

Simulation-based Inference

Inverting Simulators

Talk by Stefan Wezel

mlcolab @ Tübingen University Cluster of Excellence

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Overview

- The problem setting
- Traditional approaches and their issues
- Using Bayesian Neural Nets to alleviate them
- A worked example
- A more interesting, real-world example
- Outlook

What and Why?

An Example

- Inverting simulators - so first let's find out what a simulator is
- Imagine you are a physicist
- You have also highly sophisticated experiments that can produce observations
- You have highly sophisticated models, theories that can produce observations like from your experiment, that were developed over centuries
- But what do we actually care about? How do you perform inference?
 - What were the parameters for your observation

What and Why?

An Example

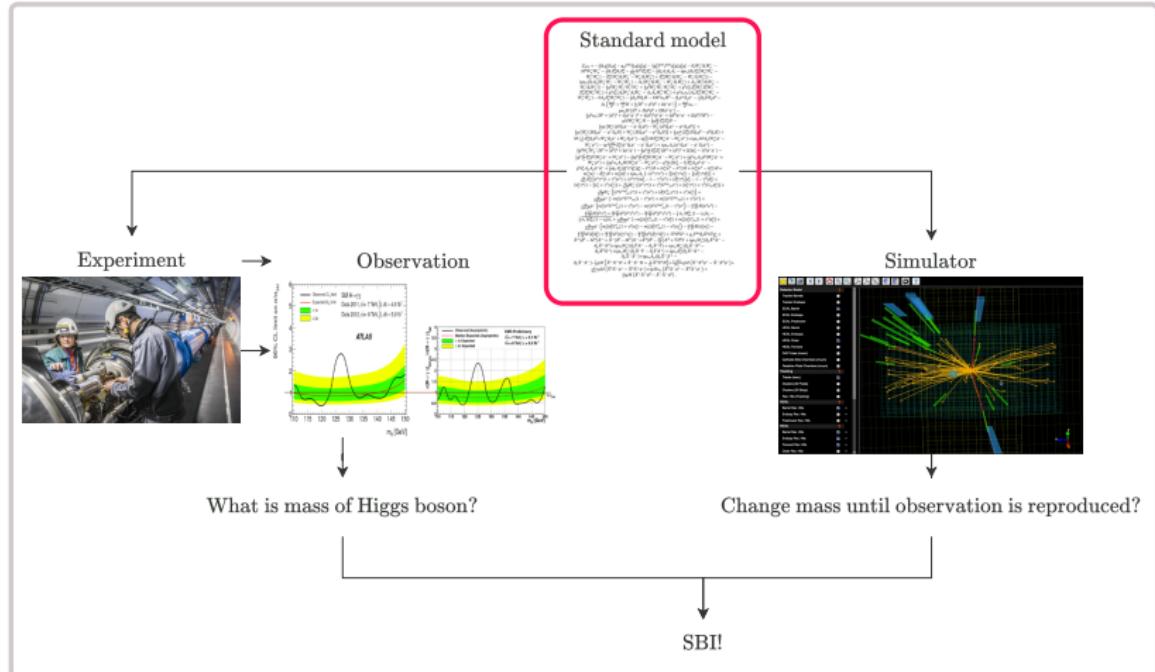


Figure derived from cern.ch, Achintya Rao and Tom McCauley, sciencealert.com

What and Why?

