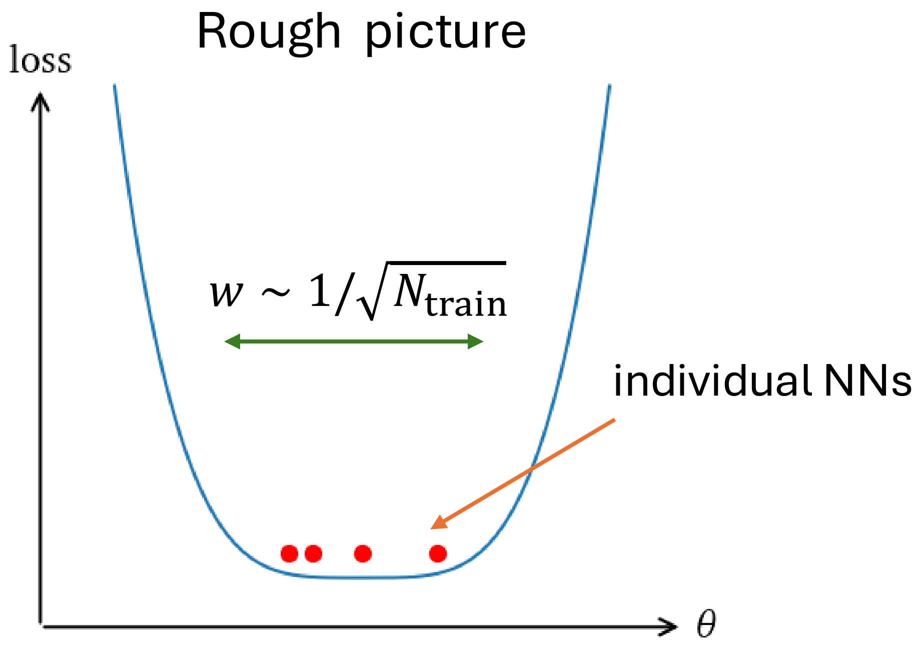
Modelling the statistical uncertainty



- train ensemble of networks
- each networks leads to slightly different result
- spread of network predictions ~ statistical uncertainty
- less data → higher spread

Modelling the statistical uncertainty





- train ensemble of networks
- each networks leads to slightly different result
- spread of network predictions ~ statistical uncertainty
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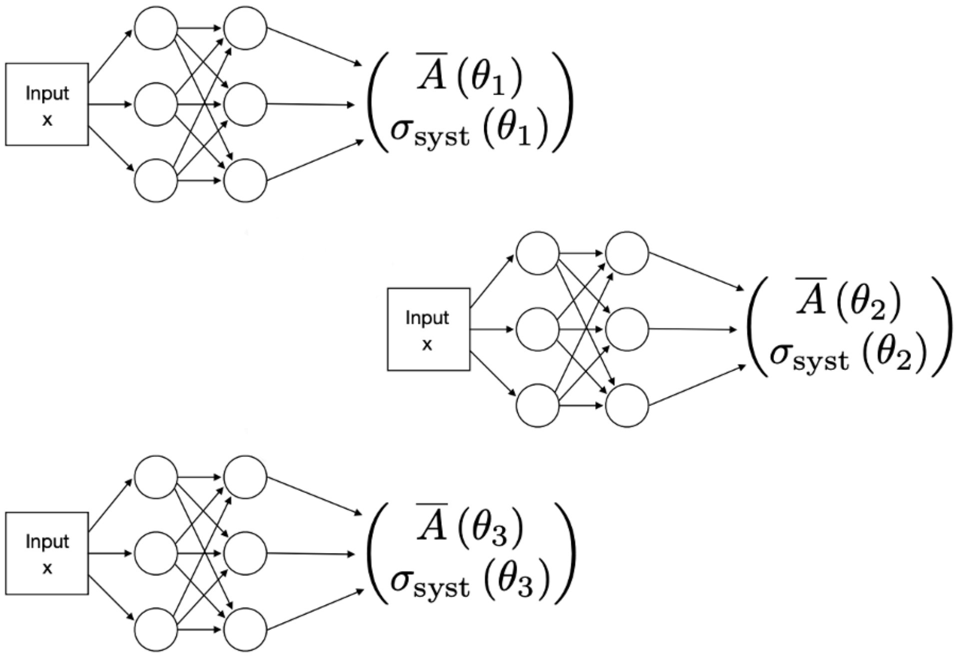
Bringing it all together



