

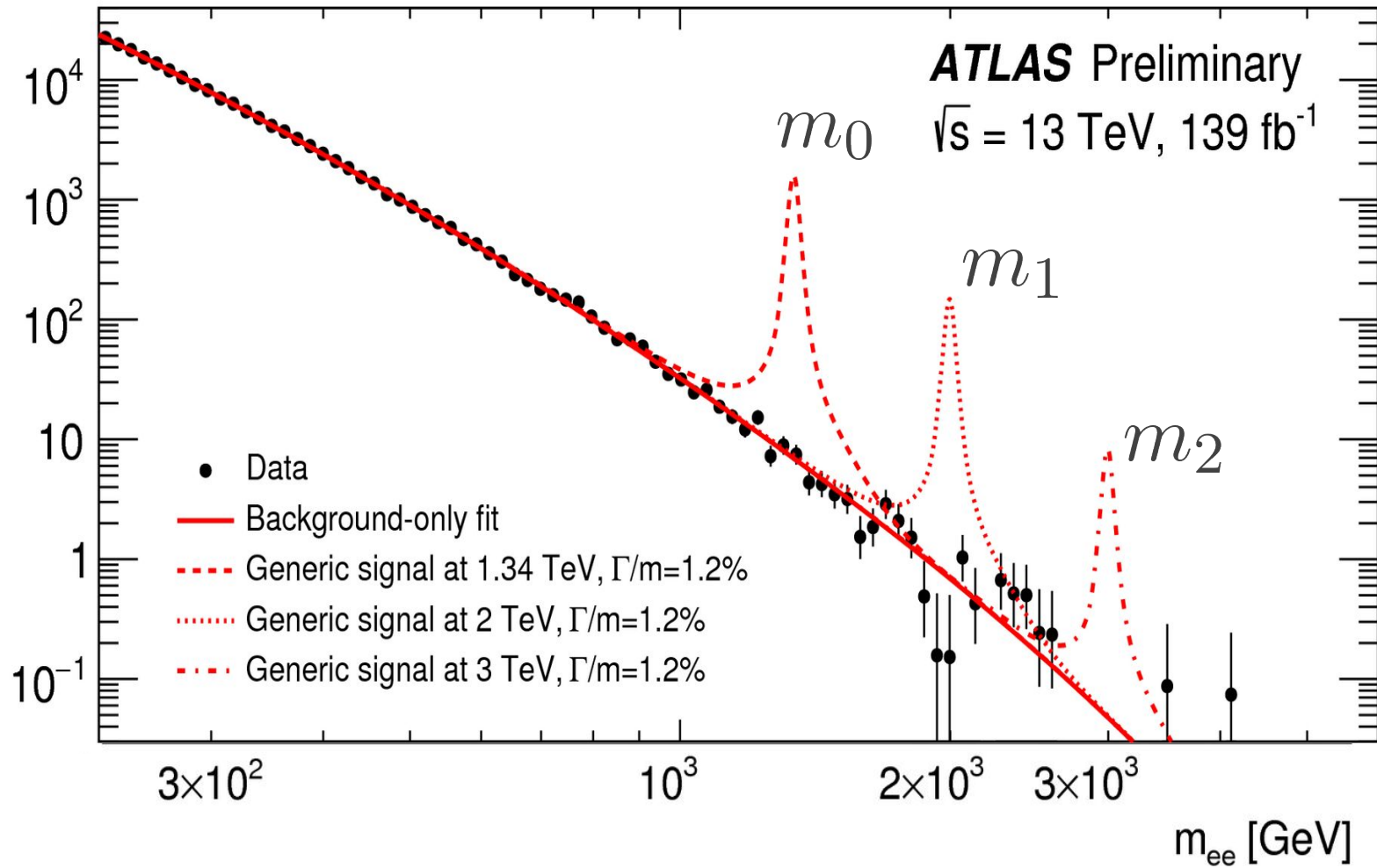
Simulation Based Inference(SBI) in RooFit