An Example

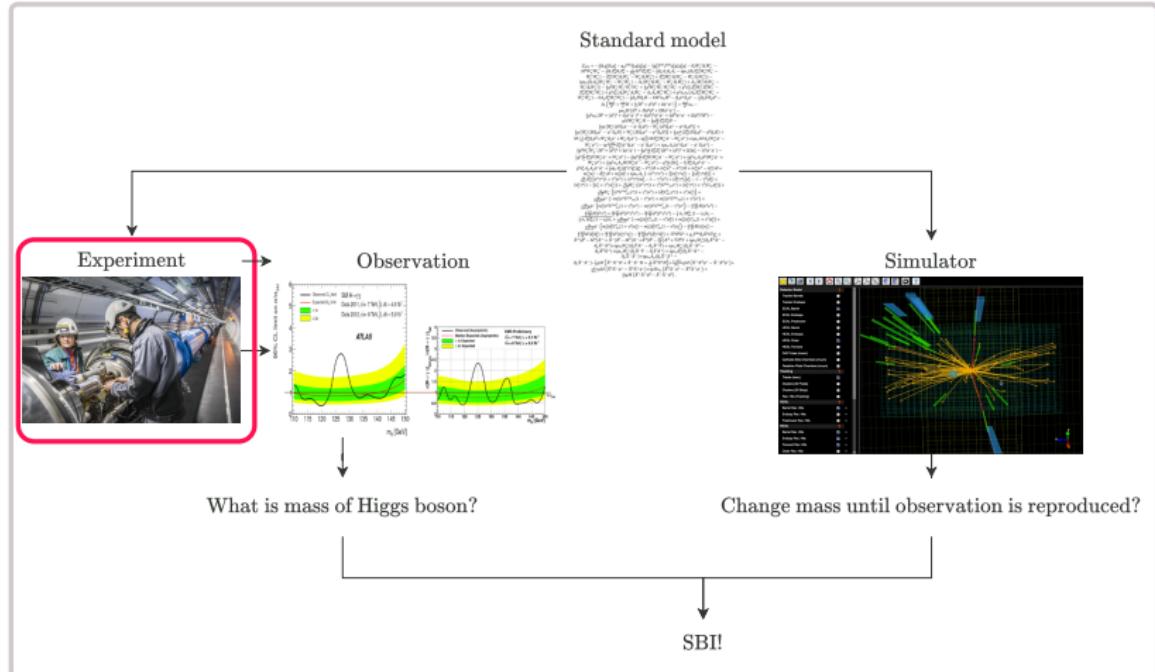


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What and Why?

An Example

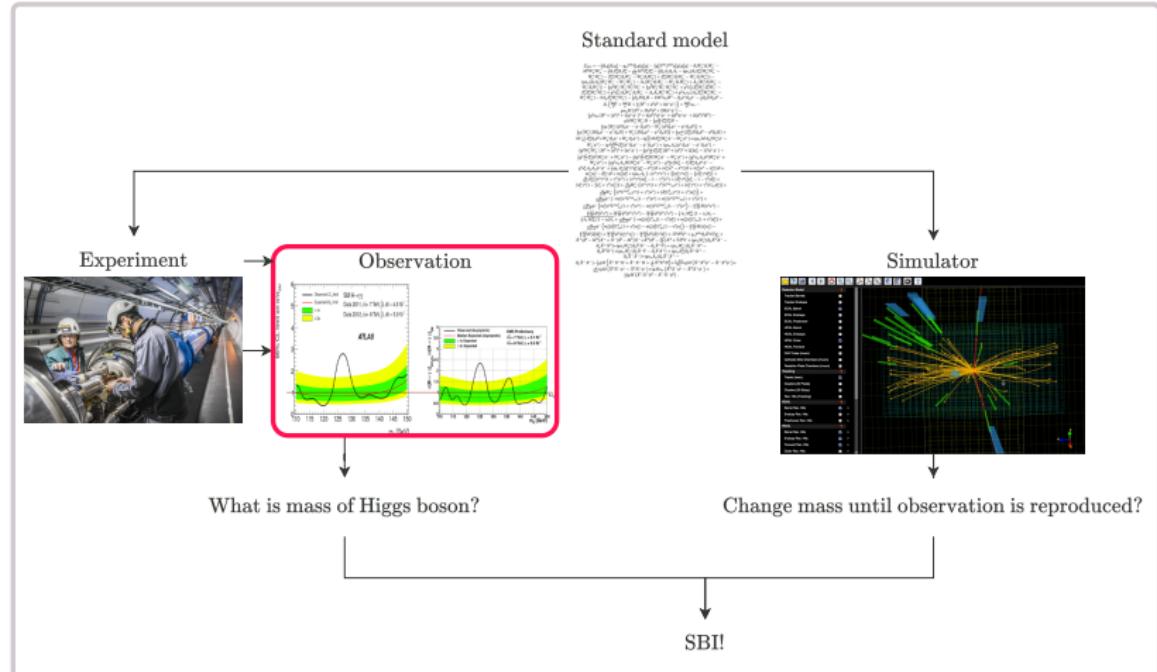


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What and Why?

