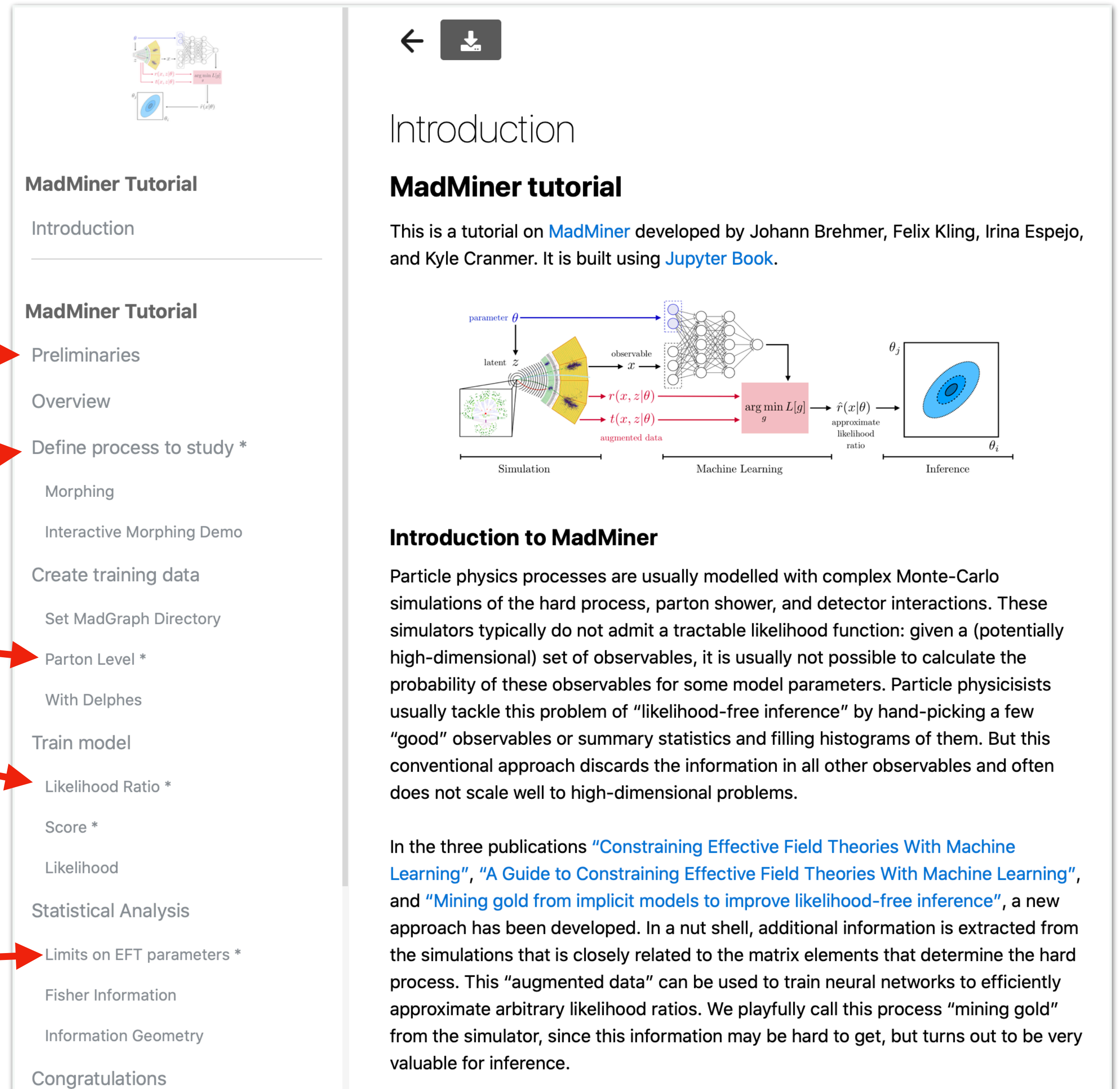


# Hands-on Tutorial

- Step-by-step instructions
- Do Preliminaries
  - Need to install Docker
  - And then start Jupyter
- Step 1 is fast
- Step 2 takes ~25 min
- Step 3 takes ~20 min
- While they are running I will lecture
- Then we will finish with results



The screenshot shows the MadMiner tutorial website. On the left is a table of contents with red arrows pointing from the list on the left to specific items. On the right is the 'Introduction' page, which includes a diagram of the MadMiner workflow and an introductory text.

