Constraining effective field theories with machine learning

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HEFT 2019, Louvain-la-Neuve


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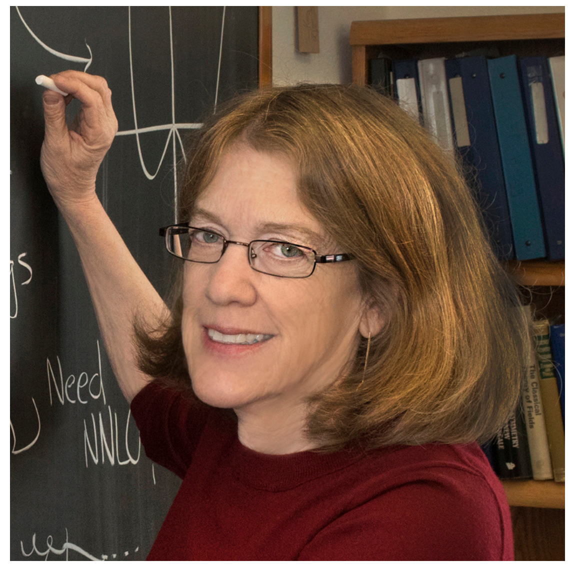
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Sam Homiller


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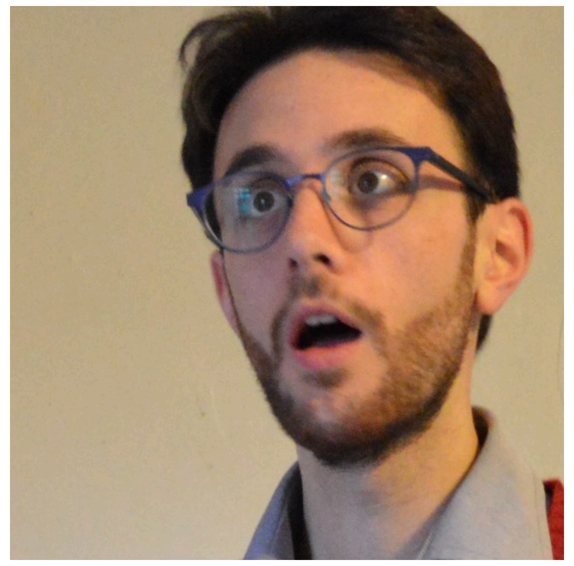
Duccio Pappadopulo


Marco Farina

Thanks to Kyle, Gilles, Felix, Irina, and Sam for material and inspiration for slides!

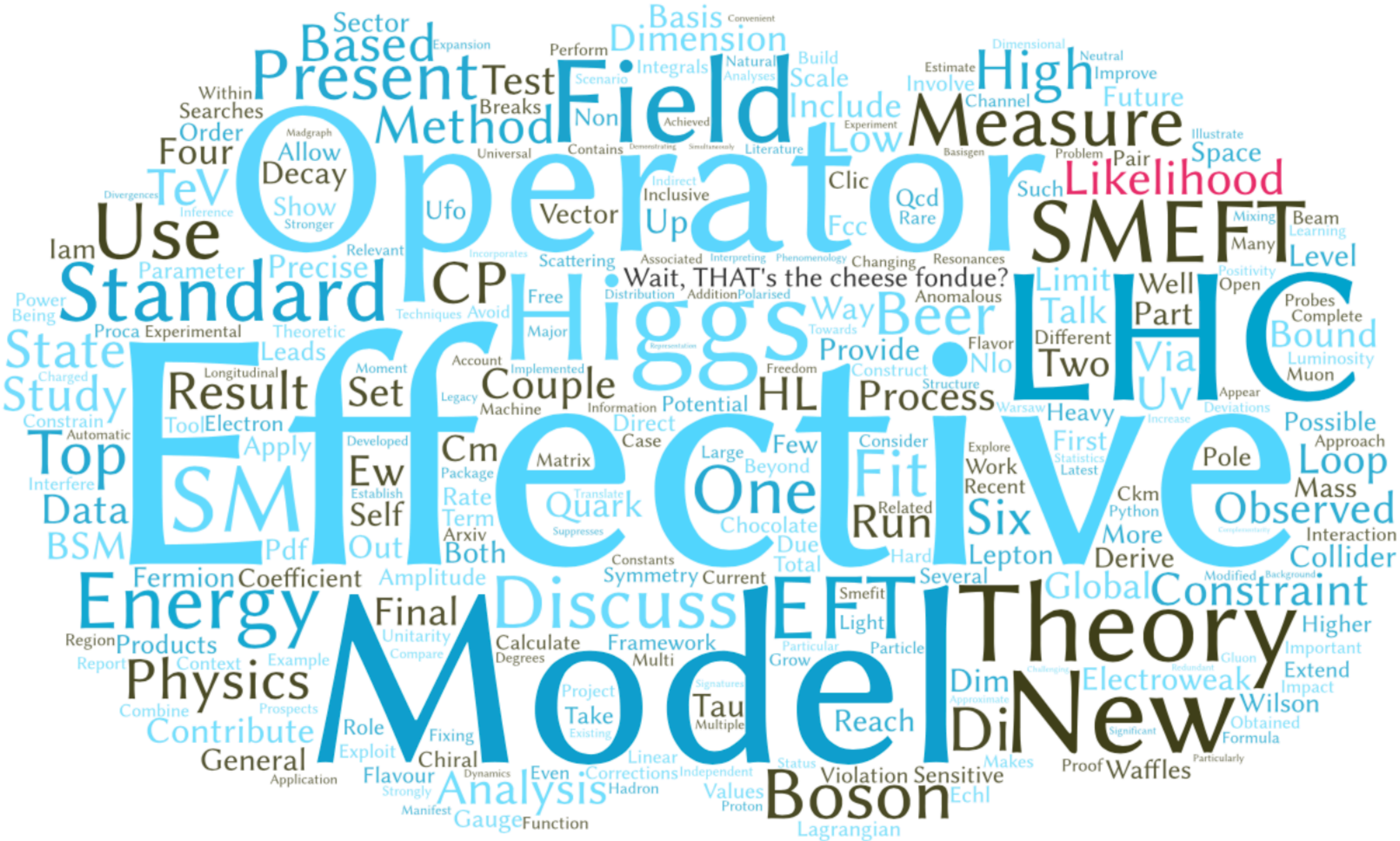
NYU

MSDSE
Moore - Sloan
Data Science Environments

dianahep

iris hep
Institute for Research and Innovation
in Software for High Energy Physics

The SCAILFIN Project
scailfin.github.io



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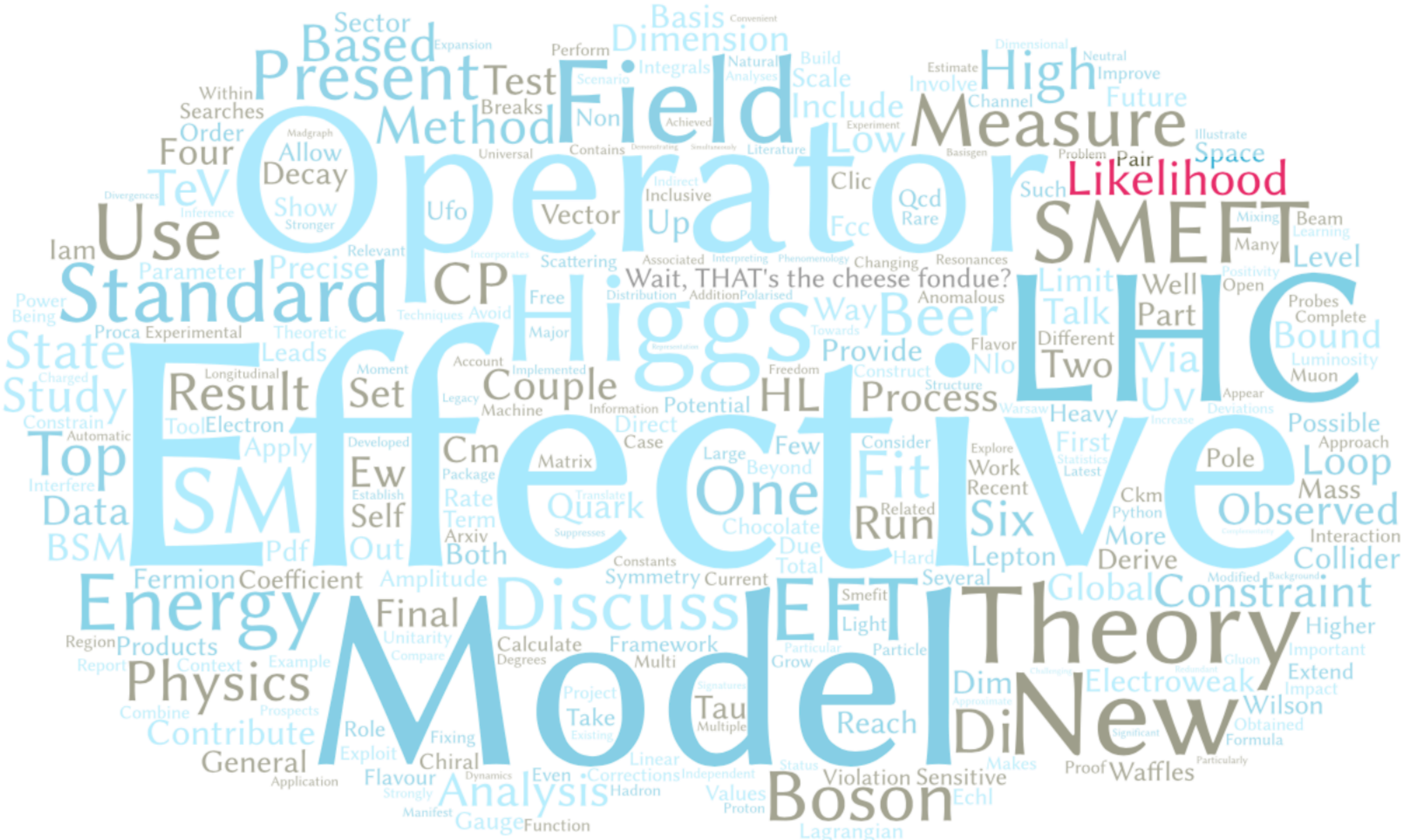
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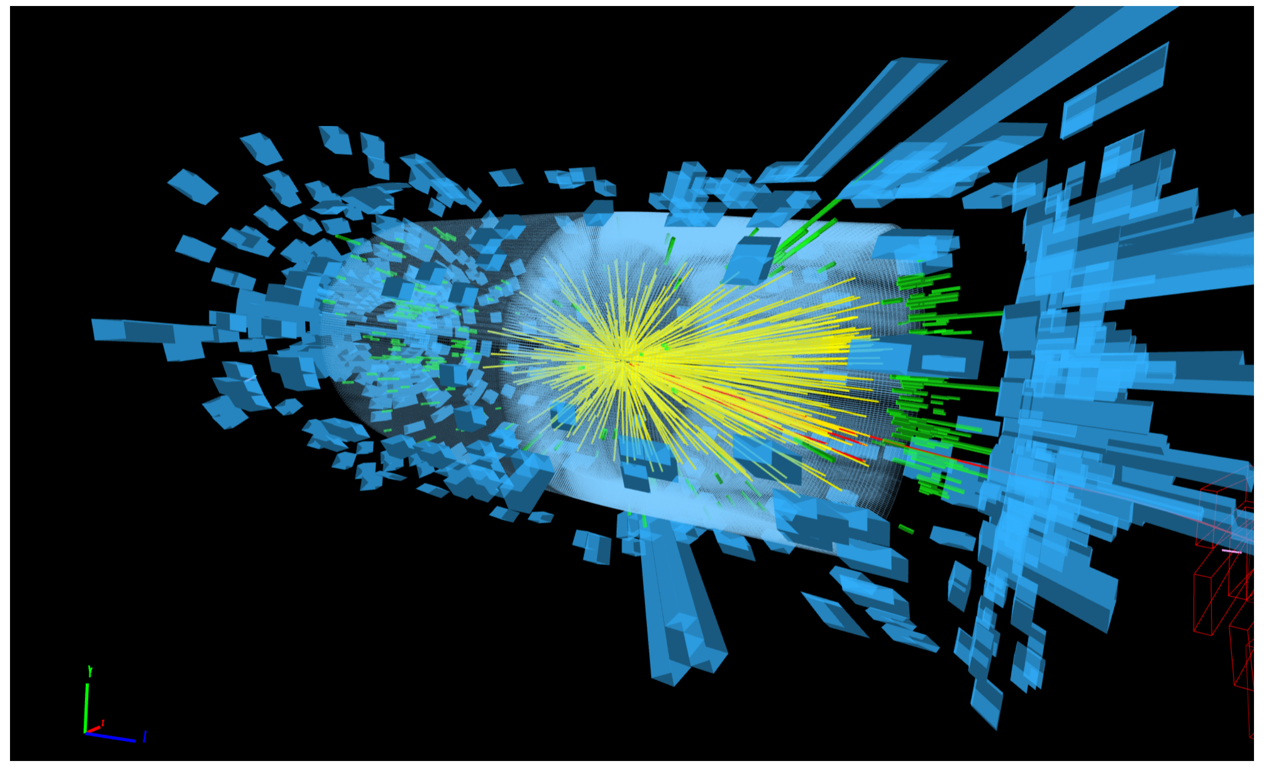
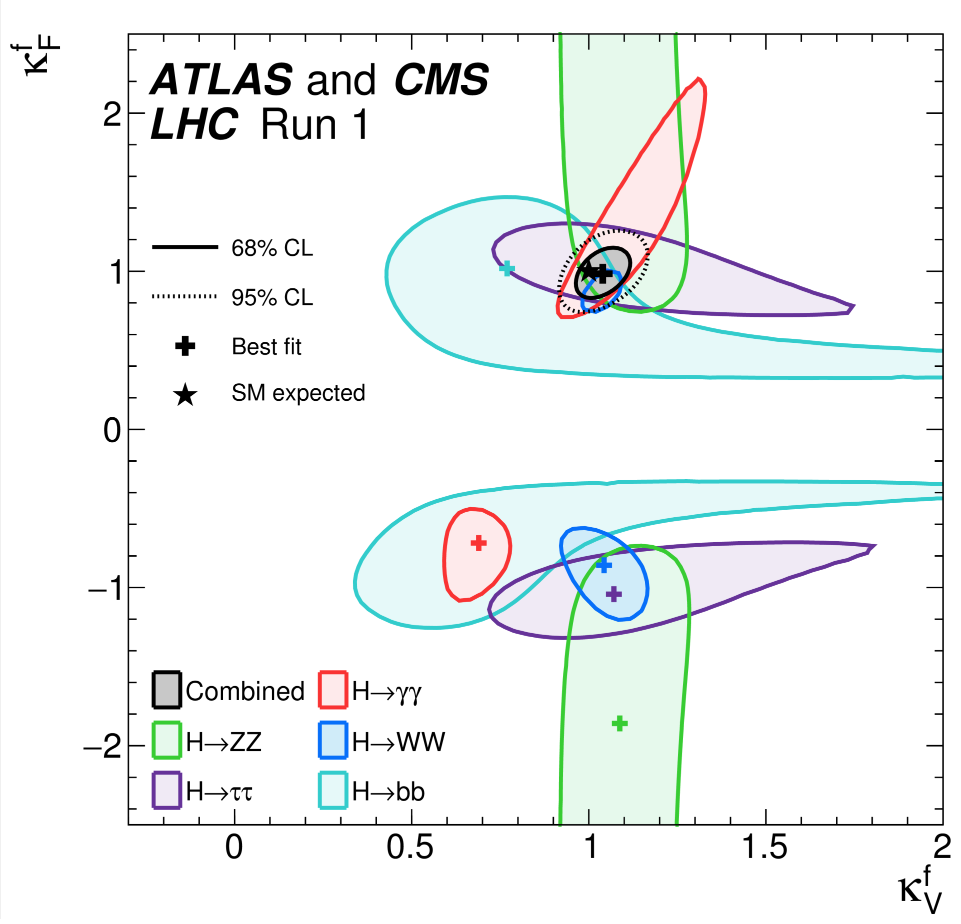
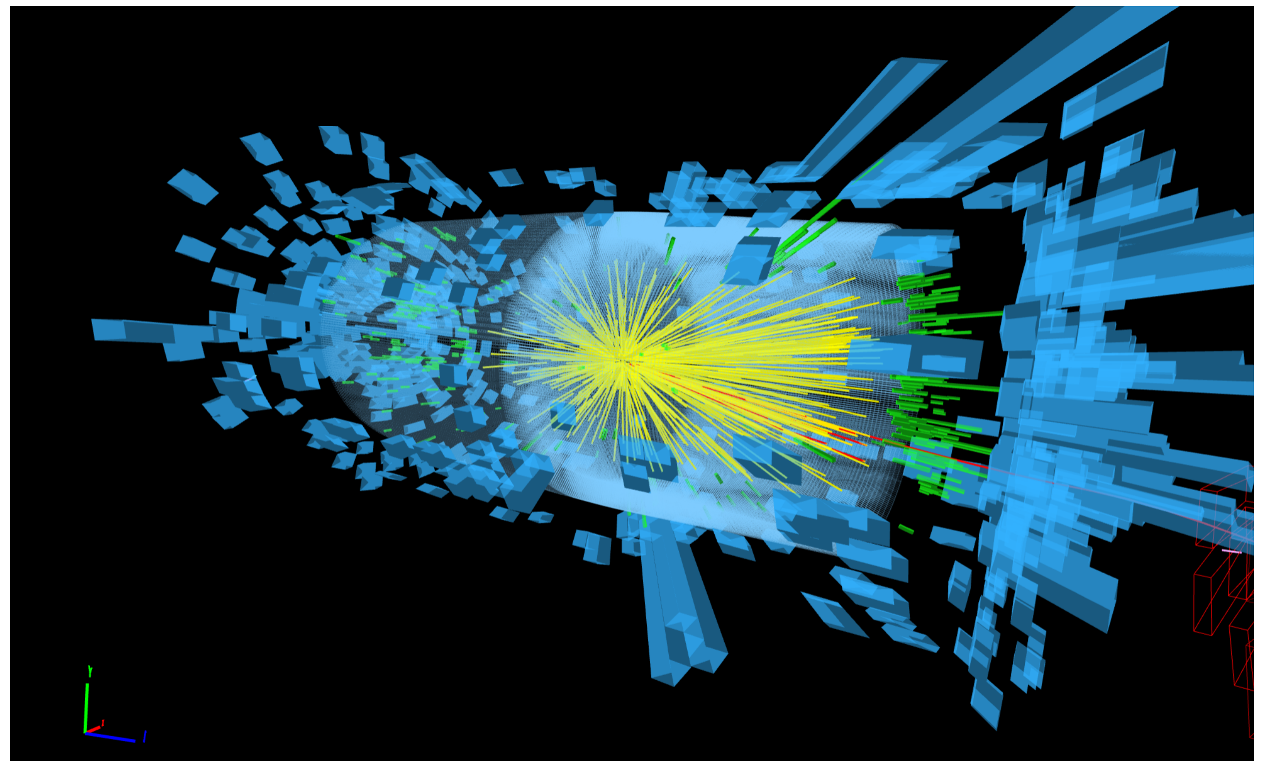