An Example

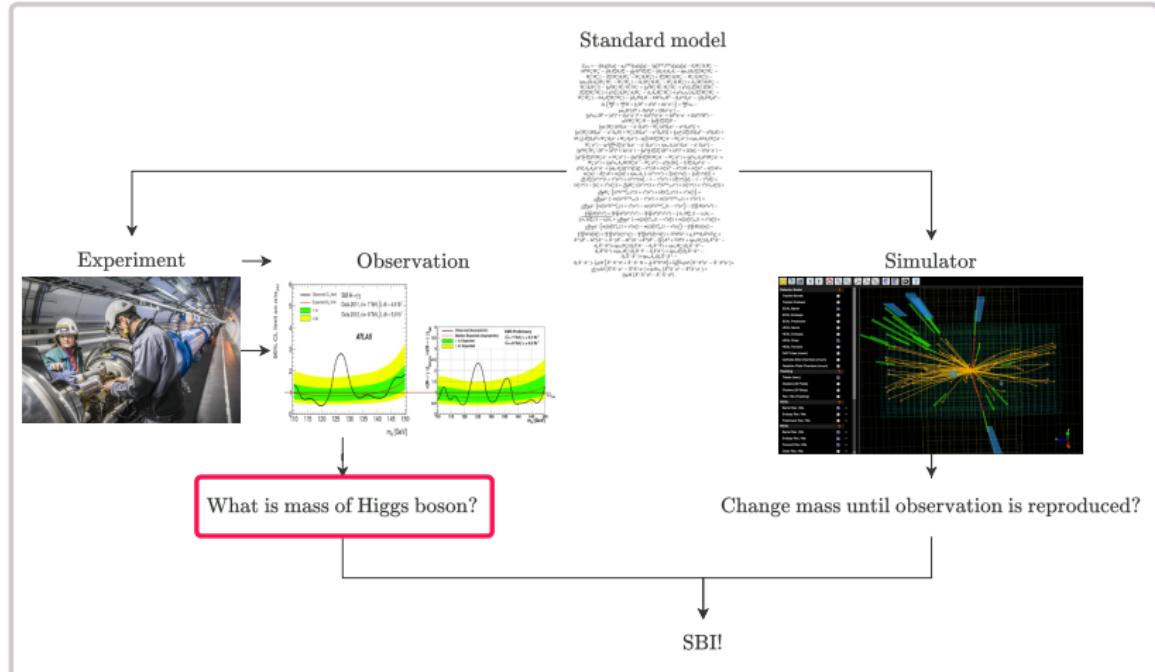


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What and Why?