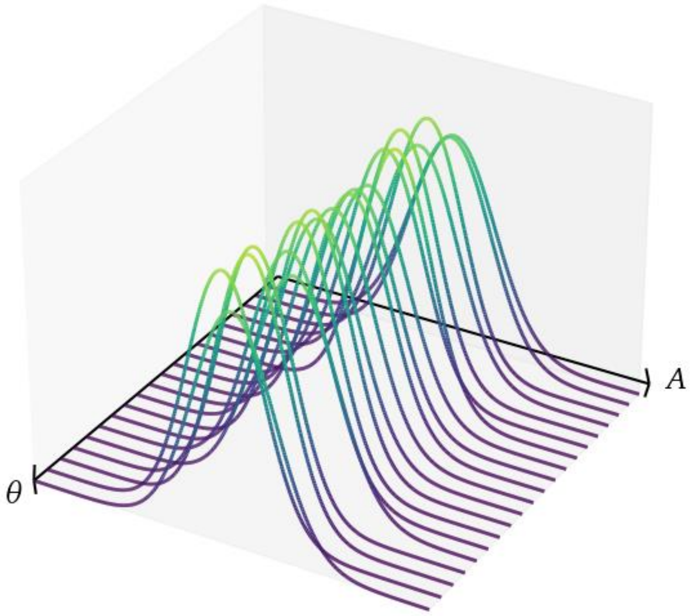
$$\begin{pmatrix} \overline{A}(\theta_1) \\ \sigma_{\text{syst}}(\theta_1) \end{pmatrix}, \quad \begin{pmatrix} \overline{A}(\theta_2) \\ \sigma_{\text{syst}}(\theta_2) \end{pmatrix}, \quad \begin{pmatrix} \overline{A}(\theta_3) \\ \sigma_{\text{syst}}(\theta_3) \end{pmatrix}$$

$$\langle A \rangle = \frac{1}{N} \sum_i^N \overline{A}(\theta_i)$$

$$\sigma^2_{\text{syst}} = \frac{1}{N} \sum_i^N \sigma^2_{\text{syst}}(\theta_i)$$

$$\sigma^2_{\text{stat}} = \frac{1}{N} \sum_i^N \left(\langle A \rangle - \overline{A}(\theta_i) \right)^2$$