High-dimensional
event data x



Constraints on
parameters θ

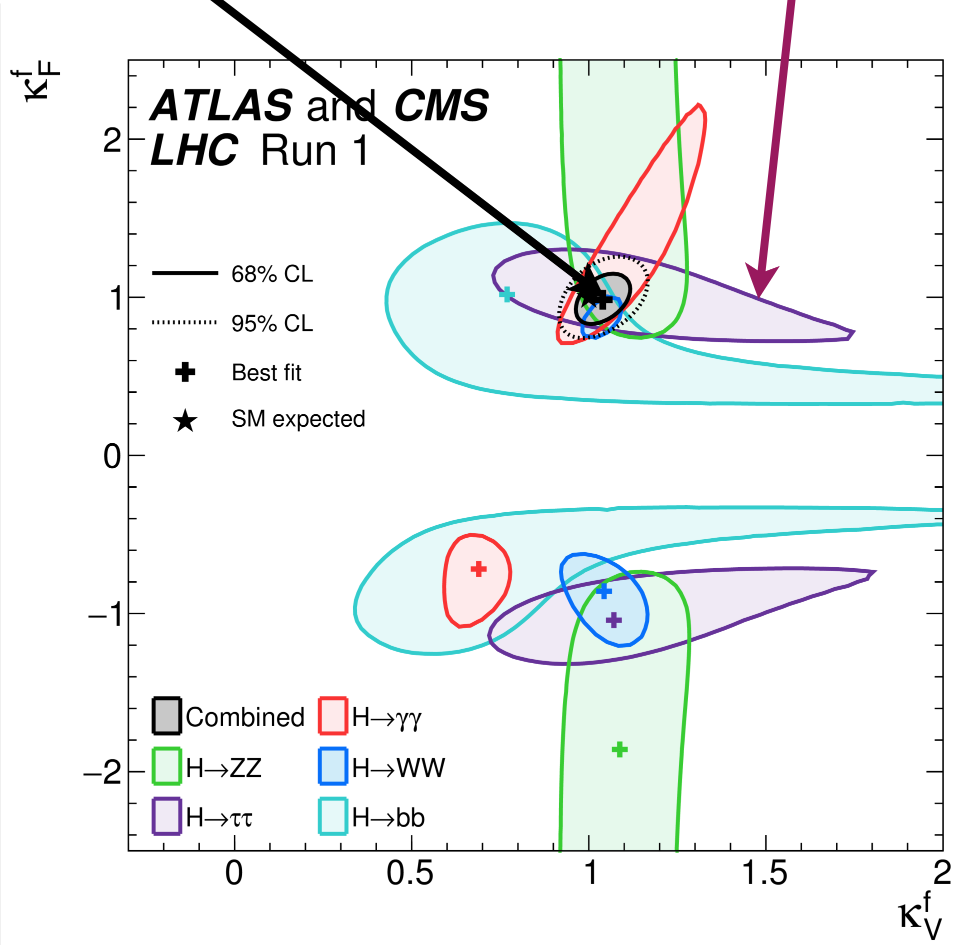


High-dimensional event data x

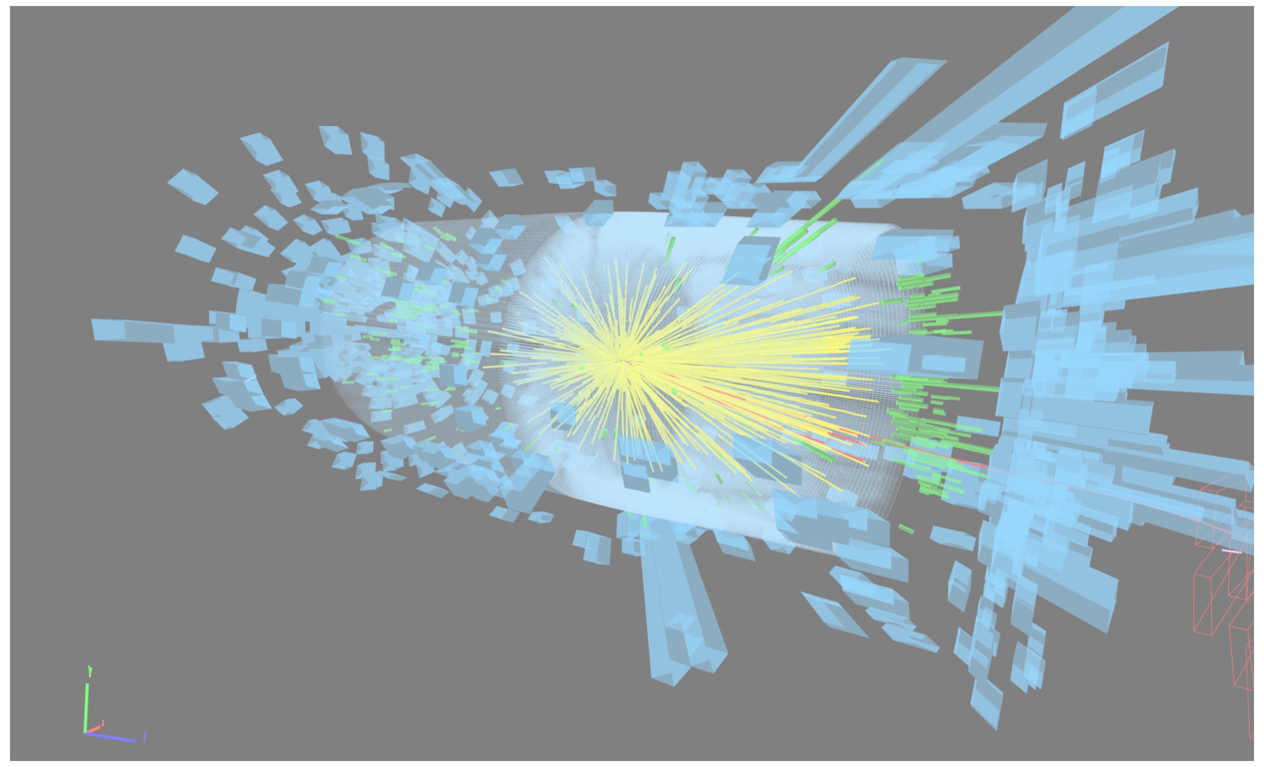
Likelihood function
$p(x|\theta)$

Maximum-likelihood estimator

Confidence limits based on likelihood ratio tests

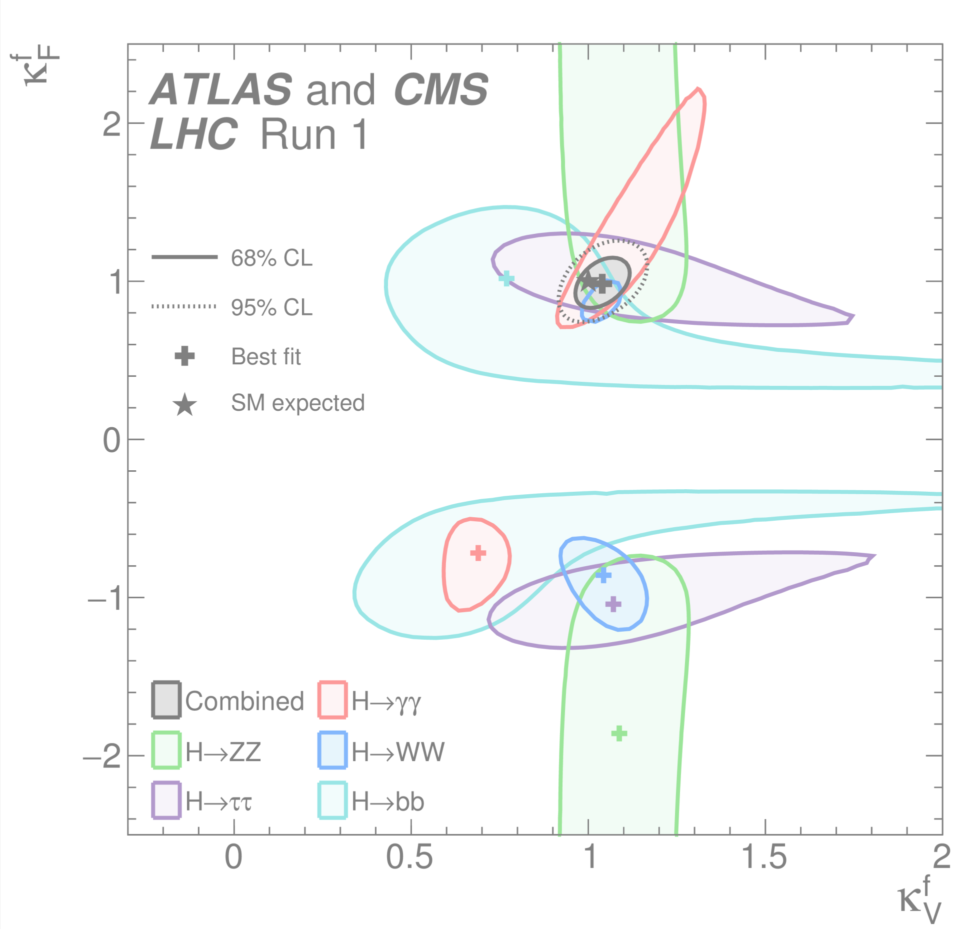


Constraints on parameters θ



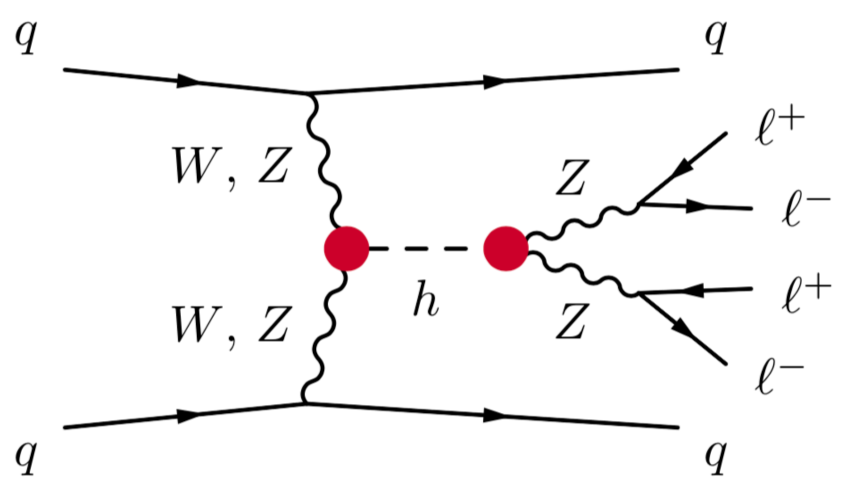
High-dimensional event data x

Likelihood function $p(x|\theta)$

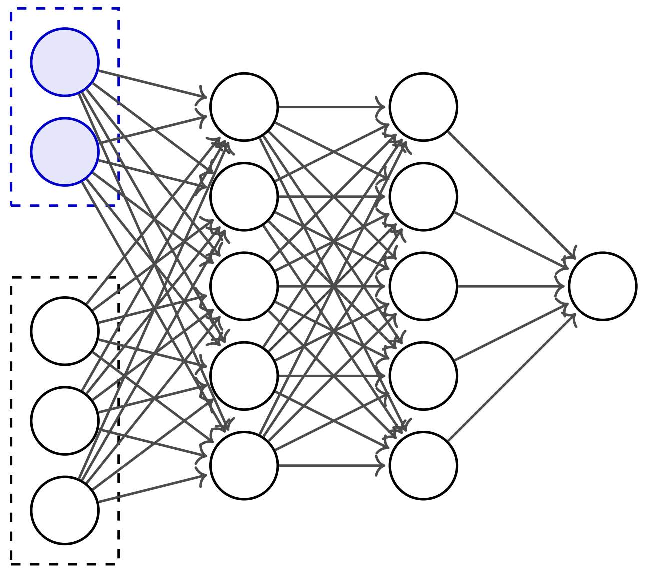


Constraints on parameters θ

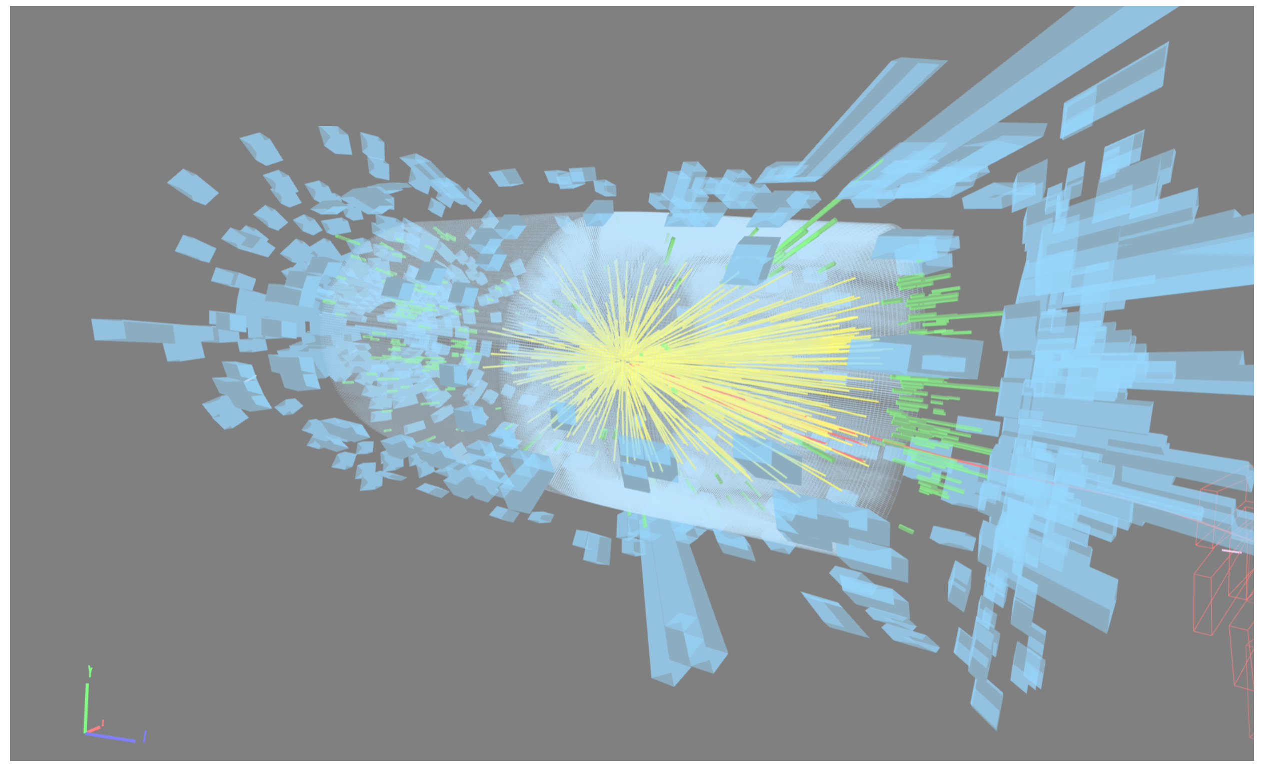
Surprisingly, when we want to use high-dimensional data and have to deal with the detector response, we do not have a good way to calculate the likelihood.



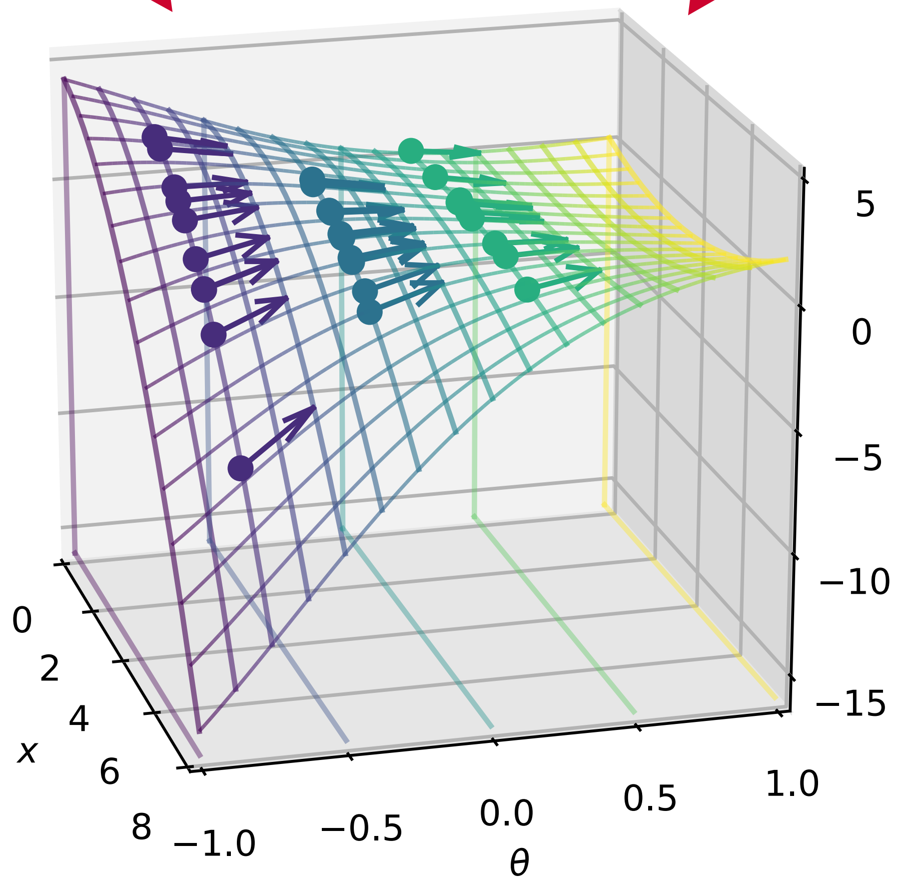
Physics insight:
matrix element information