An Example

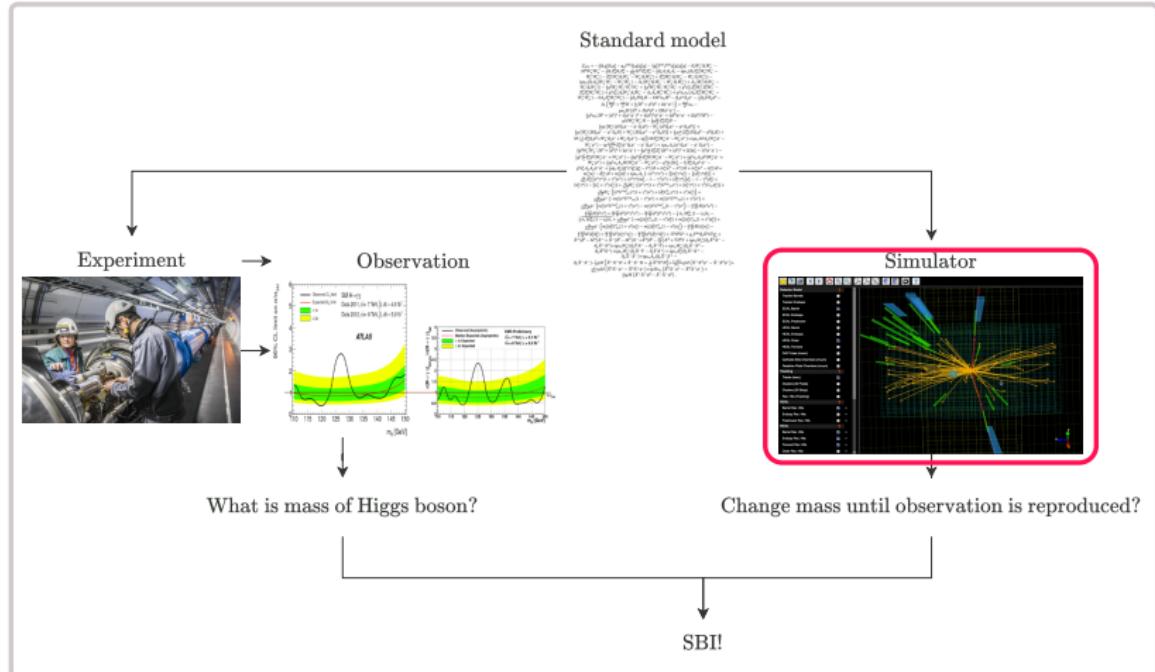


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What and Why?

An Example

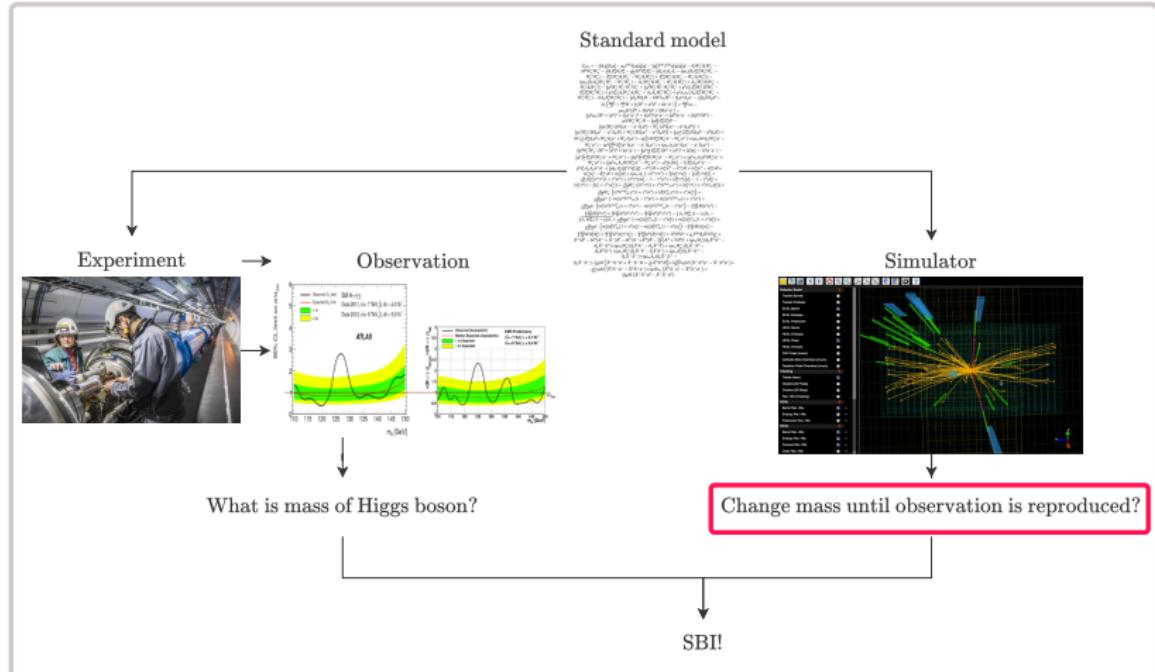


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What and Why?