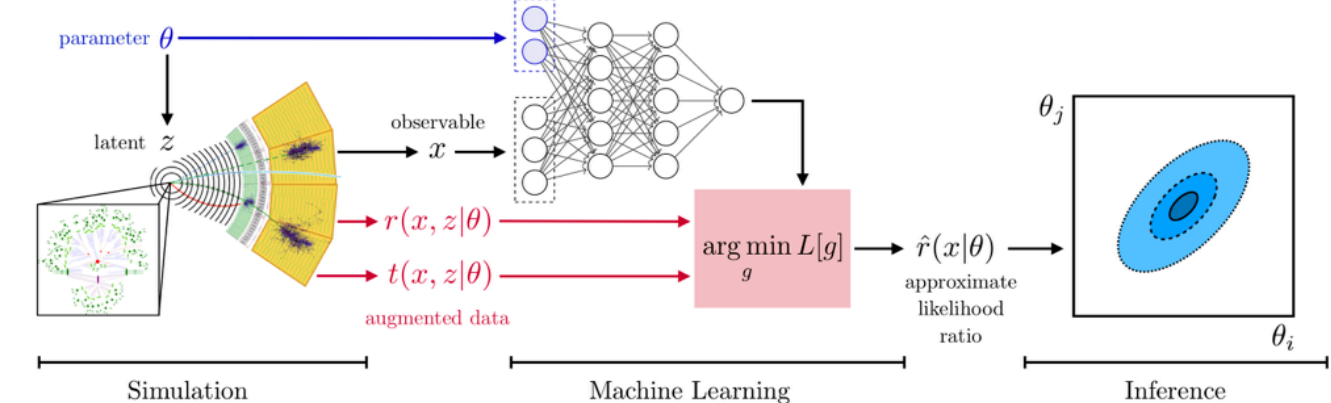
**MadMiner Tutorial**

- Introduction
- MadMiner Tutorial**
- Preliminaries
- Overview
- Define process to study \*
- Morphing
- Interactive Morphing Demo
- Create training data
  - Set MadGraph Directory
  - Parton Level \*
  - With Delphes
- Train model
  - Likelihood Ratio \*
  - Score \*
  - Likelihood
- Statistical Analysis
  - Limits on EFT parameters \*
  - Fisher Information
  - Information Geometry
- Congratulations

**Introduction**

**MadMiner tutorial**

This is a tutorial on [MadMiner](#) developed by Johann Brehmer, Felix Kling, Irina Espejo, and Kyle Cranmer. It is built using [Jupyter Book](#).



**Introduction to MadMiner**

Particle physics processes are usually modelled with complex Monte-Carlo simulations of the hard process, parton shower, and detector interactions. These simulators typically do not admit a tractable likelihood function: given a (potentially high-dimensional) set of observables, it is usually not possible to calculate the probability of these observables for some model parameters. Particle physicists usually tackle this problem of “likelihood-free inference” by hand-picking a few “good” observables or summary statistics and filling histograms of them. But this conventional approach discards the information in all other observables and often does not scale well to high-dimensional problems.

In the three publications “[Constraining Effective Field Theories With Machine Learning](#)”, “[A Guide to Constraining Effective Field Theories With Machine Learning](#)”, and “[Mining gold from implicit models to improve likelihood-free inference](#)”, a new approach has been developed. In a nut shell, additional information is extracted from the simulations that is closely related to the matrix elements that determine the hard process. This “augmented data” can be used to train neural networks to efficiently approximate arbitrary likelihood ratios. We playfully call this process “mining gold” from the simulator, since this information may be hard to get, but turns out to be very valuable for inference.