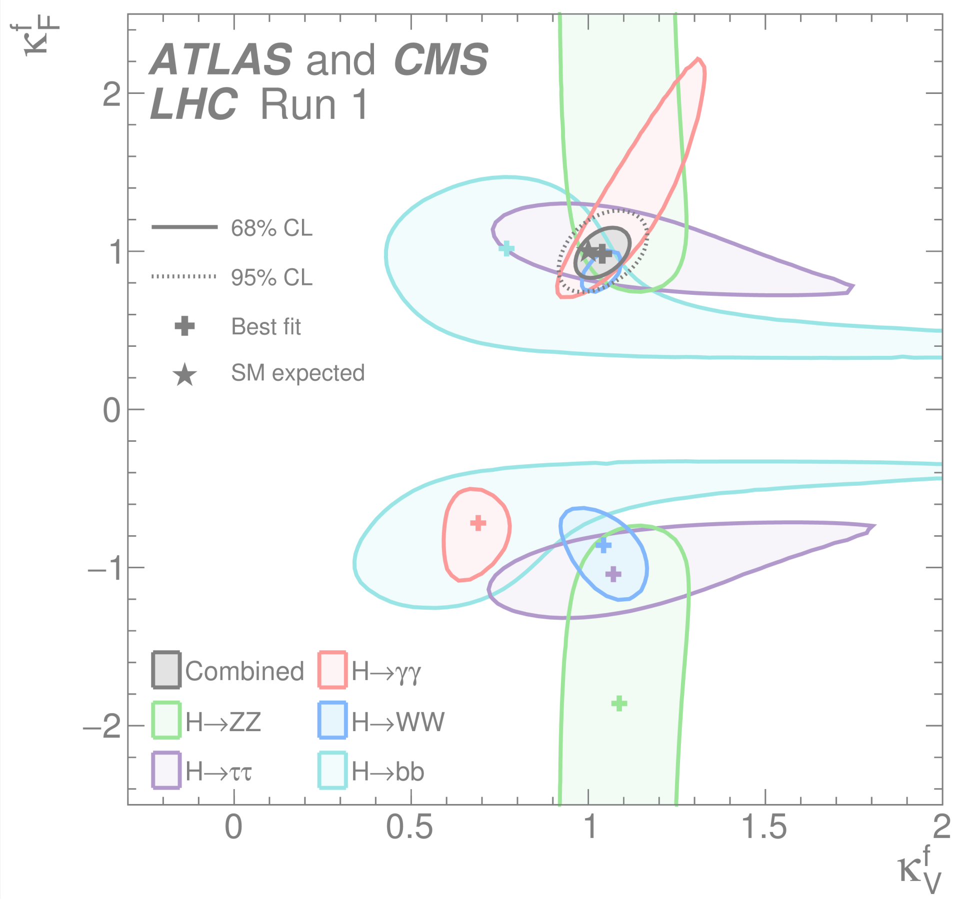
Machine learning



High-dimensional
event data x



Estimator of the
likelihood $p(x|\theta)$



Constraints on
parameters θ

LHC measurements as a likelihood-free inference problem

Modelling particle physics processes

Theory
parameters
θ

Evolution

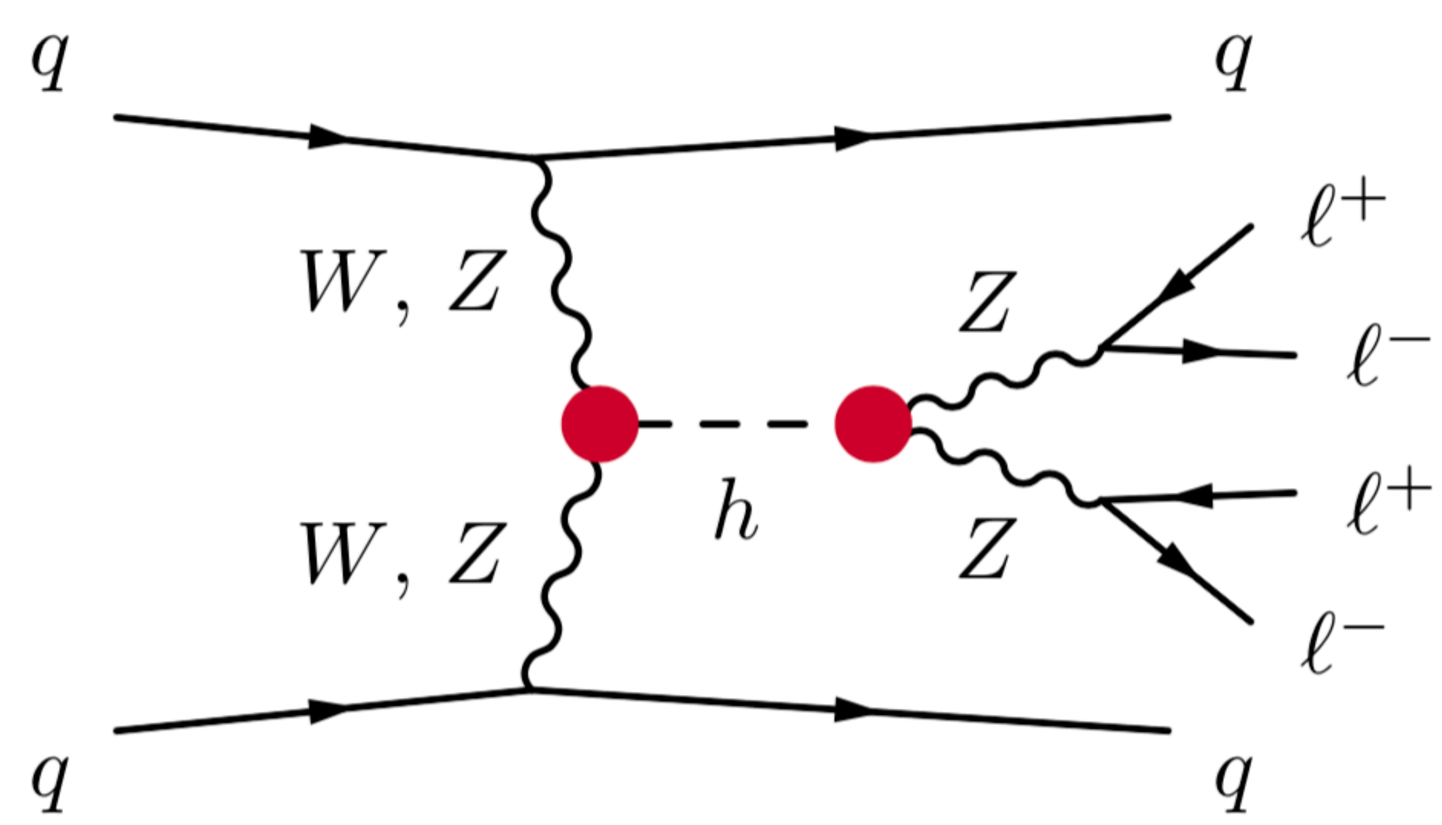
Modelling particle physics processes

Latent variables

Parton-level momenta

Theory parameters

$z_p \longleftarrow \theta$

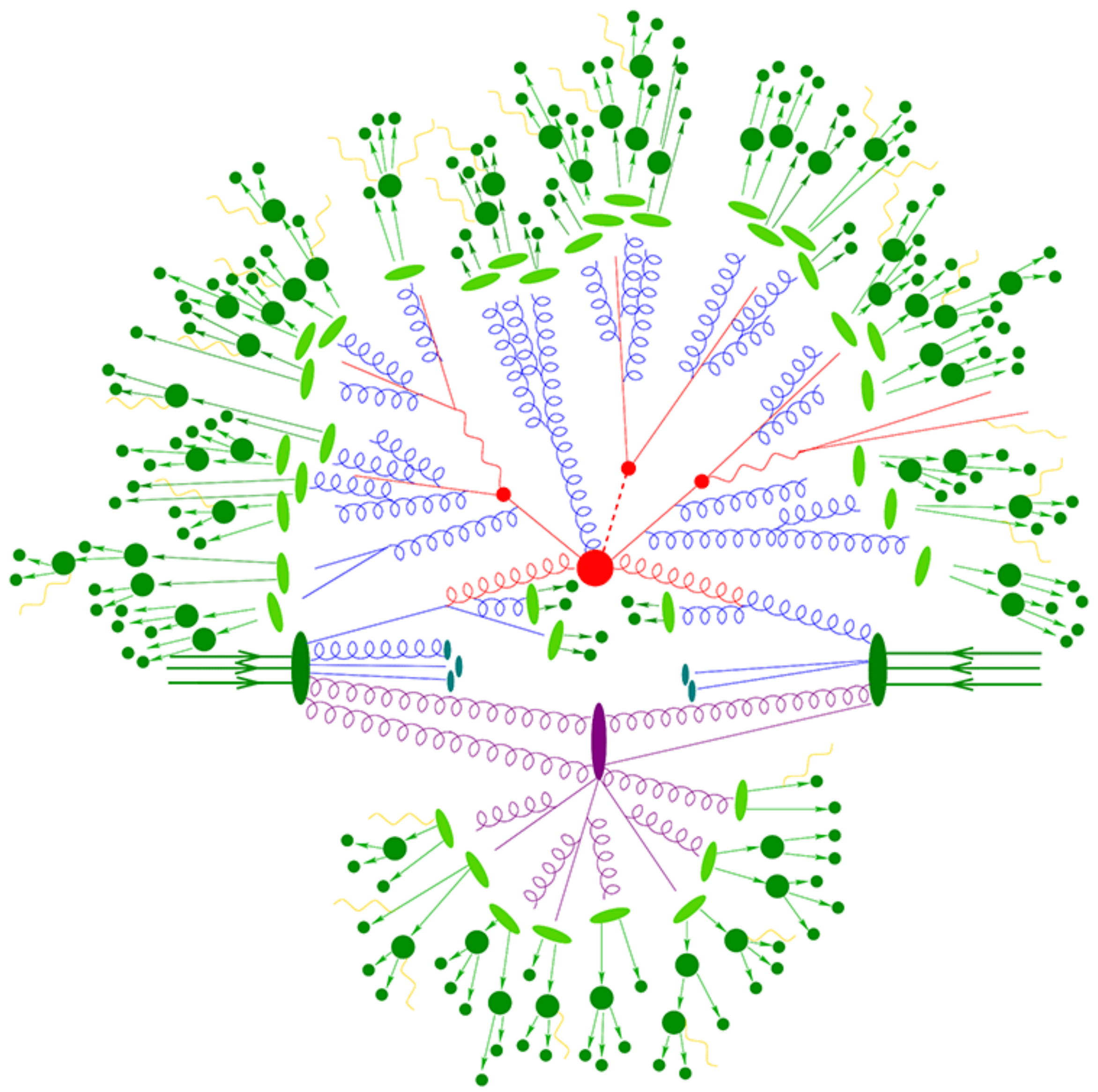


Evolution

Modelling particle physics processes

Latent variables

Shower splittings z_s ← Parton-level momenta z_p ← Theory parameters θ



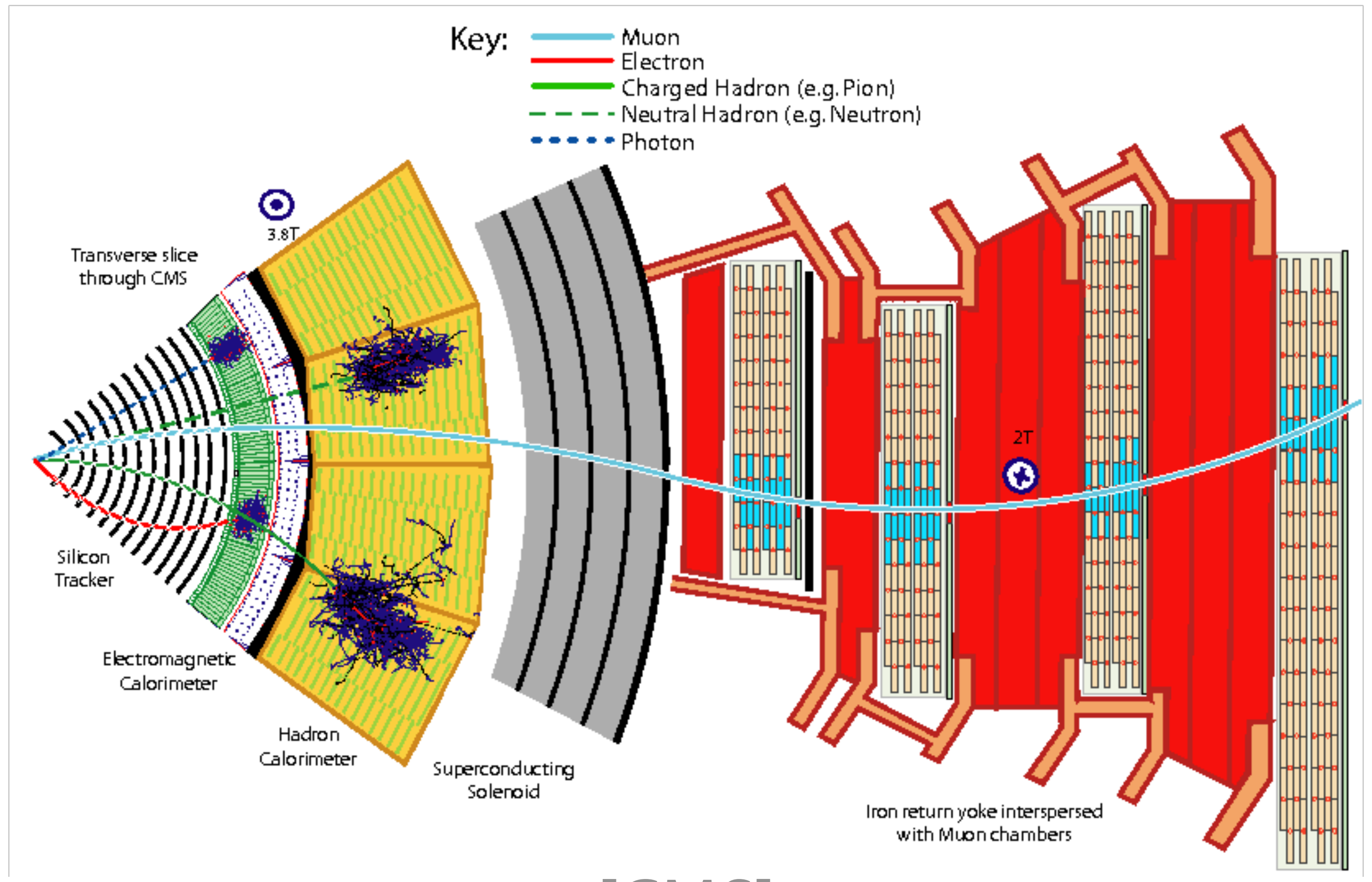
[F. Krauss]

Evolution

Modelling particle physics processes

Latent variables

Detector interactions		Shower splittings		Parton-level momenta		Theory parameters
z_d	$\longleftarrow$	z_s	$\longleftarrow$	z_p	$\longleftarrow$	θ



[CMS]

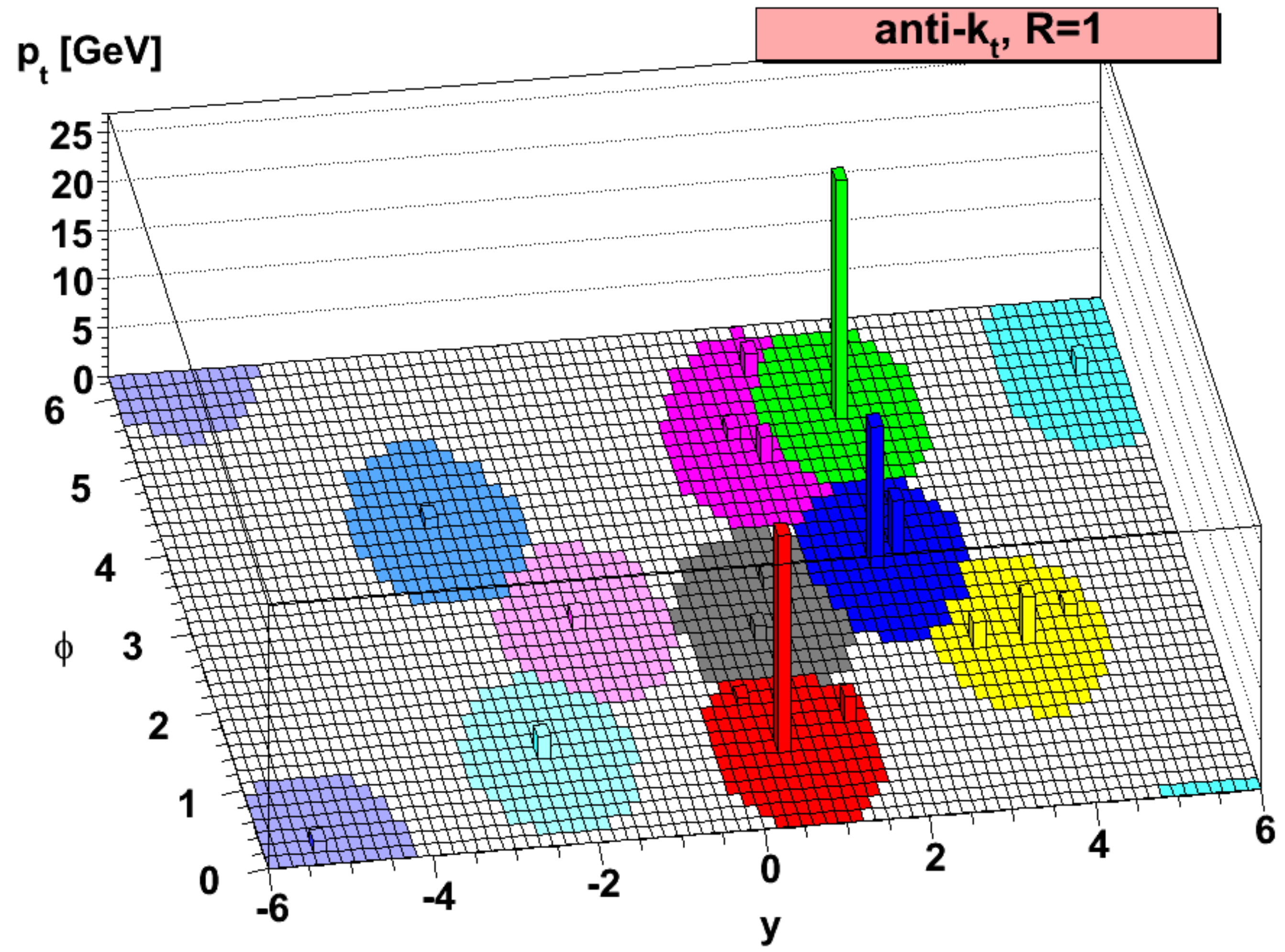
$\longleftarrow$

Evolution

Modelling particle physics processes

Latent variables

Observables		Detector interactions		Shower splittings		Parton-level momenta		Theory parameters
x	$\longleftarrow$	z_d	$\longleftarrow$	z_s	$\longleftarrow$	z_p	$\longleftarrow$	θ



[M. Cacciari, G. Salam, G. Soyez 0802.1189]

Evolution

Modelling particle physics processes

Latent variables

Observables		Detector interactions		Shower splittings		Parton-level momenta		Theory parameters
x	$\longleftarrow$	z_d	$\longleftarrow$	z_s	$\longleftarrow$	z_p	$\longleftarrow$	θ
Sample from	$p(x\|z_d)$		$p(z_d\|z_s)$		$p(z_s\|z_p)$		$p(z_p\|\theta)$	

GEANT4 A SIMULATION TOOLKIT

MADGRAPH5_aMC@NLO

Prediction (simulation)