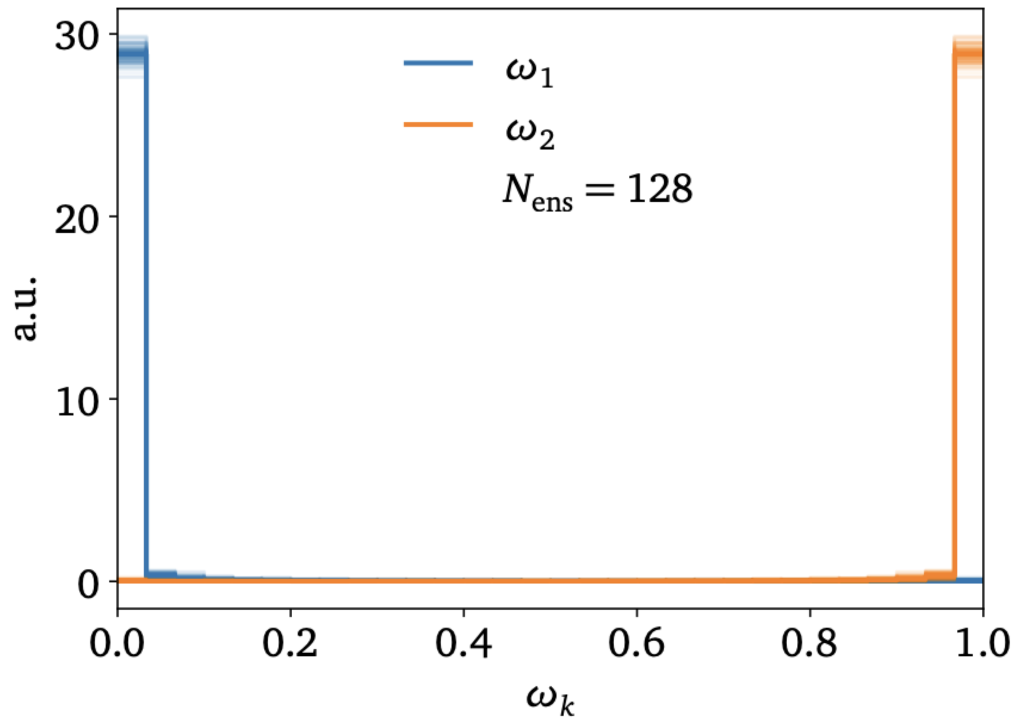
$$\sigma^2_{\text{tot}} = \sigma^2_{\text{syst}} + \sigma^2_{\text{stat}}$$



➡ Combined learnable modelling of systematic and statistical uncertainties!

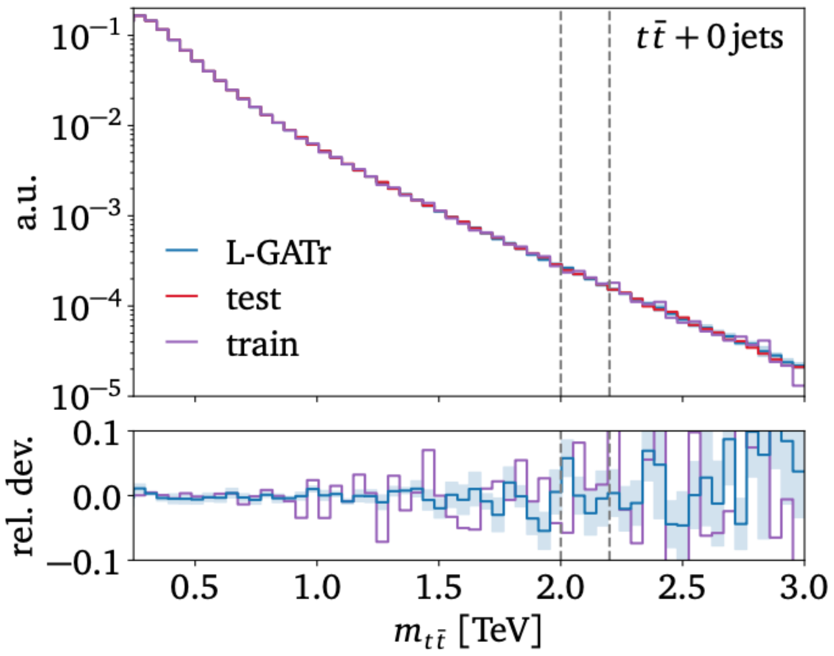
Alternative approaches: Bayesian neural networks, evidential regression