An Example

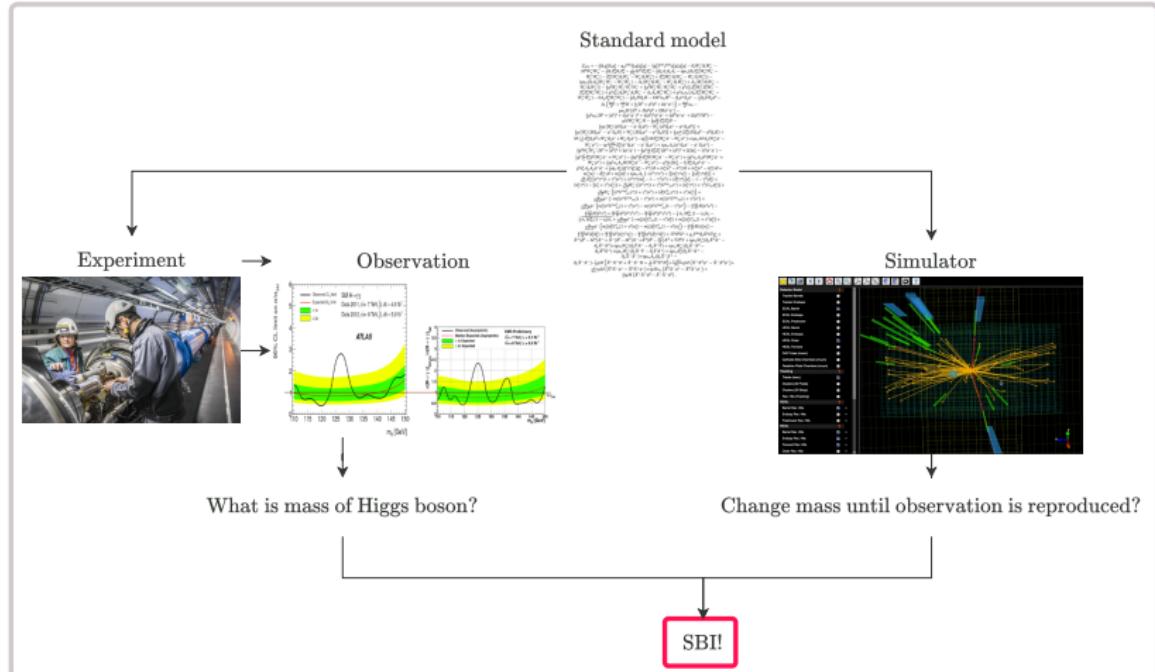


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What and Why?

Formalizing our Example

- Mechanistic model (simulator) has parameters θ and produces data \hat{x}
 - It implicitly defines $p(\hat{x}|\theta)$ (it yields samples from this distribution)
- Given a (real) observation x_0 , we would be interested in the parameters that produced it
 - $p(\theta|x_0)$ -> posterior over parameters
 - In simple cases, we could apply Bayes' rule and compute it analytically
 - What is simple? If we know Likelihood
 - But often we would not

What and Why?

Simulation-based Inference to the rescue

- This is exactly a problem setting that scientists often deal with
 - They have a sophisticated model (the simulator) that encapsulates a lot of prior knowledge
 - But inference in this setting often boils down to: What were parameters that produced this observation
- Simulation-based Inference inference tries to solve this problem
 - by inverting the simulator

Simulation-based Inference

Traditional Approach

- Broader term: Approximate Bayesian Computation (ABC)
 - Rejection ABC
 - Sampling ABC (perturb initial params)
 - Sequential ABC
 - But gives only point estimates, not full posterior
 - within ϵ
- Some improvements are MCMC ABC and Sequential ABC but they only improve sample efficiency but still produce merely point estimate

Learning a Posterior

Bayesian Neural Nets to the Rescue

- Create n training samples
- learn posterior over parameters by parametrizing GMM with DNN

How to use SBI?

Some advertisement

- Now that you are pretty excited about SBI and its applications
- mlcolab and mackelab is developing a python (and eventually Julia) library (that I've used earlier)
- If you are interested: try it out and give us your feedback
- link to colab
- link to github



References

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How

Approximate Bayesian Computation

- Finding parameters/posterior over parameters with
 - Rejection ABC
 - Markov Chain Monte Carlo ABC
 - Sequential Monte Carlo ABC
 - ...
- Problems
 -

What

is Simulation-based Inference?

- If we know generating factors, we can build a simulator
- But we want to constrain simulator output on observations from real world
- Thus we need realistic values for simulator parameters
- -> inverse problem
- SBI solvers this inverse problem using Bayesian inference

How

does Simulation-based Inference work?