Modelling particle physics processes

Latent variables

Observables		Detector interactions		Shower splittings		Parton-level momenta		Theory parameters
x	$\longleftarrow$	z_d	$\longleftarrow$	z_s	$\longleftarrow$	z_p	$\longleftarrow$	θ

$$p(x|\theta) = \int \mathrm{d}z_d \int \mathrm{d}z_s \int \mathrm{d}z_p \quad p(x|z_d) \quad p(z_d|z_s) \quad p(z_s|z_p) \quad p(z_p|\theta)$$

$\longrightarrow$

Inference

Modelling particle physics processes

Latent variables

Observables		Detector interactions		Shower splittings		Parton-level momenta		Theory parameters
x	$\longleftarrow$	z_d	$\longleftarrow$	z_s	$\longleftarrow$	z_p	$\longleftarrow$	θ

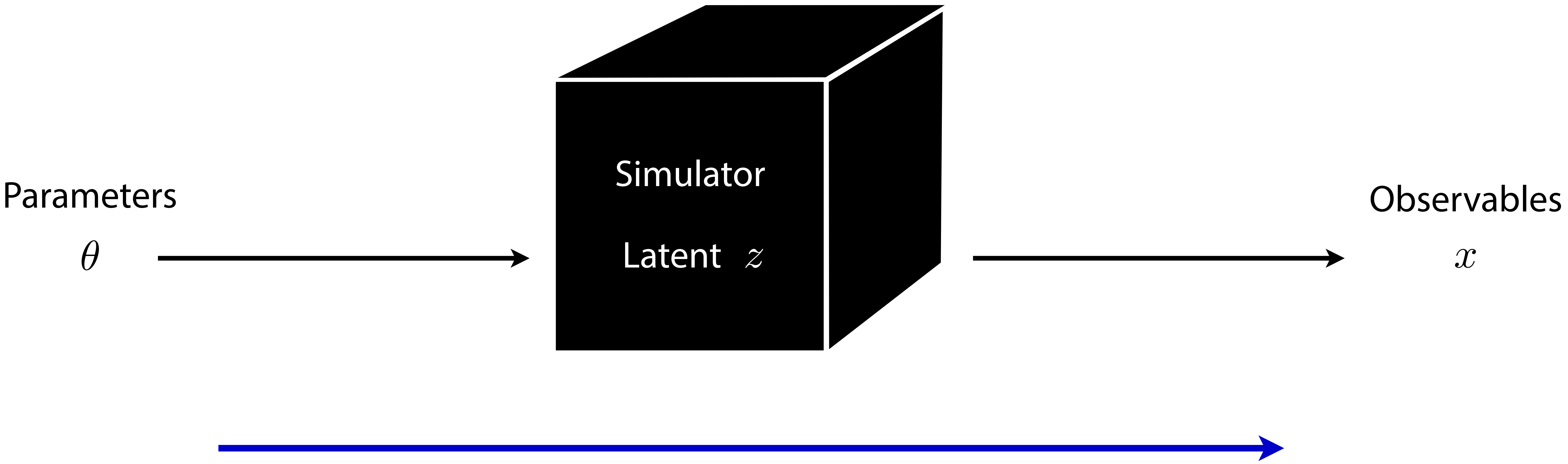
$$p(x|\theta) = \boxed{\int \mathrm{d}z_d \int \mathrm{d}z_s \int \mathrm{d}z_p} \; p(x|z_d) \quad p(z_d|z_s) \quad p(z_s|z_p) \quad p(z_p|\theta)$$

It's infeasible to calculate the integral over this enormous space!

(More subtle: We cannot sample from $p(z|x,\theta)$ efficiently.)

Inference

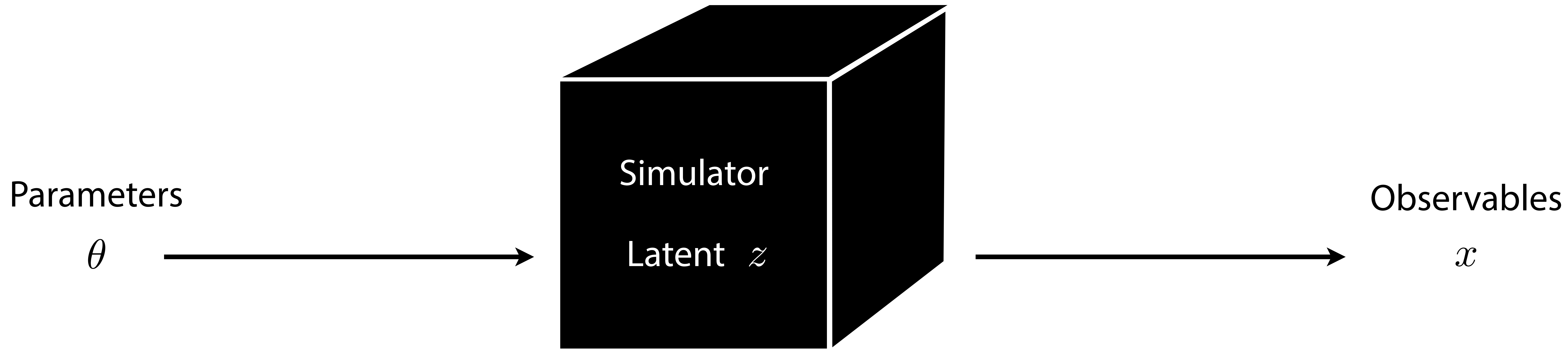
Likelihood-free inference / implicit models



Prediction:

- Well-understood mechanistic model
- Simulator can generate samples

Likelihood-free inference / implicit models

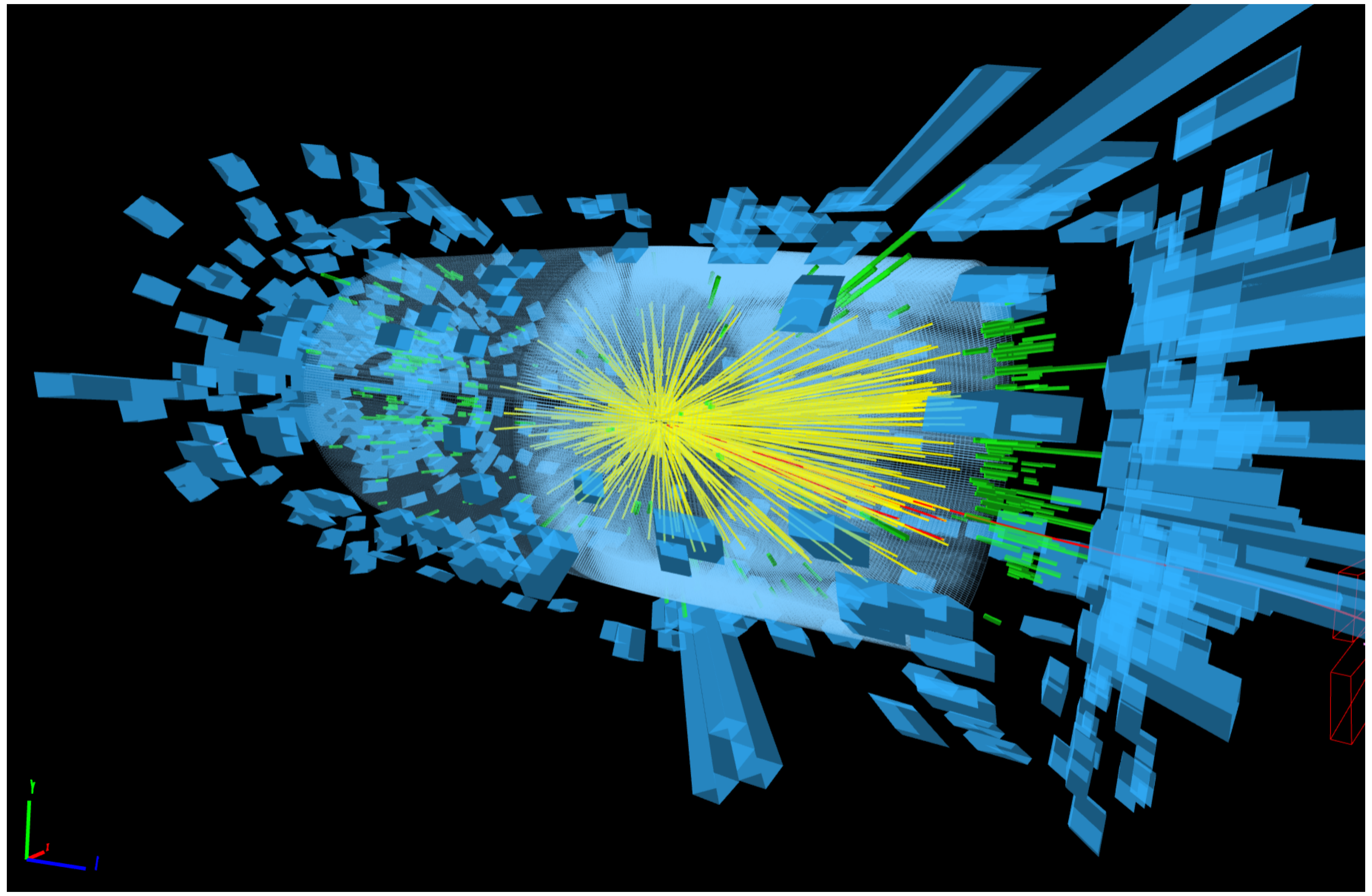


Prediction:
- Well-understood mechanistic model
- Simulator can generate samples

Inference:
- Likelihood function $p(x|\theta)$ is intractable
- Inference based on estimator $\hat{p}(x|\theta)$

Why has that not stopped us before?

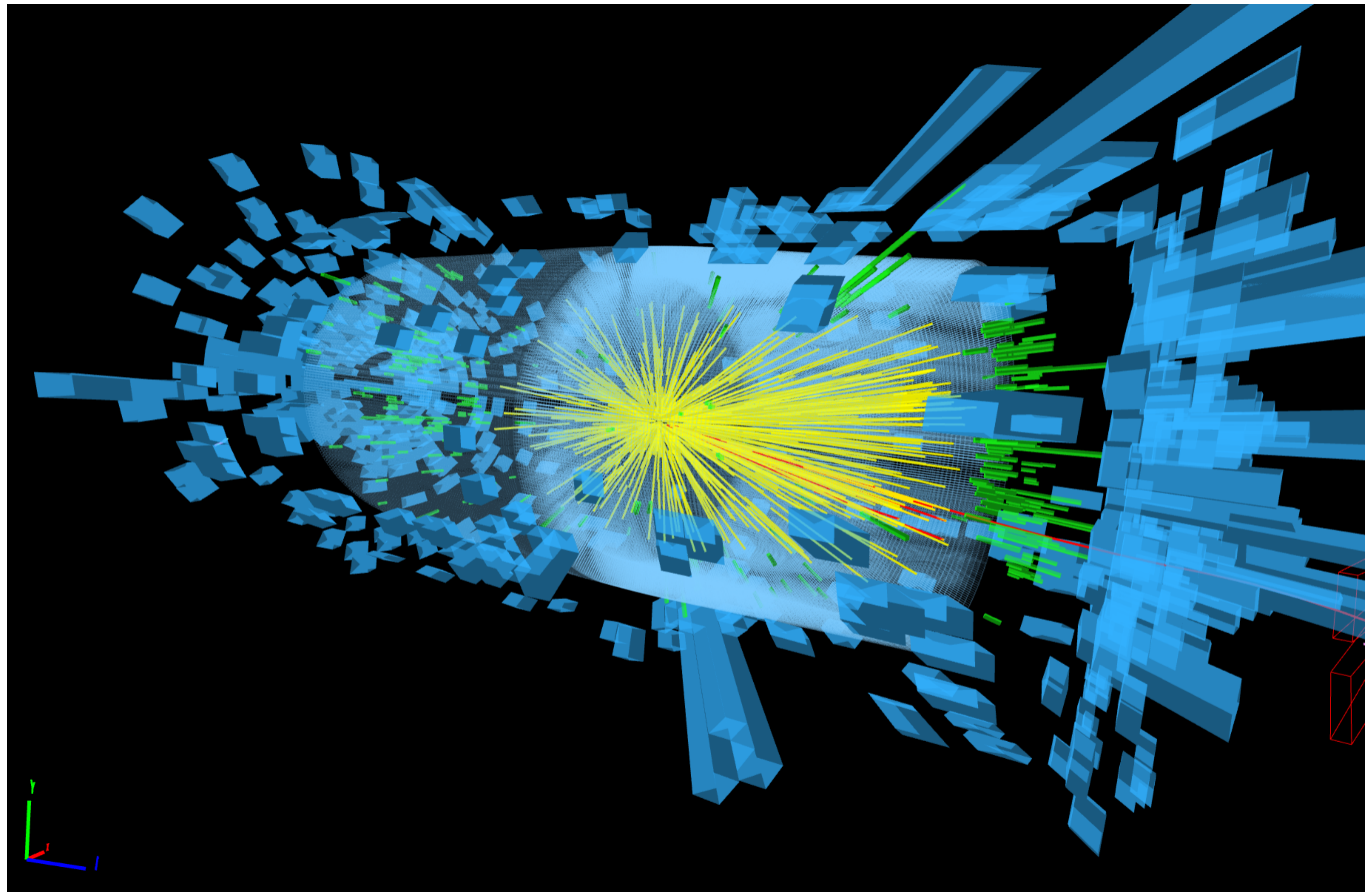
Solve it with summary statistics

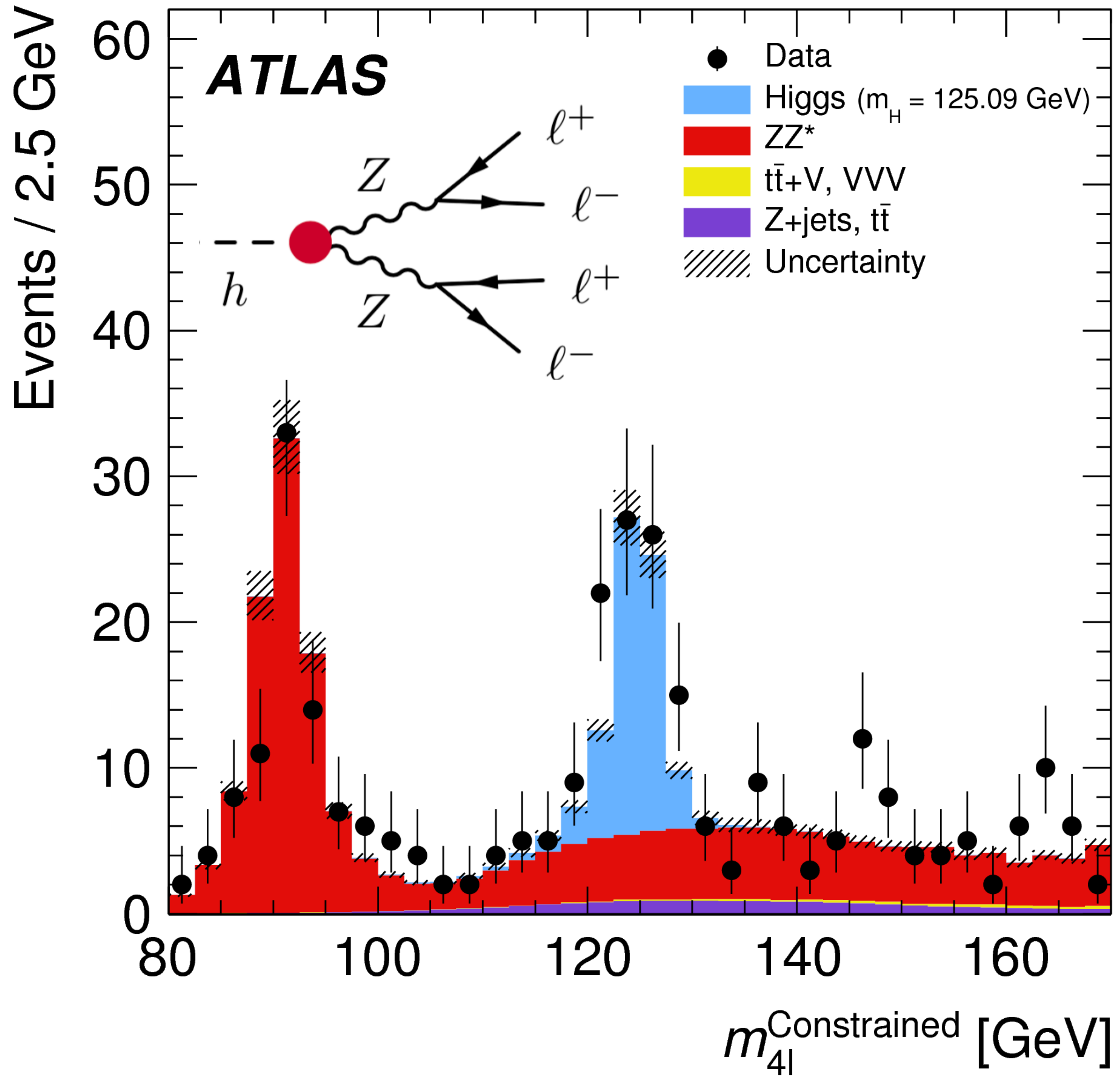


High-dimensional event data x

$p(x|\theta)$ cannot be calculated

Solve it with summary statistics





[ATLAS 1712.02304]

High-dimensional event data x

$p(x|\theta)$ cannot be calculated

One or two summary statistics x'

$p(x'|\theta)$ can be estimated with histograms, KDE, …

Summary statistics for EFT measurements?