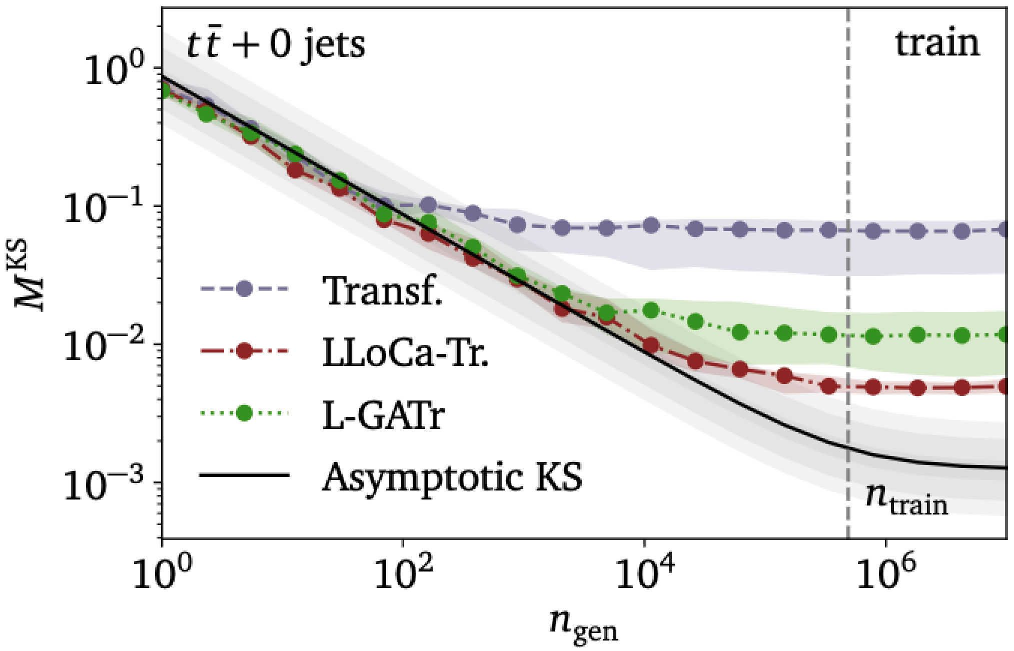
Gaussian mixture model



$$p_{\text{GMM}}(A|x,\theta) = \sum_{k=1}^{K} \omega_k(x,\theta)\,\mathcal{N}\big(A\,\big|\,\bar{A}_k(x,\theta),\,\sigma_k^2(x,\theta)\big), \quad \text{with} \quad \sum_{k=1}^{K} \omega_k(x,\theta) = 1$$