Robin Syring

Supervisor: Jonas Rembser

Student Sessions - 09/08/2024

Events / 10 GeV





▶ hypothesis mass m_0

▶ measured data with mass m

$$\mathcal{L}(m_0) = p(m|m_0)$$

▶ Likelihood \mathcal{L}

▶ probability density function p



$$\mathcal{L}_{ratio}(m_0) = \prod_i \frac{p(m_i|m_0)}{p_{ref}(m_i)}$$

$$p(m_i|m_0) = \int dz_d \int dz_s \int dz_p p(m_i, z_d, z_s, z_p|m_0)$$

- ▶ Integrals cannot be evaluated directly
 - Detector simulations take time



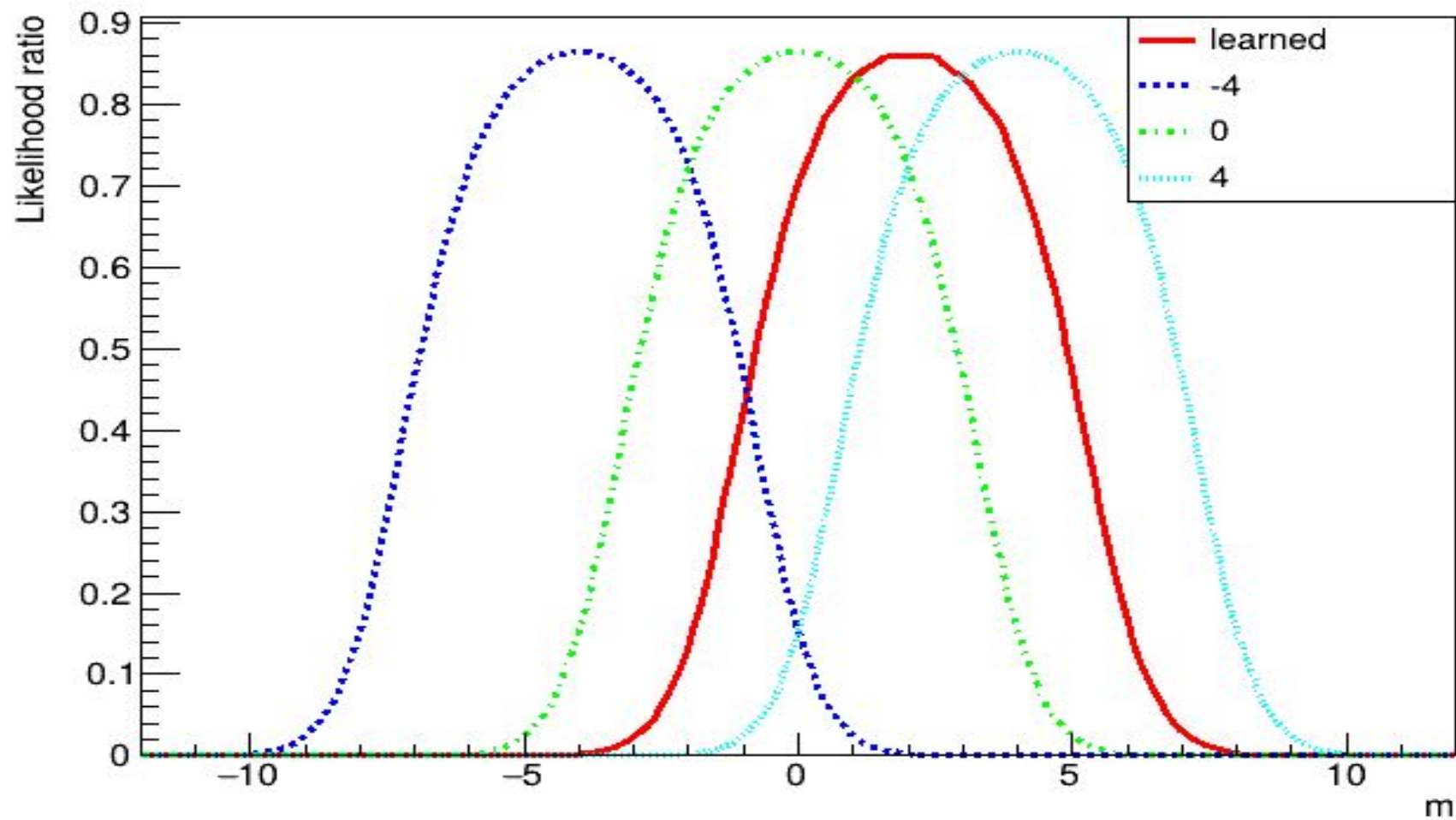
SBI = Use of ML to learn the
likelihood function



- ▶ train **classifier** to
 - ▶ **discriminate** between samples $m_i \sim p(m_i|m_0)$ $m_i \sim p_{ref}(m_i)$
 - ▶ **transform** output of classifier $\hat{s}(m_i|m_0)$ to estimator of likelihood ratio function by

$$\mathcal{L}_{ratio}(m_0) = \prod_i \frac{1 - \hat{s}(m_i|m_0)}{\hat{s}(m_i|m_0)}$$