- Choosing summary statistics x' is difficult and problem-dependent

- Often there is no single good standard variable — compressing to any x' loses information!
  [JB, K. Cranmer, F. Kling, T. Plehn 1612.05261; JB, F. Kling, T. Plehn , T. Tait 1712.02350]

- Ideally: analyze high-dimensional x including all correlations
  ("fully differential cross section")

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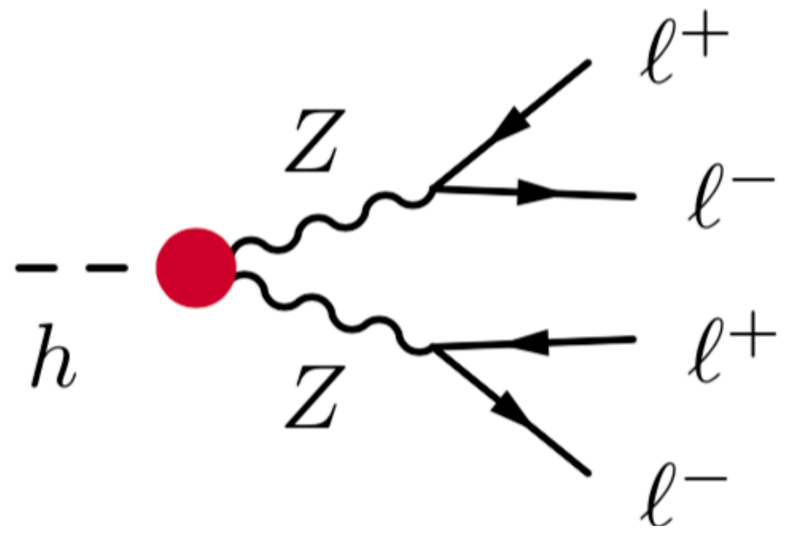
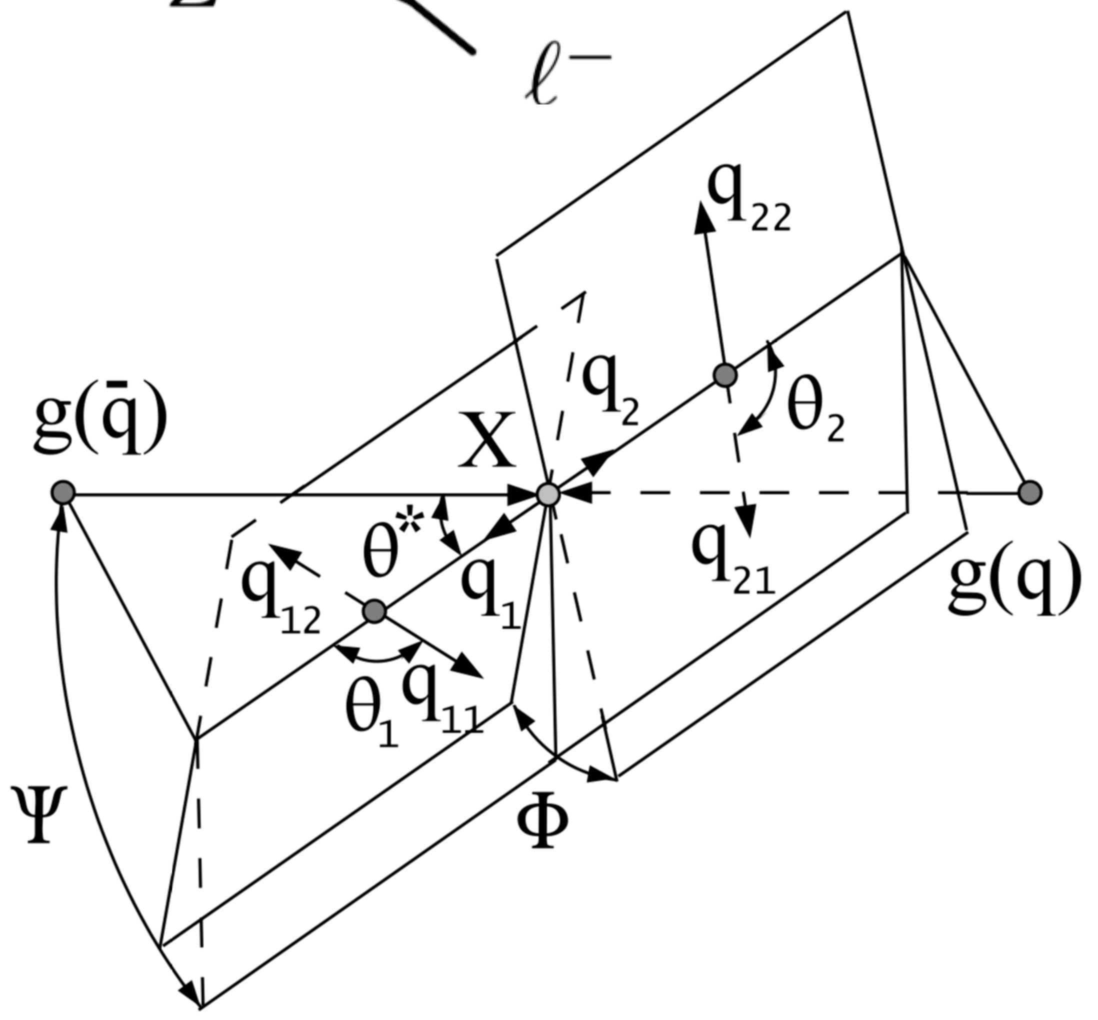
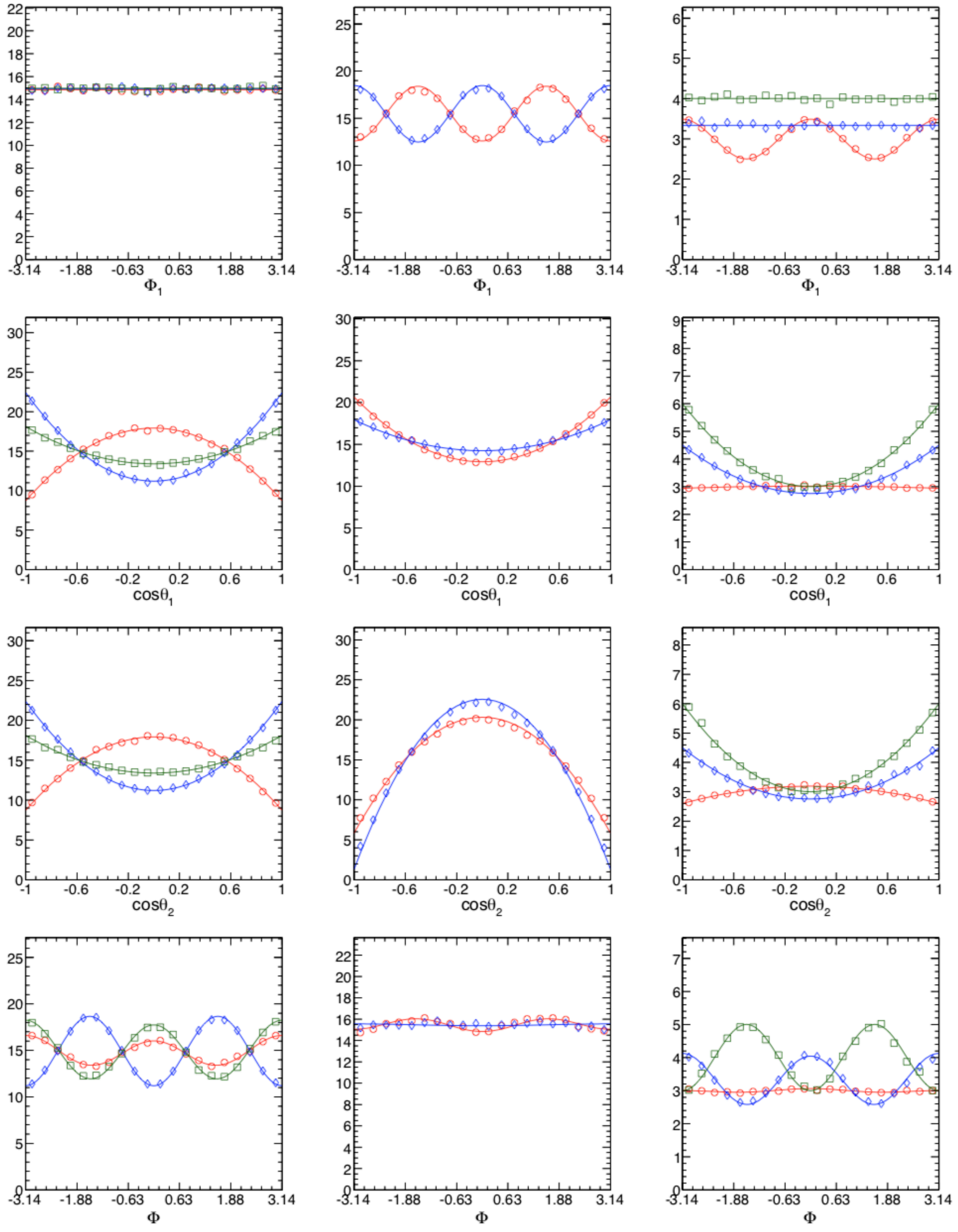






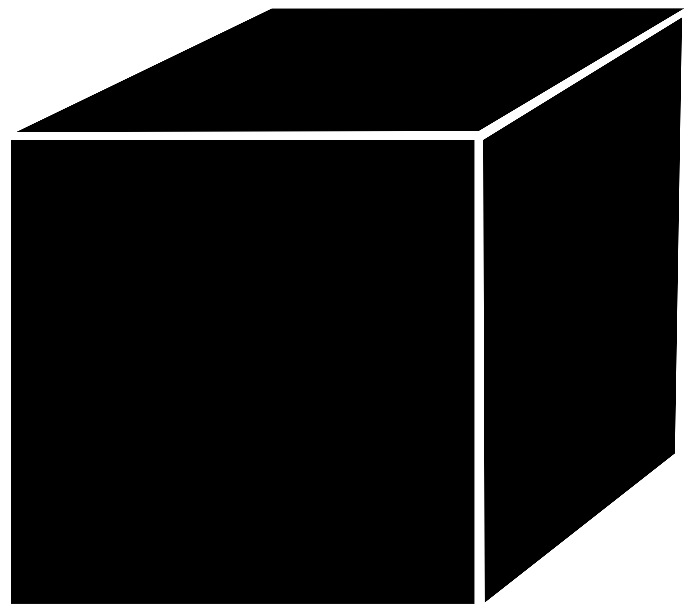
[Bolognesi et al. 1208.4018]

An incomplete list of likelihood-free inference methods

Treat simulator as black box:

- Histograms of observables,
  Approximate Bayesian Computation
  Rely on summary statistics

- Machine learning techniques
  Density networks, CARL, autoregressive models,
  normalizing flows, …



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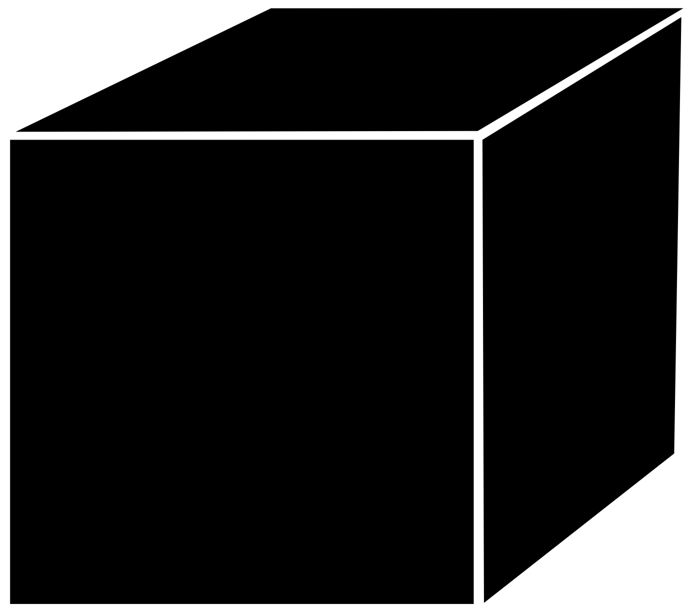
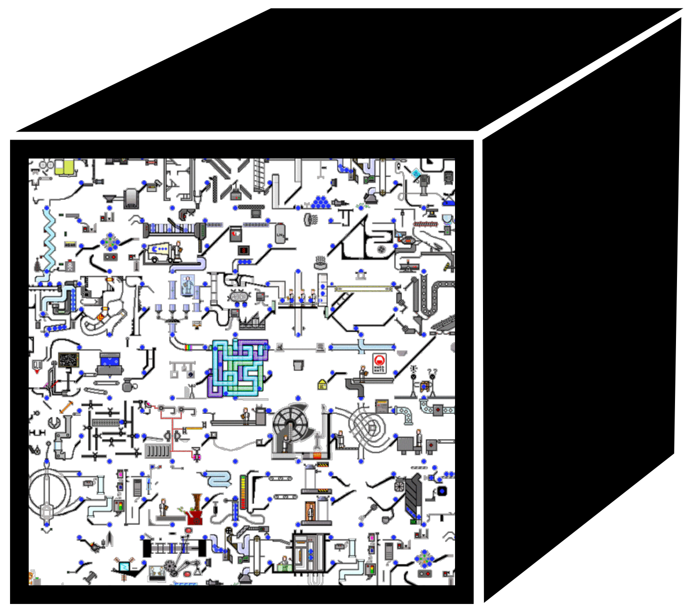


Use physics insights:

- Matrix Element Method, Optimal Observables, Shower Deconstruction, Event Deconstruction
  Neglect or approximate shower + detector, explicitly calculate z integral



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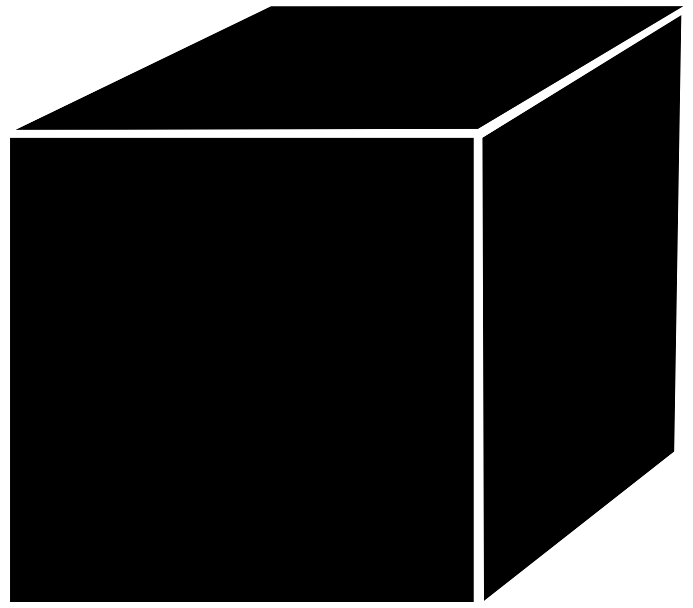

Use physics insights:

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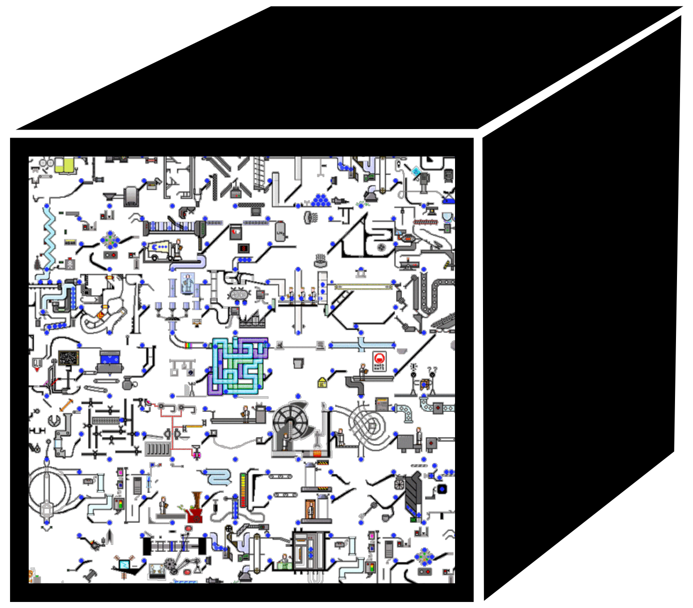
New!

- Mining gold from the simulator
  Leverage matrix-element information + machine learning



A new approach:
"Mining gold" from the simulator

[JB, K. Cranmer, G. Louppe, J. Pavez 1805.00013, 1805.00020, 1805.12244]

What if we could estimate the likelihood…

- for high-dimensional observables, including correlations?

  like MEM: no need to pick summary statistics

- including state-of-the-art shower and detector models?

  allowing for extra radiation, no need for transfer functions

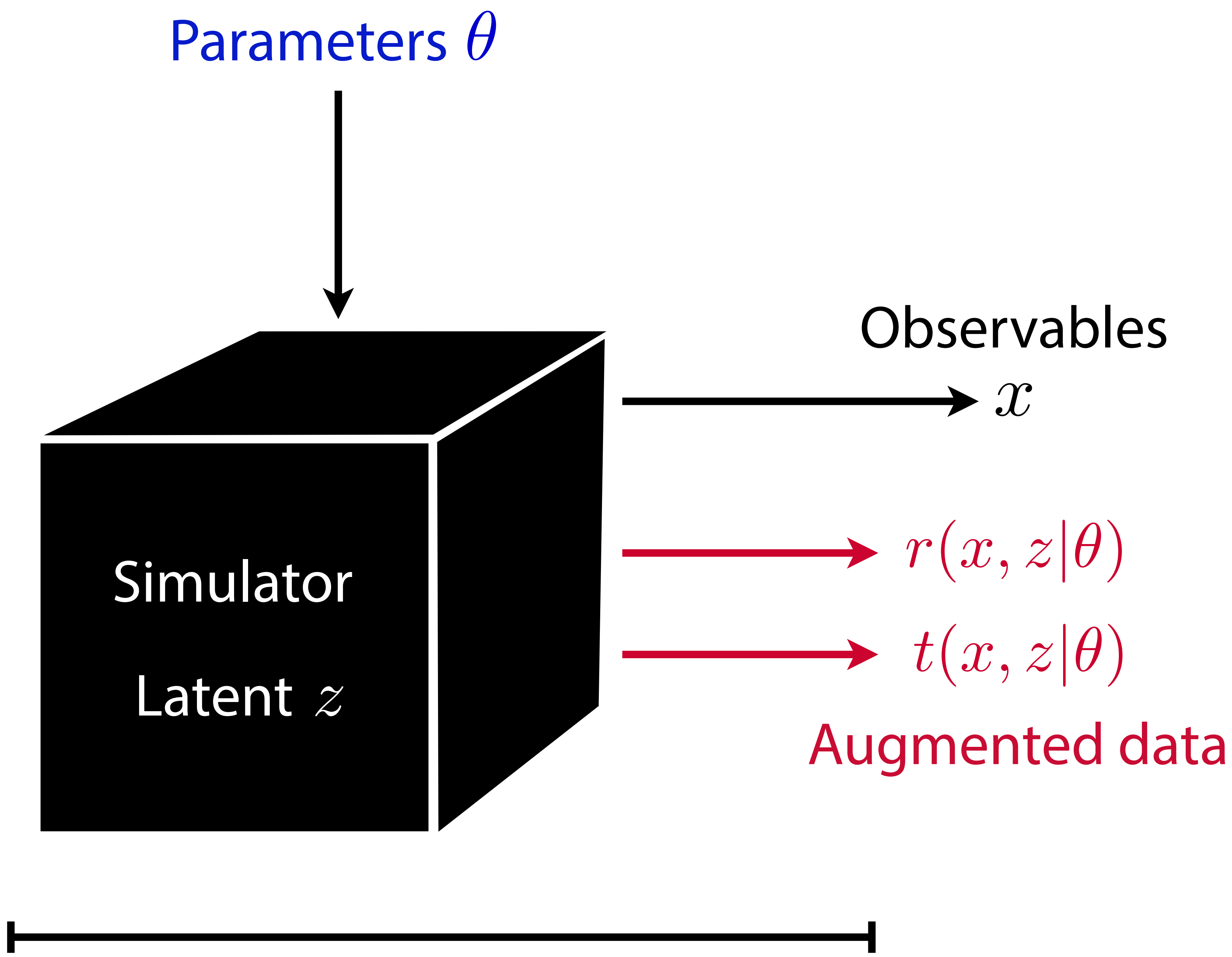
- in microseconds?