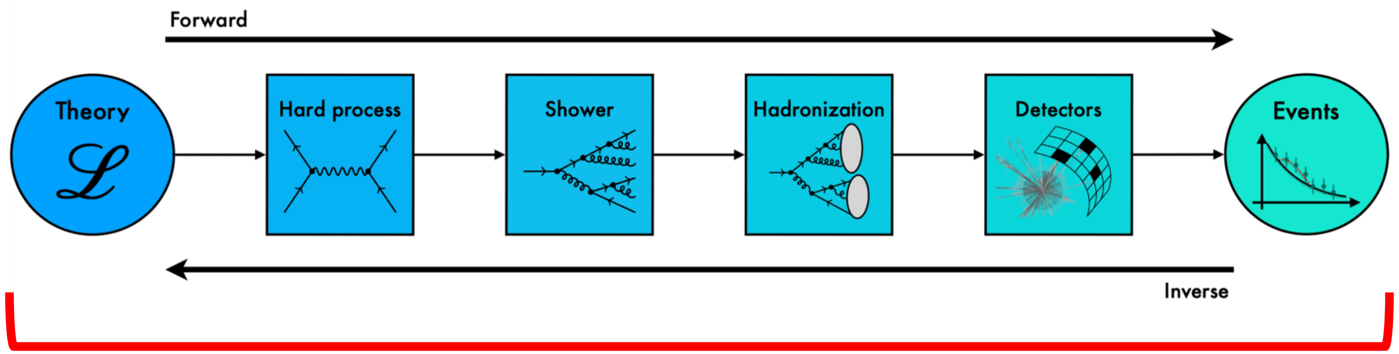
Controlling generative ML





Simulation-Based Inference

fully exploiting high-dimensional data

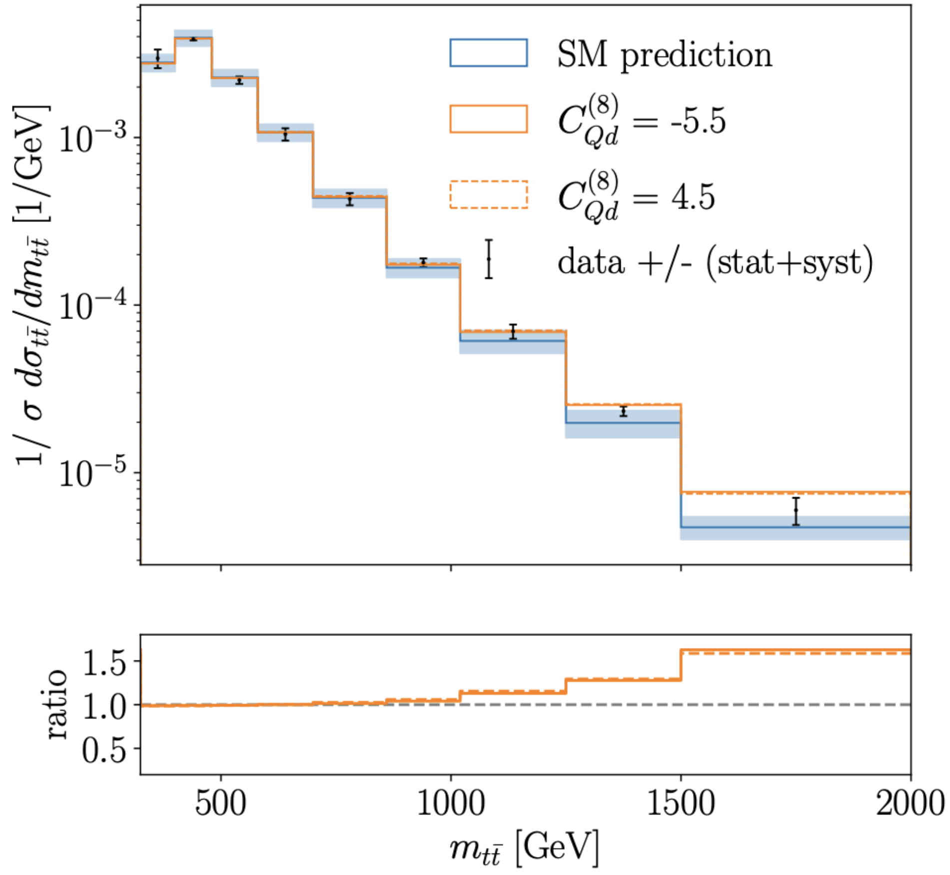


Classical parameter inference

- reduce dimension of phase space summary statistics
- bin summary statistics
- compare resulting histogram to SM/BSM predictions

→

[Elmer et al.,2312.12502]



Advantage: humanly digestible plots

Disadvantage: loss of information

Full likelihood

phase space point

theory parameters

- Monte-Carlo simulation chain allows us to sample full likelihood $p(x|\theta)$. But cannot directly compute it.

- Neyman-Pearson lemma: likelihood ratio $r(x|\theta,\theta_0) \equiv \frac{p(x|\theta)}{p(x|\theta_0)}$ is most powerful statistical test

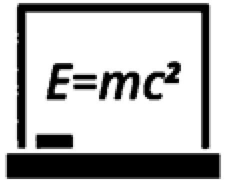
- but we can regress to reco-level $r(x|\theta,\theta_0)$ using known parton-level $r(z_p|\theta,\theta_0)$:

$$\mathcal{L} = \left\langle \left[r(z_p|\theta,\theta_0) - \underbrace{r_\varphi(x|\theta,\theta_0)}_{\text{NN}} \right]^2 \right\rangle_{\underbrace{x,z_p \sim p(x|z_p)p(z_p|\theta);\theta\sim q(\theta)}_{\text{average over event sample}}}$$

→ unbinned multi-dimensional inference without information loss

Encoding amplitude structure

[Schöfbeck et al., 2107.10859, 2205.12976]