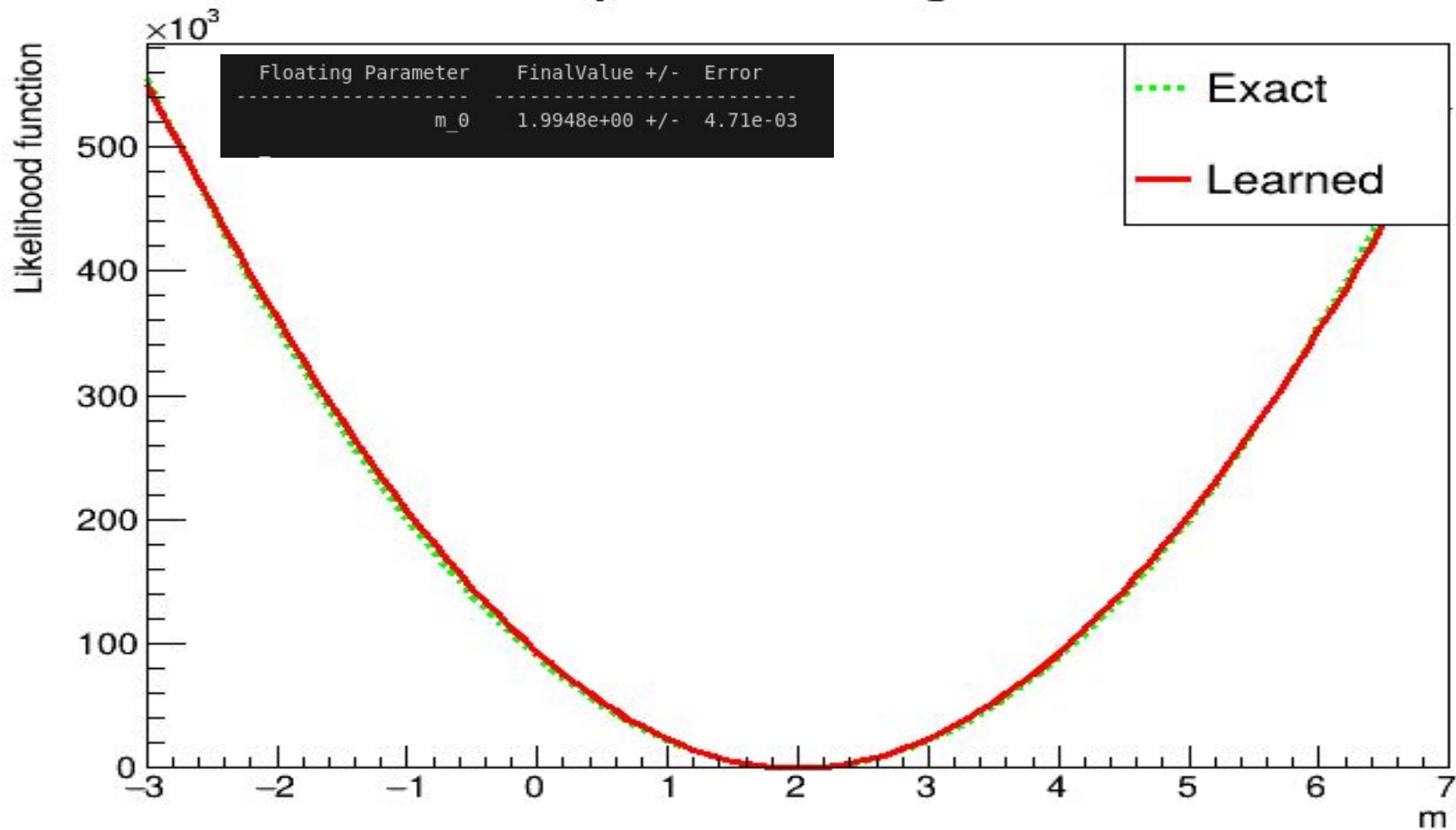
Extrapolation via SBI





- ▶ Model generalizes from 'seen' values to 'unseen'
- ▶ reduction of necessary data samples i.e. detector simulations

Learned vs analytical summed logarithmic Likelihood





Implementation



- ▶ **ROOT** for High Energy Physics:
 - Powerful **data analysis framework** for HEP
 - Developed at **CERN** for processing, analysis, and visualization
- ▶ **RooFit**:
 - ROOT's library for statistical analysis in HEP
 - Provide tools for parameter estimation as likelihoods





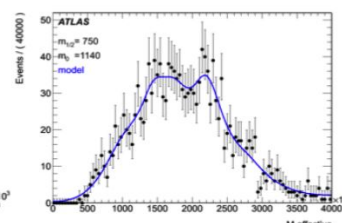
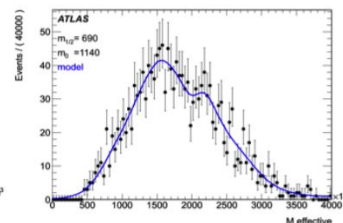
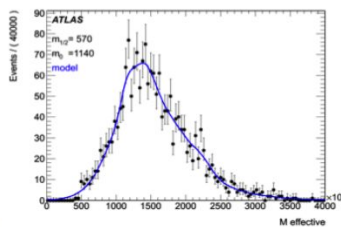
- ▶ wrapper to call [arbitrary python functions](#) in ROOT
- ▶ For showcase: MLP from Sklearn
- ▶ integrate declaration and definition of class in running codebase



Next Steps



- ▶ Provide test/use case for high dimensional problems
- ▶ comparison to currently used methods (template histograms)
 - evaluate proposed generalization behavior
- ▶ Final result: `rf615_learned_likelihoods.py`





Thank you!