  amortized inference: train once, then always evaluate fast

- requiring less training examples than established machine learning methods?

  using matrix element information: "ML version of MEM"

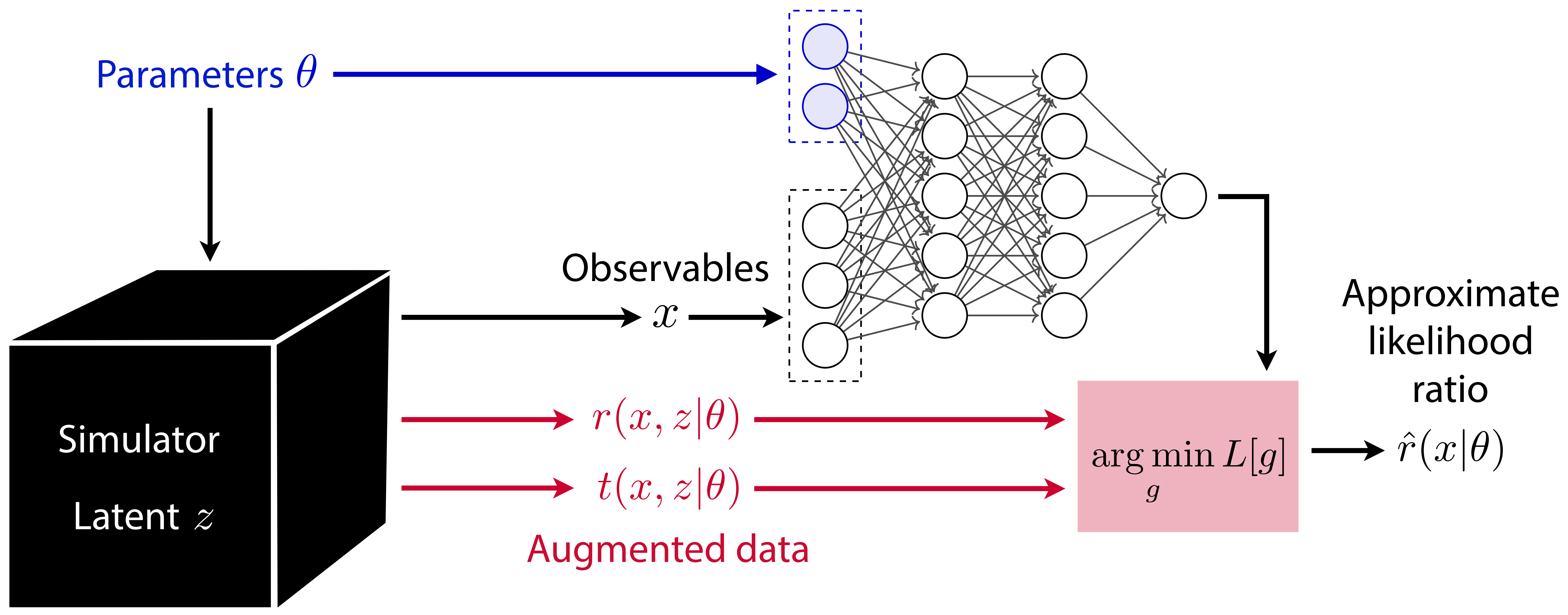
Bird’s-eye view



1. Simulation

“Mining gold”: Extract additional information from simulator

Bird's-eye view



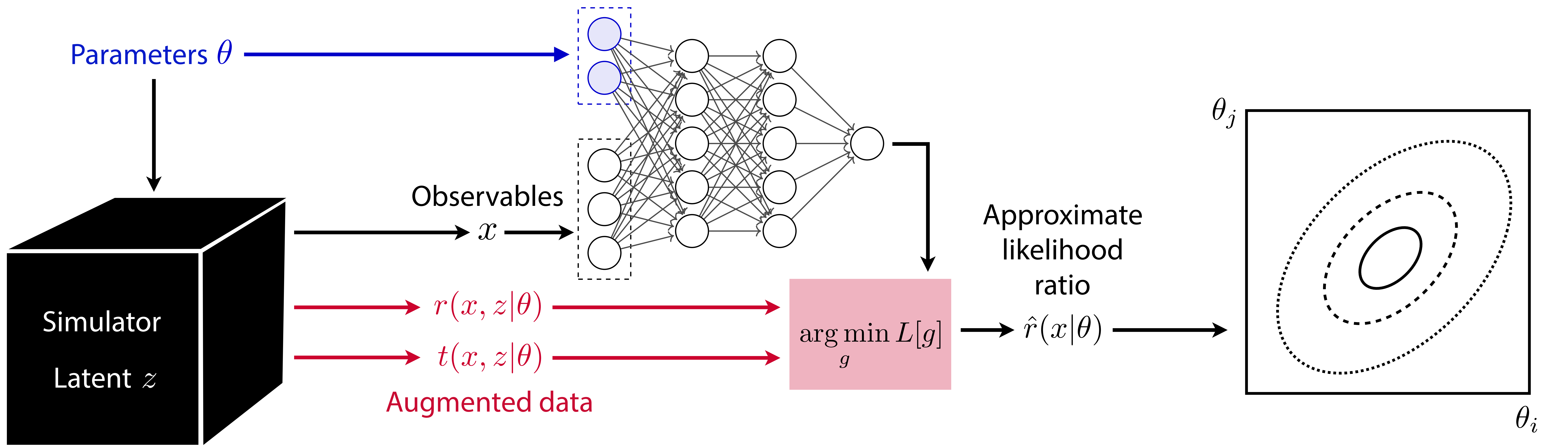
1. Simulation

"Mining gold": Extract additional information from simulator

2. Machine Learning

Use this information to train estimator for likelihood ratio

Bird's-eye view



1. Simulation

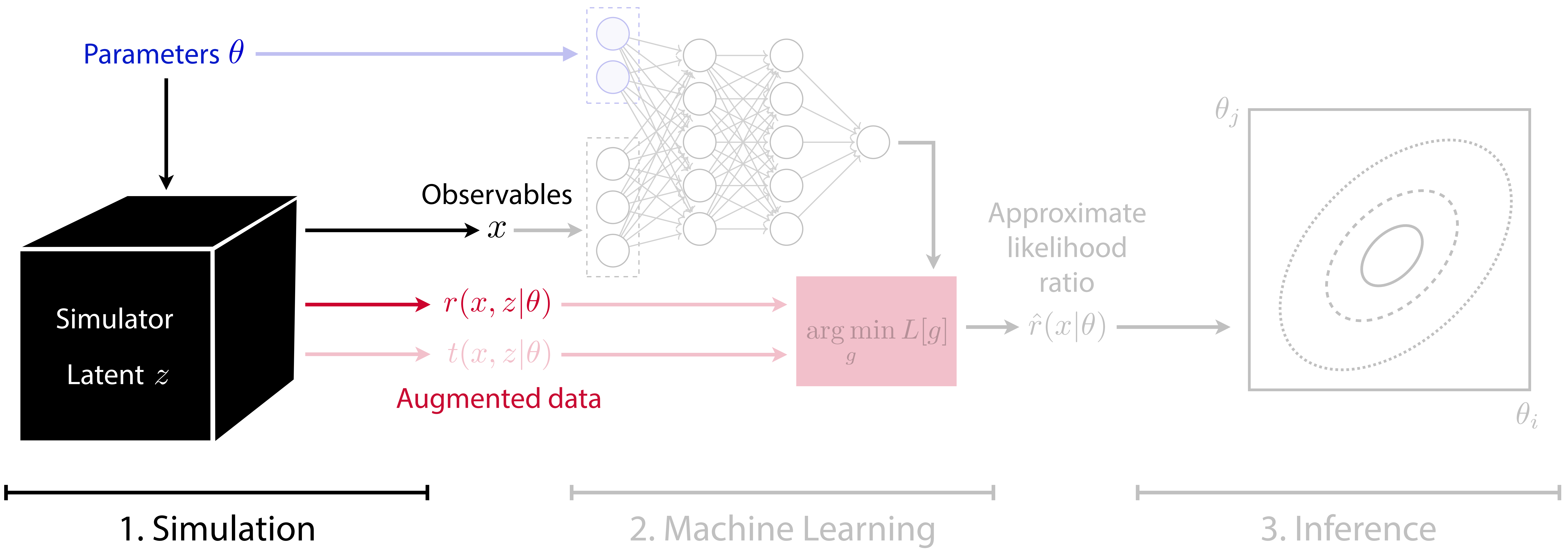
"Mining gold": Extract additional information from simulator

2. Machine Learning

Use this information to train estimator for likelihood ratio

3. Inference

Limit setting with standard hypothesis tests


Parameters θ
Observables
x
Simulator
Latent z
$r(x, z|\theta)$
$t(x, z|\theta)$
Augmented data
$\arg\min_g L[g]$
Approximate likelihood ratio
$\hat{r}(x|\theta)$
θ_j
θ_i
1. Simulation
2. Machine Learning
3. Inference

Mining gold from the simulator

Latent variables

Observables	Detector interactions	Shower splittings	Parton-level momenta	Theory parameters

$$x \longleftarrow z_d \longleftarrow z_s \longleftarrow z_p \longleftarrow \theta$$

$$p(x|\theta) = \boxed{\int \mathrm{d}z_d \int \mathrm{d}z_s \int \mathrm{d}z_p} \; p(x|z_d) \quad p(z_d|z_s) \quad p(z_s|z_p) \quad p(z_p|\theta)$$

Intractable integrals

Mining gold from the simulator

Latent variables

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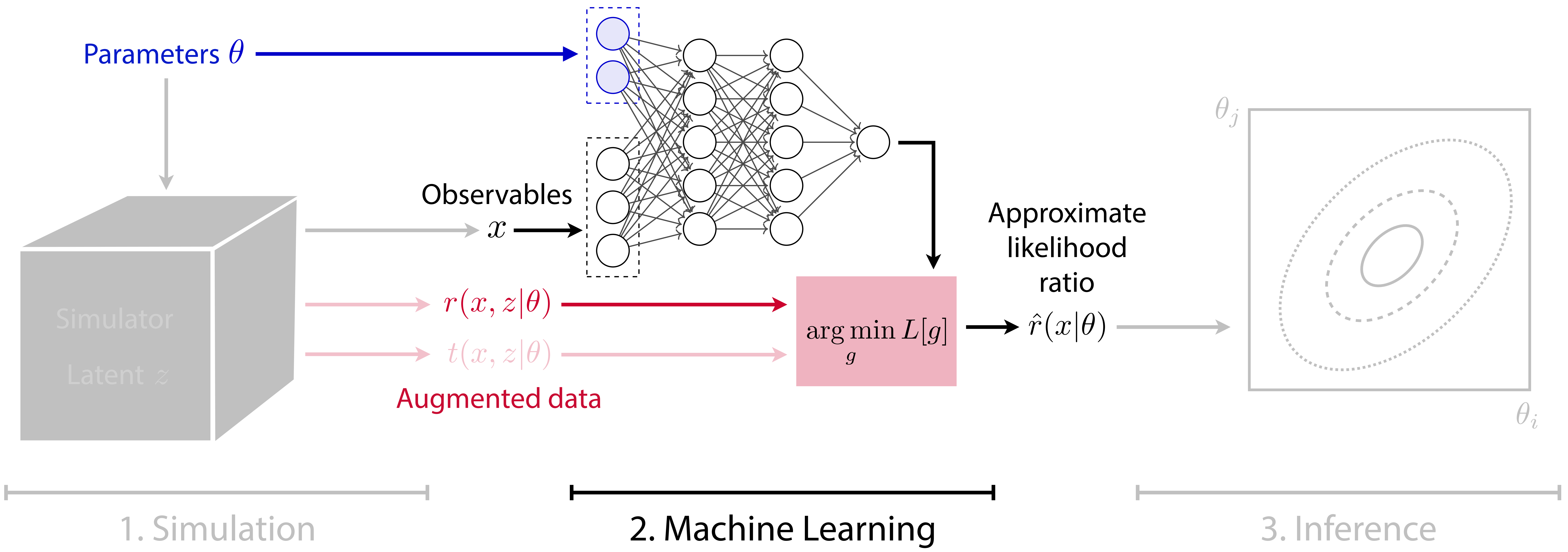
Parton-level likelihood
is given by matrix element
and can be evaluated!

⇒ For each simulated event, we can calculate the joint likelihood ratio which depends on the specific evolution of the simulation:

$$r(x, z|\theta_0, \theta_1) \equiv \frac{p(x, z_d, z_s, z_p|\theta_0)}{p(x, z_d, z_s, z_p|\theta_1)} = \frac{p(x|z_d)}{p(x|z_d)} \frac{p(z_d|z_s)}{p(z_d|z_s)} \frac{p(z_s|z_p)}{p(z_s|z_p)} \boxed{\frac{p(z_p|\theta_0)}{p(z_p|\theta_1)} \sim \frac{|\mathcal{M}(z_p|\theta_0)|^2}{|\mathcal{M}(z_p|\theta_1)|^2}}$$


Parameters θ
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The value of gold

We can calculate the joint likelihood ratio

$$r(x, z|\theta_0, \theta_1) \equiv \frac{p(x, z_d, z_s, z_p|\theta_0)}{p(x, z_d, z_s, z_p|\theta_1)}$$

("How much more likely is this simulated event, including all intermediate states, for θ_0 compared to θ_1?")

We want the likelihood ratio function

$$r(x|\theta_0, \theta_1) \equiv \frac{p(x|\theta_0)}{p(x|\theta_1)}$$

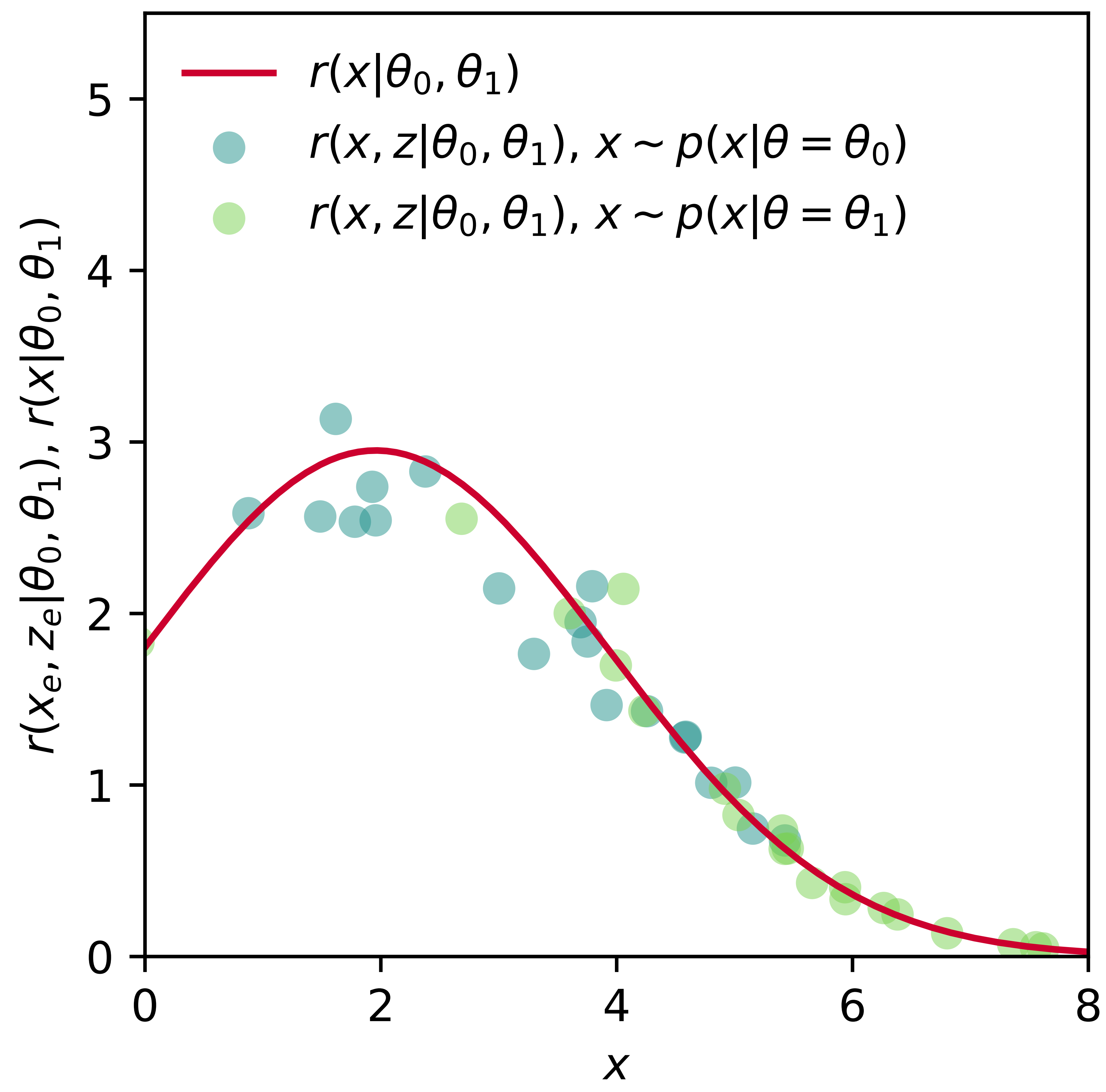
("How much more likely is the observation x for θ_0 compared to θ_1?")

The value of gold

We can calculate the joint likelihood ratio

$$r(x, z|\theta_0, \theta_1) \equiv \frac{p(x, z_d, z_s, z_p|\theta_0)}{p(x, z_d, z_s, z_p|\theta_1)}$$

$r(x, z|\theta_0, \theta_1)$ are scattered around $r(x|\theta_0, \theta_1)$



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The value of gold

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$$r(x, z|\theta_0, \theta_1) \equiv \frac{p(x, z_d, z_s, z_p|\theta_0)}{p(x, z_d, z_s, z_p|\theta_1)}$$

With $r(x, z|\theta_0, \theta_1)$, we define a functional like

$$L_r[\hat{r}(x|\theta_0, \theta_1)] = \int \mathrm{d}x \int \mathrm{d}z \; p(x, z|\theta_1) \left[\left(\hat{r}(x|\theta_0, \theta_1) - r(x, z|\theta_0, \theta_1) \right)^2 \right].$$

It is minimized by

$$r(x|\theta_0, \theta_1) = \underset{\hat{r}(x|\theta_0, \theta_1)}{\arg\min} \; L_r[\hat{r}(x|\theta_0, \theta_1)]!$$

(And we can sample from $p(x, z|\theta)$ by running the simulator.)