Theory structure for e.g. SMEFT:

$$\mathscr{L}_{\mathrm{SMEFT}} = \mathscr{L}_{\mathrm{SM}} + \sum_i \frac{c_i}{\Lambda^2} O_i \equiv \mathscr{L}_{\mathrm{SM}} + \sum_i \theta_i O_i$$

$$|\mathcal{M}(z_p|\theta)|^2 = |\mathcal{M}_{\mathrm{SM}}(z_p)|^2 + \theta_i |\mathcal{M}_i(z_p)|^2 + \theta_i \theta_j |\mathcal{M}_{ij}(z_p)|^2$$

encode into likelihood

$$R(x|\theta,\theta_0) \equiv \frac{d\sigma(x|\theta)/dx}{d\sigma(x|\theta_0)/dx} = \frac{\sigma(\theta)p(x|\theta)}{\sigma(\theta_0)p(x|\theta_0)}$$

$$R(x|\theta,\theta_0) = 1 + (\theta-\theta_0)_i R_i(x) + (\theta-\theta_0)_i(\theta-\theta_0)_j R_{ij}(x)$$

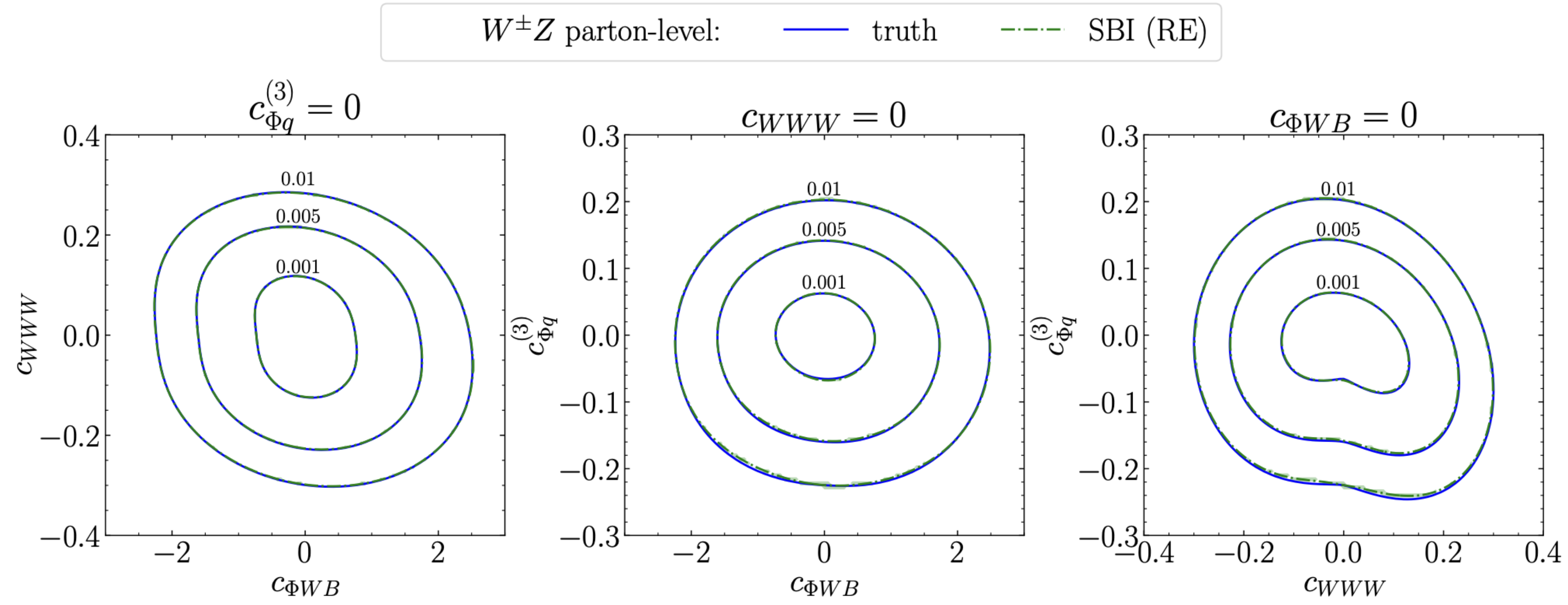
$$R_i(z_p) \equiv \frac{\partial}{\partial\theta_i} \frac{d\sigma(z_p|\theta)/dz_p}{d\sigma(z_p|\theta_0)/dz_p}\bigg|_{\theta=\theta_0} = \frac{\partial_{\theta_i}|\mathcal{M}(z_p|\theta)|^2}{|\mathcal{M}(z_p|\theta_0)|^2}\bigg|_{\theta_0}$$