We want the likelihood ratio function

$$r(x|\theta_0, \theta_1) \equiv \frac{p(x|\theta_0)}{p(x|\theta_1)}$$

Machine learning = applied calculus of variatios

So to get a good estimator of the likelihood ratio, we need to mimimize a functional numerically:

Variational family

Extremization

Functional with integral

$$r(x|\theta_0, \theta_1) = \arg\min_{\hat{r}(x|\theta_0,\theta_1)} L_r[\hat{r}(x|\theta_0, \theta_1)]$$

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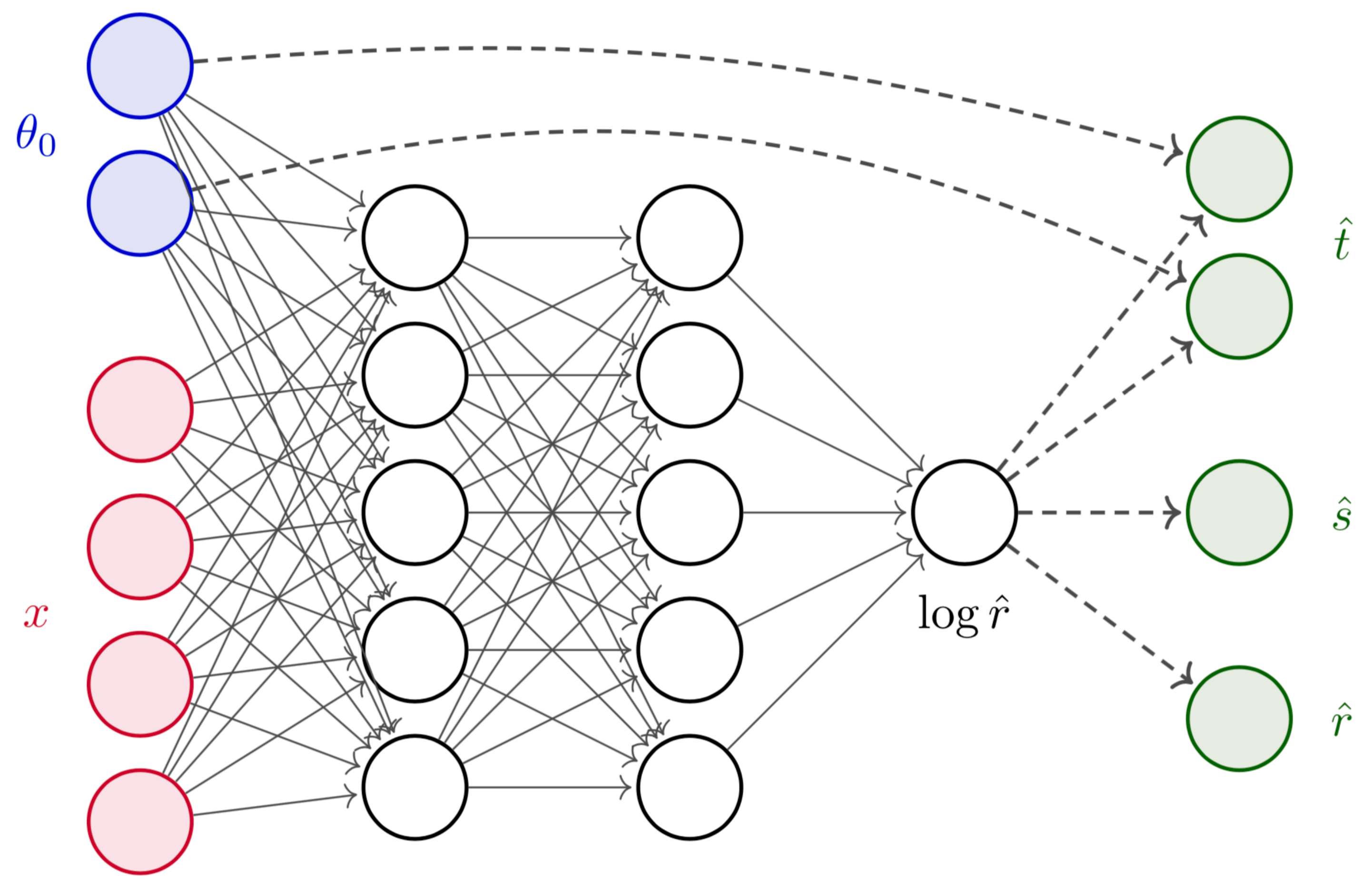
This is where machine learning comes in!

Loss function with
finite sum over samples

Neural network

Stochastic gradient descent



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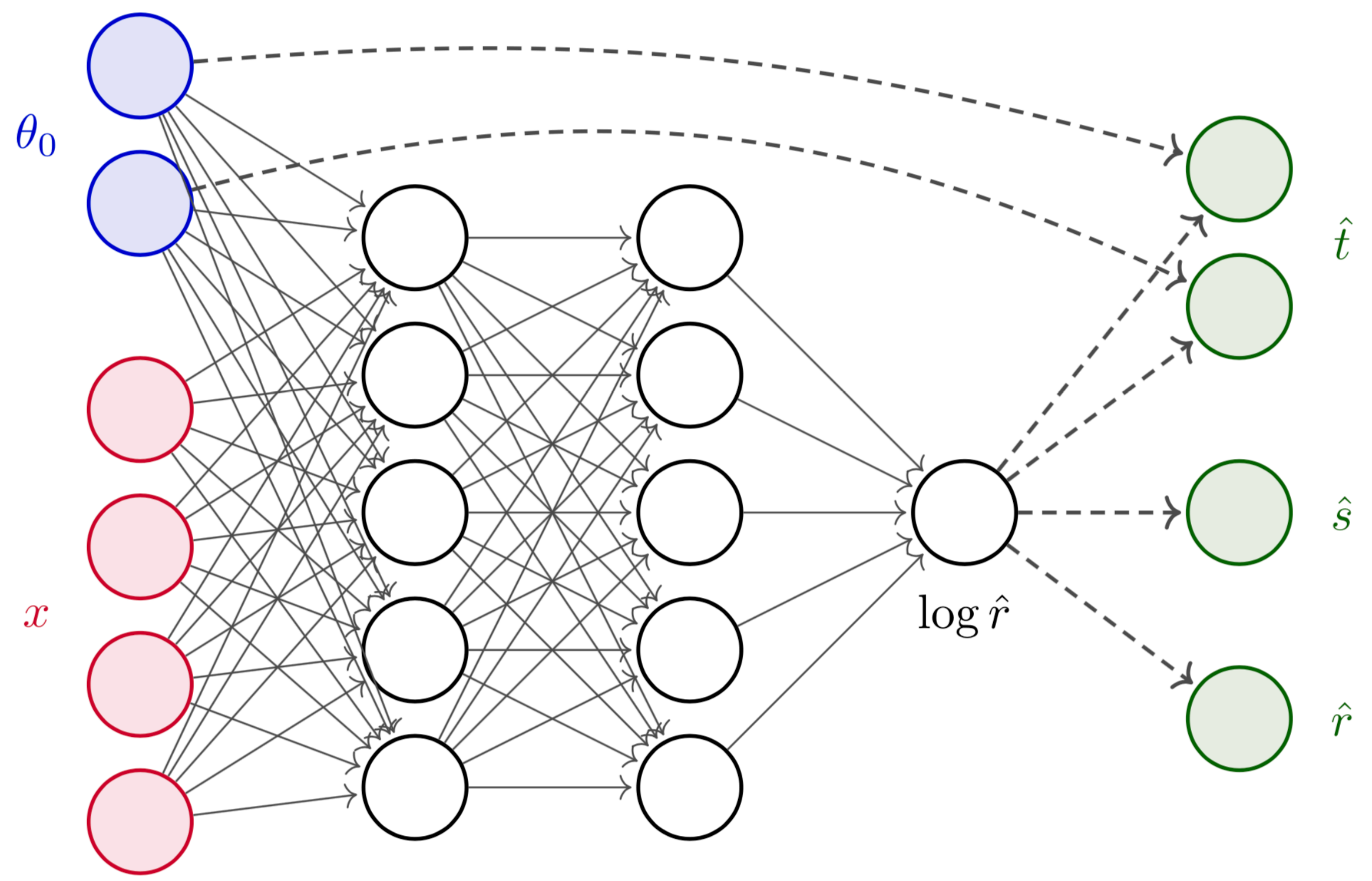
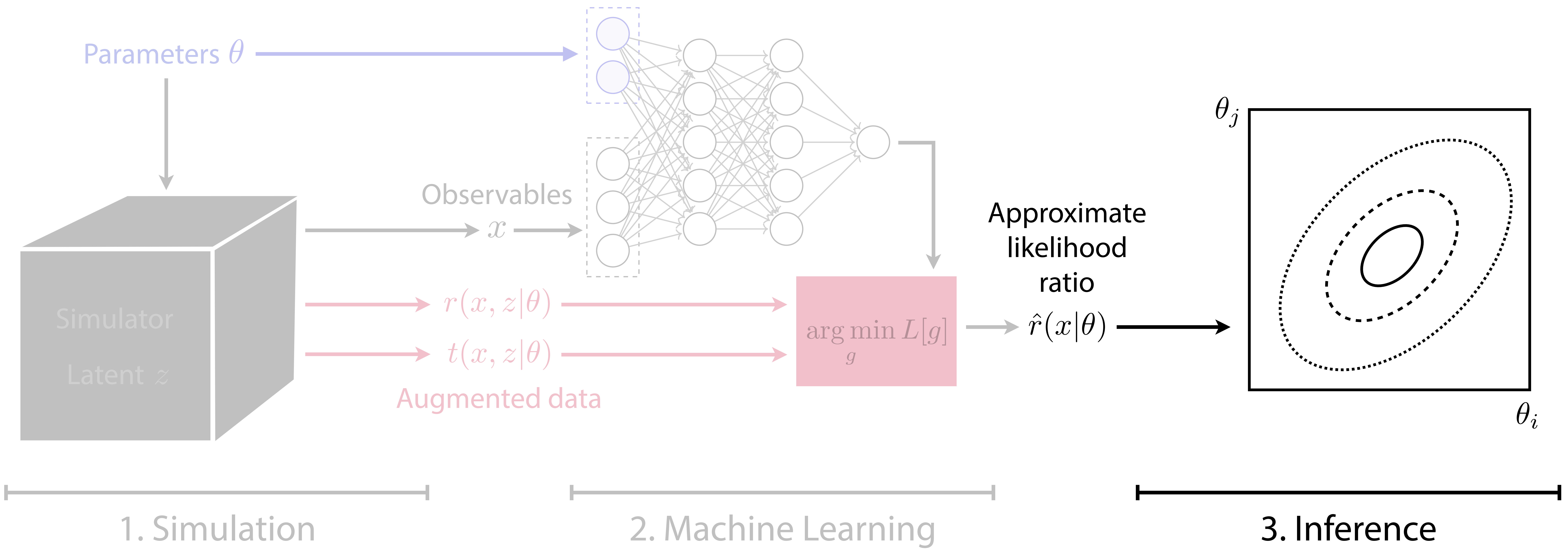


A sufficiently expressive neural network
efficiently trained in this way
with enough data will learn
the likelihood ratio function $r(x|\theta_0, \theta_1)$!



Parameters θ
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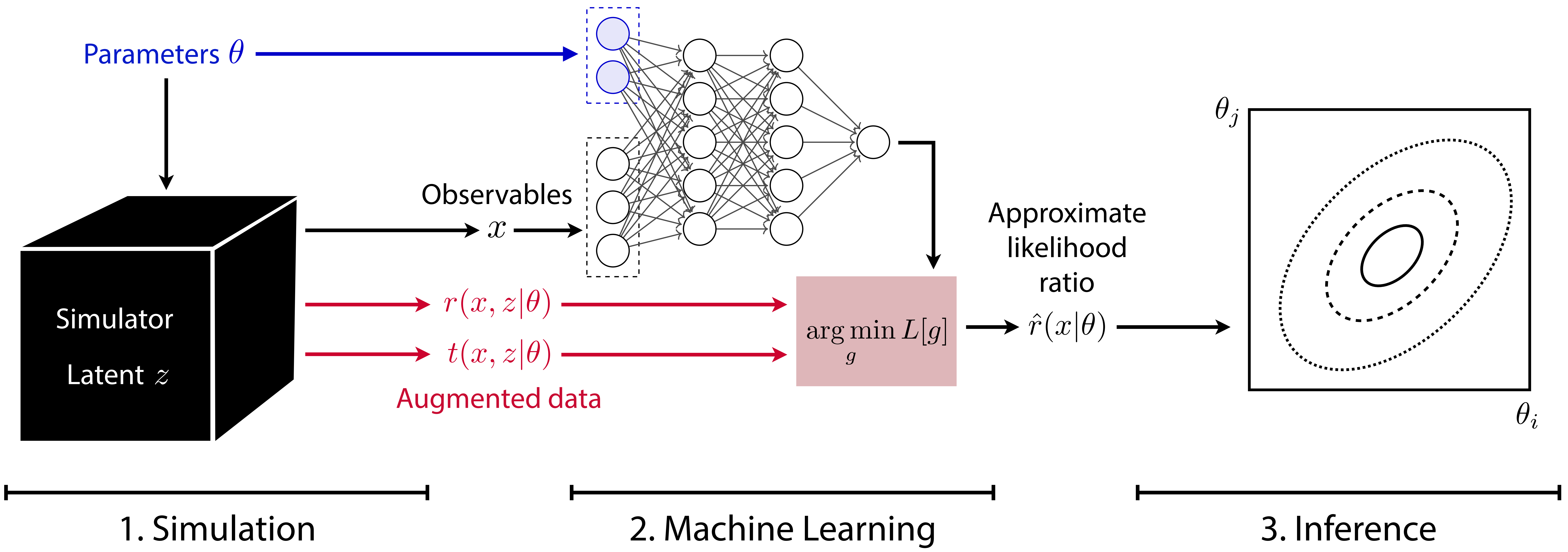
Putting the pieces together: RASCAL (Ratio and score approximate likelihood ratio)



"The machine learning version of the Matrix Element Method"

Learning optimal observables

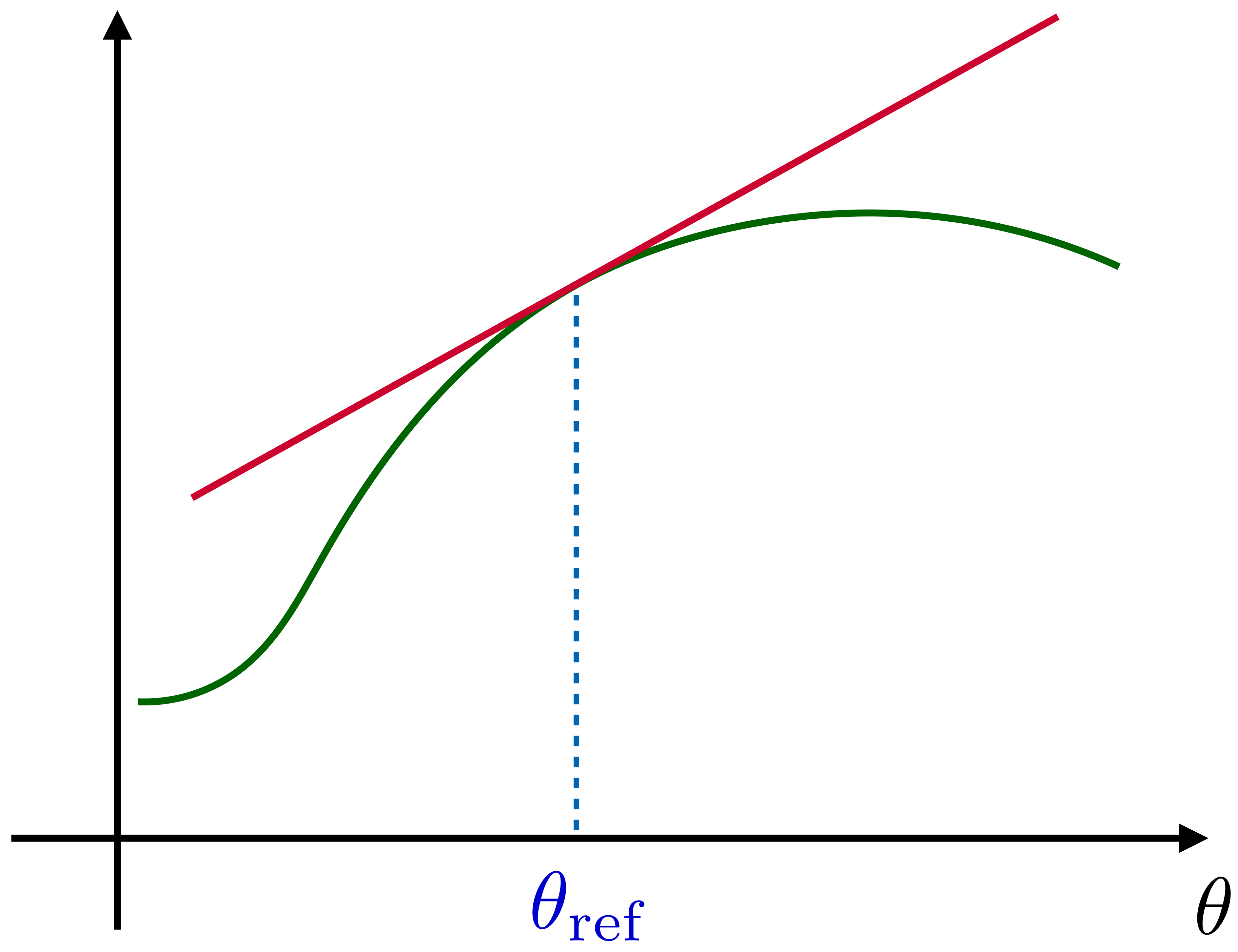
[JB, K. Cranmer, G. Louppe, J. Pavez 1805.00013, 1805.00020, 1805.12244]

The local model

[see also J. Alsing, B. Wandelt 1712.00012; J. Alsing, B. Wandelt. S. Freeney 1801.01497; P. de Castro, T. Dorigo 1806.04743; J. Alsing, B. Wandelt 1903.01473]

Taylor expansion of $\log p(x|\theta)$ around θ_{ref}:

$$\begin{aligned}\log p(x|\theta) = \log p(x|\theta_{\mathrm{ref}}) \\ + \underbrace{\nabla_\theta \log p(x|\theta)\Big|_{\theta_{\mathrm{ref}}}}_{\equiv t(x|\theta_{\mathrm{ref}})} \cdot (\theta - \theta_{\mathrm{ref}}) \\ + \mathcal{O}\left((\theta - \theta_{\mathrm{ref}})^2\right)\end{aligned}$$