$$R_{ij}(z_p) \equiv \frac{\partial^2}{\partial\theta_i\partial\theta_j} \frac{d\sigma(z_p|\theta)/dz_p}{d\sigma(z_p|\theta_0)/dz_p}\bigg|_{\theta=\theta_0} = \frac{\partial_{\theta_i}\partial_{\theta_j}|\mathcal{M}(z_p|\theta)|^2}{|\mathcal{M}(z_p|\theta)|^2}\bigg|_{\theta_0}$$

➡ learn coefficients $R_{i,ij}$ separately → theory parameter dependence fully factored out

Parton-level cross-check: $W^{\pm}Z$ production

- consider effects of three SMEFT operators

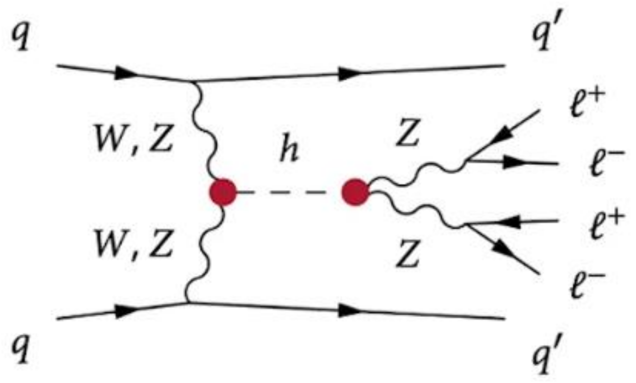


[HB et al.,2410.07315]

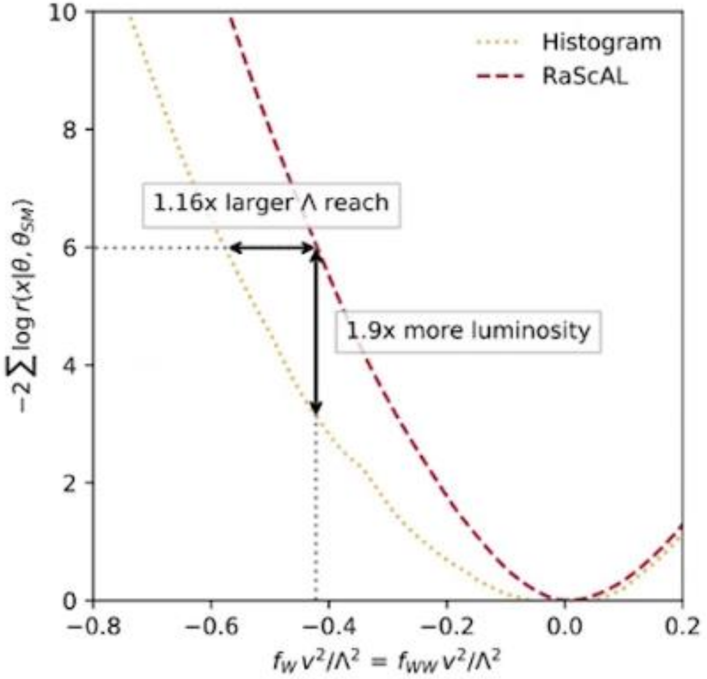
almost perfectly learns high-dimensional likelihood

Reco-level: VBF with $H \to 4\ell$

[Brehmer et al., 1805.00013]



$$\mathcal{L} = \mathcal{L}_{\mathrm{SM}} + \boxed{\frac{f_W}{\Lambda^2}} \underbrace{\frac{ig}{2}\,(D^\mu\phi)^\dagger\,\sigma^a\,D^\nu\phi\,W^a_{\mu\nu}}_{\mathcal{O}_W} - \boxed{\frac{f_{WW}}{\Lambda^2}} \underbrace{\frac{g^2}{4}\,(\phi^\dagger\phi)\,W^a_{\mu\nu}\,W^{\mu\nu\,a}}_{\mathcal{O}_{WW}}$$



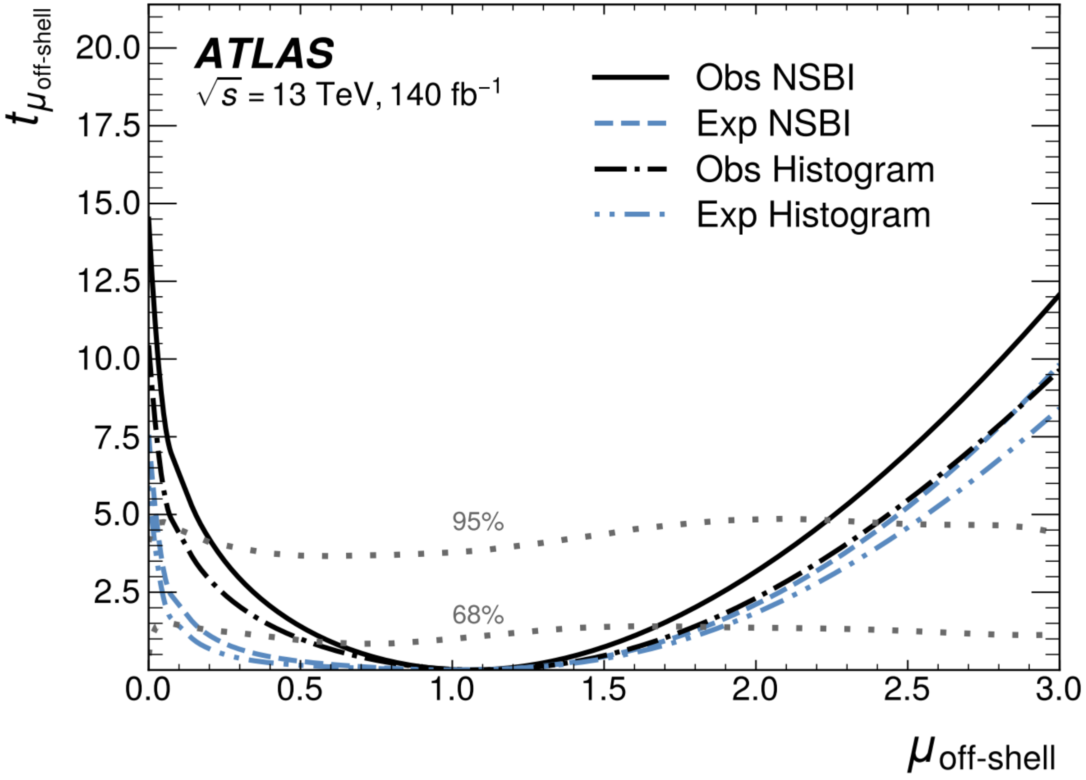
Huge potential to improve sensitivity of a wide variety of measurements/searches

But is SBI also viable in a realistic analysis including uncertainties etc.?

1st experimental SBI analysis

[ATLAS-CONF-2024-016]

- goal: measure off-shell signal strength in $H \to ZZ$ channel
- full treatment of statistical and systematic uncertainties
- large sensitivity improvement for low $\mu_{\text{off-shell}}$



➡ proves potential of SBI for full experimental analysis