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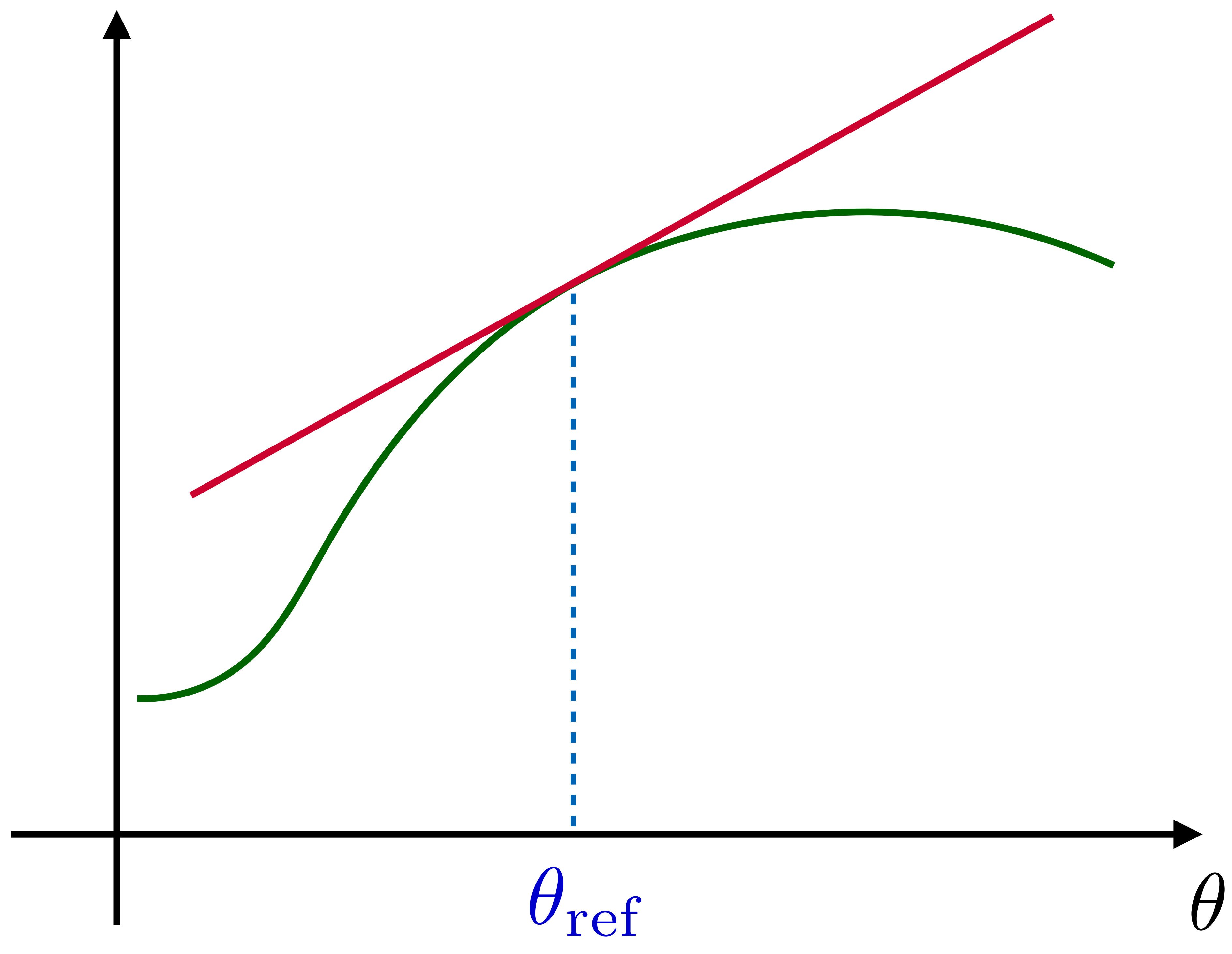
$$\log p(x|\theta) = \log p(x|\theta_{\text{ref}}) + \underbrace{\nabla_\theta \log p(x|\theta)\Big|_{\theta_{\text{ref}}}}_{\equiv t(x|\theta_{\text{ref}})} \cdot (\theta - \theta_{\text{ref}}) + \mathcal{O}\left((\theta - \theta_{\text{ref}})^2\right)$$

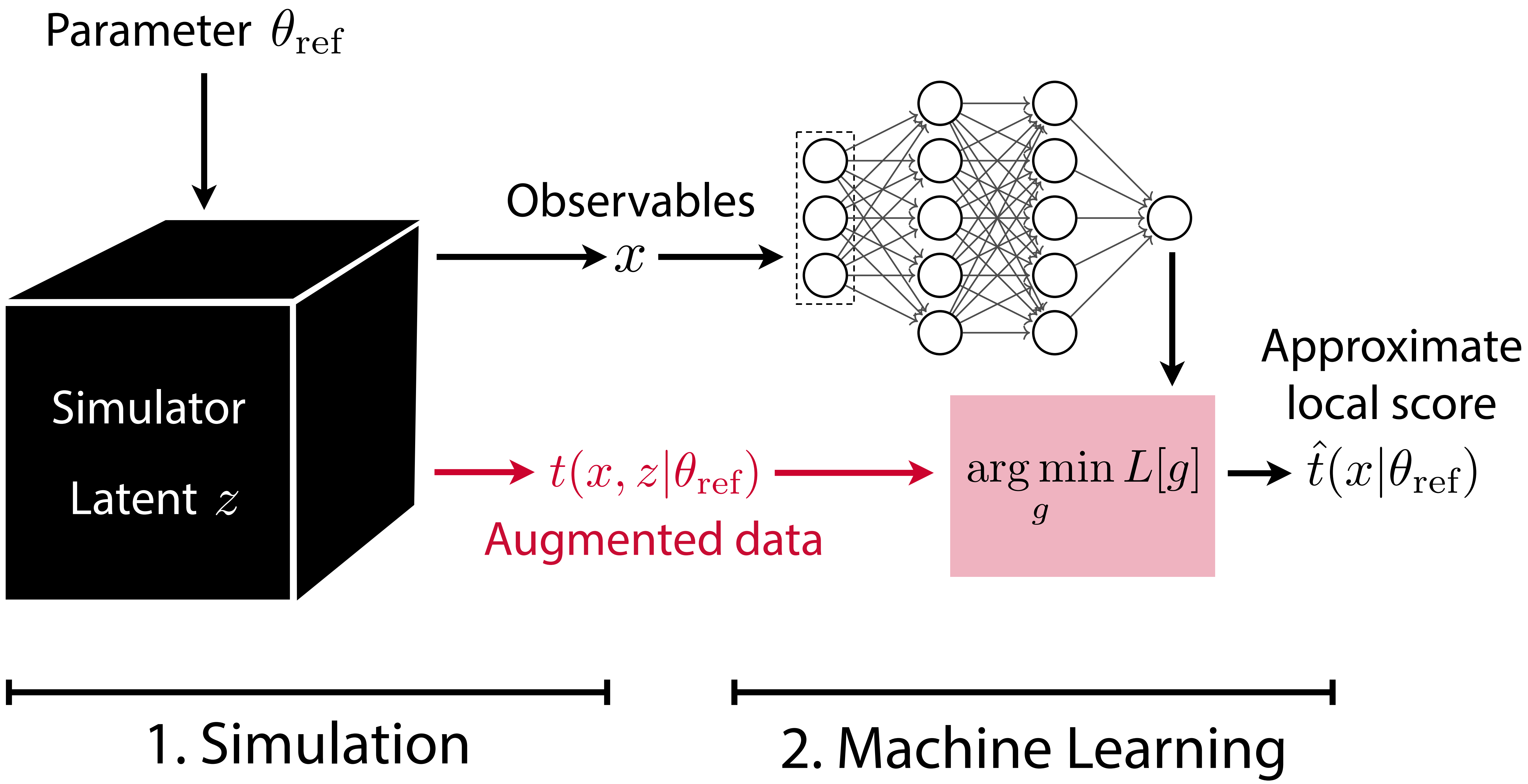
In the neighborhood of θ_{ref} (e.g. close to the SM):

- the score vector $t(x|\theta_{\text{ref}})$ is the sufficient statistics
- knowing $t(x|\theta_{\text{ref}})$ is just as powerful as knowing the full function $\log p(x|\theta)$
- $t(x|\theta_{\text{ref}})$ is the most powerful observable



The score itself is intractable. But we can use the same trick as for the likelihood ratio!

SALLY (Score approximates likelihood locally)



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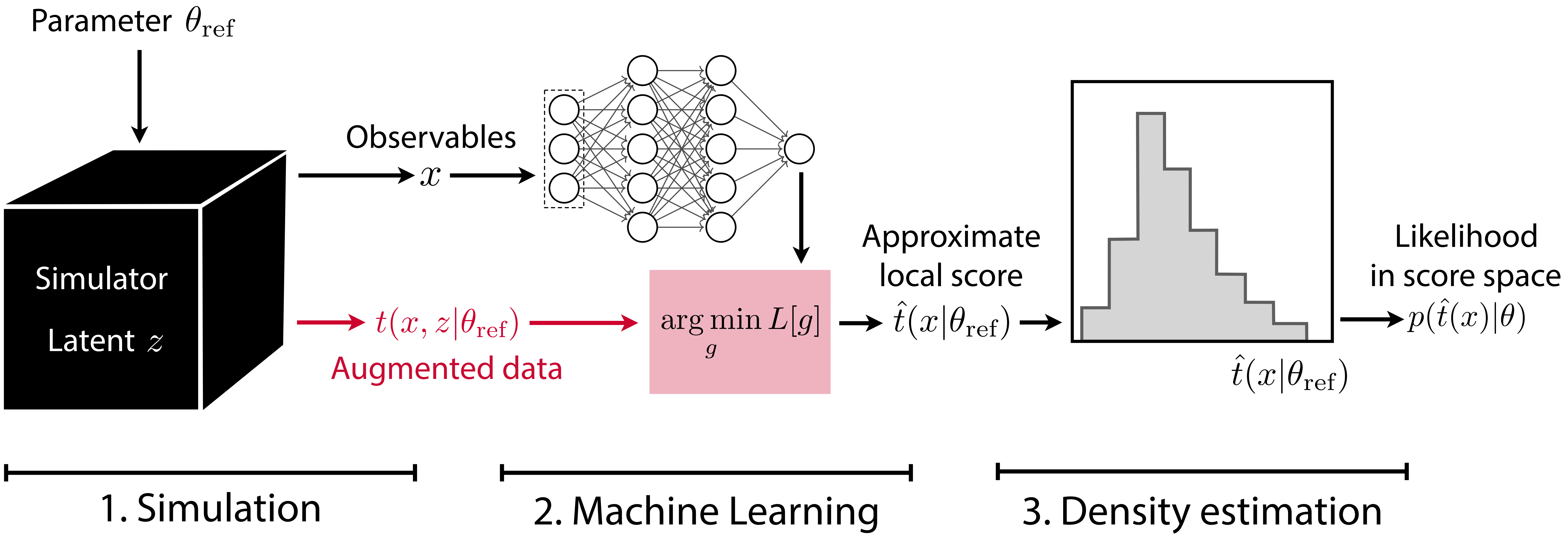

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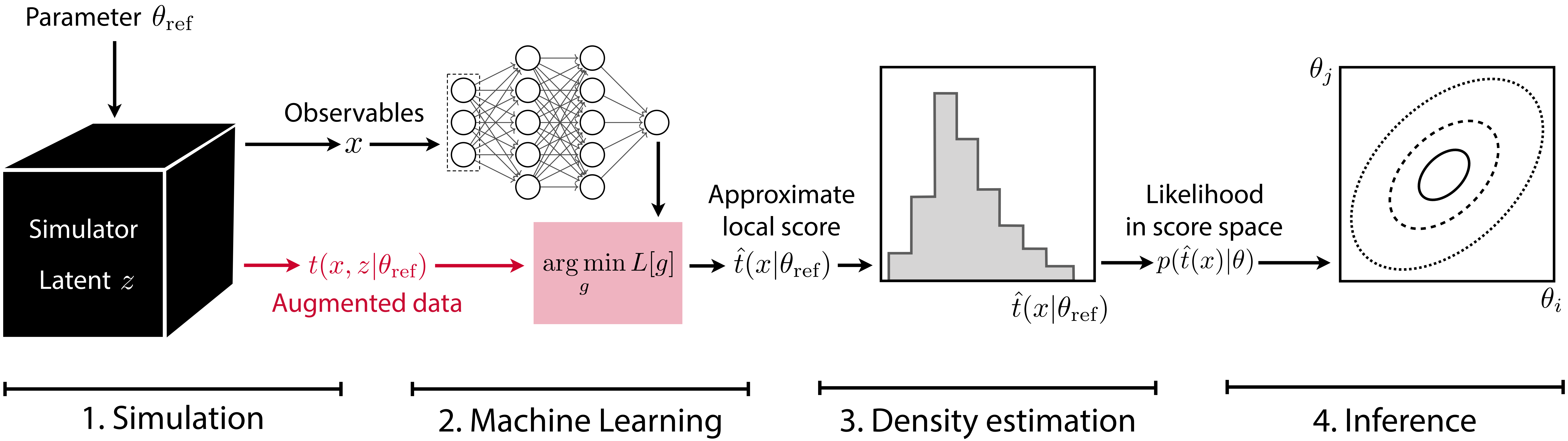

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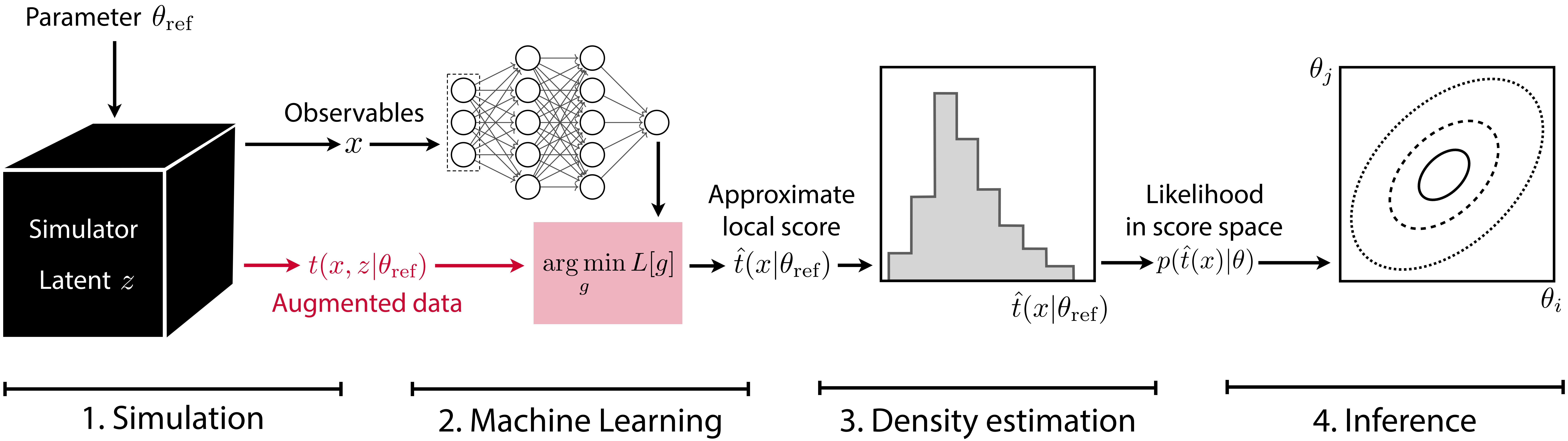
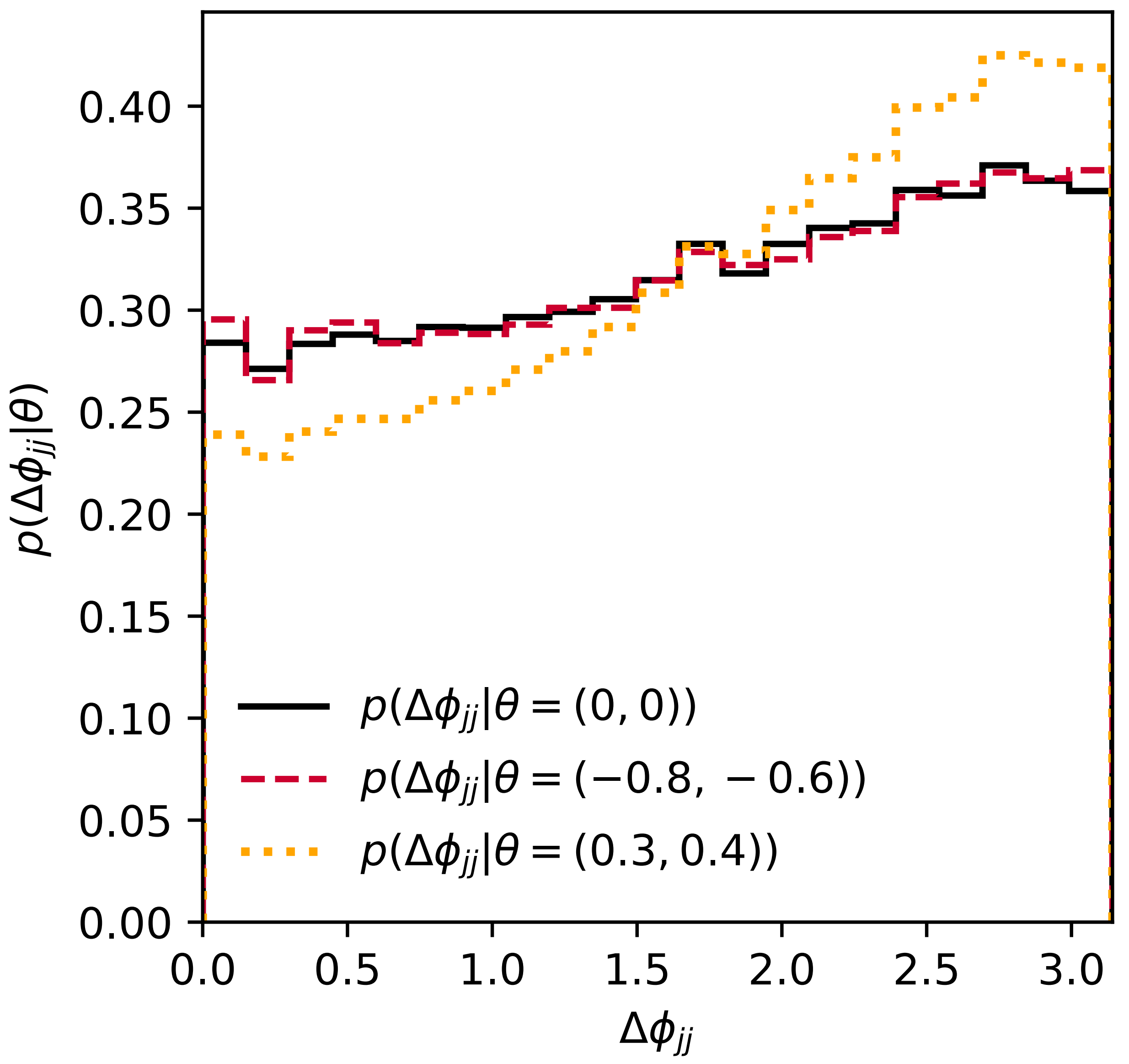


"The machine learning version of Optimal Observables":

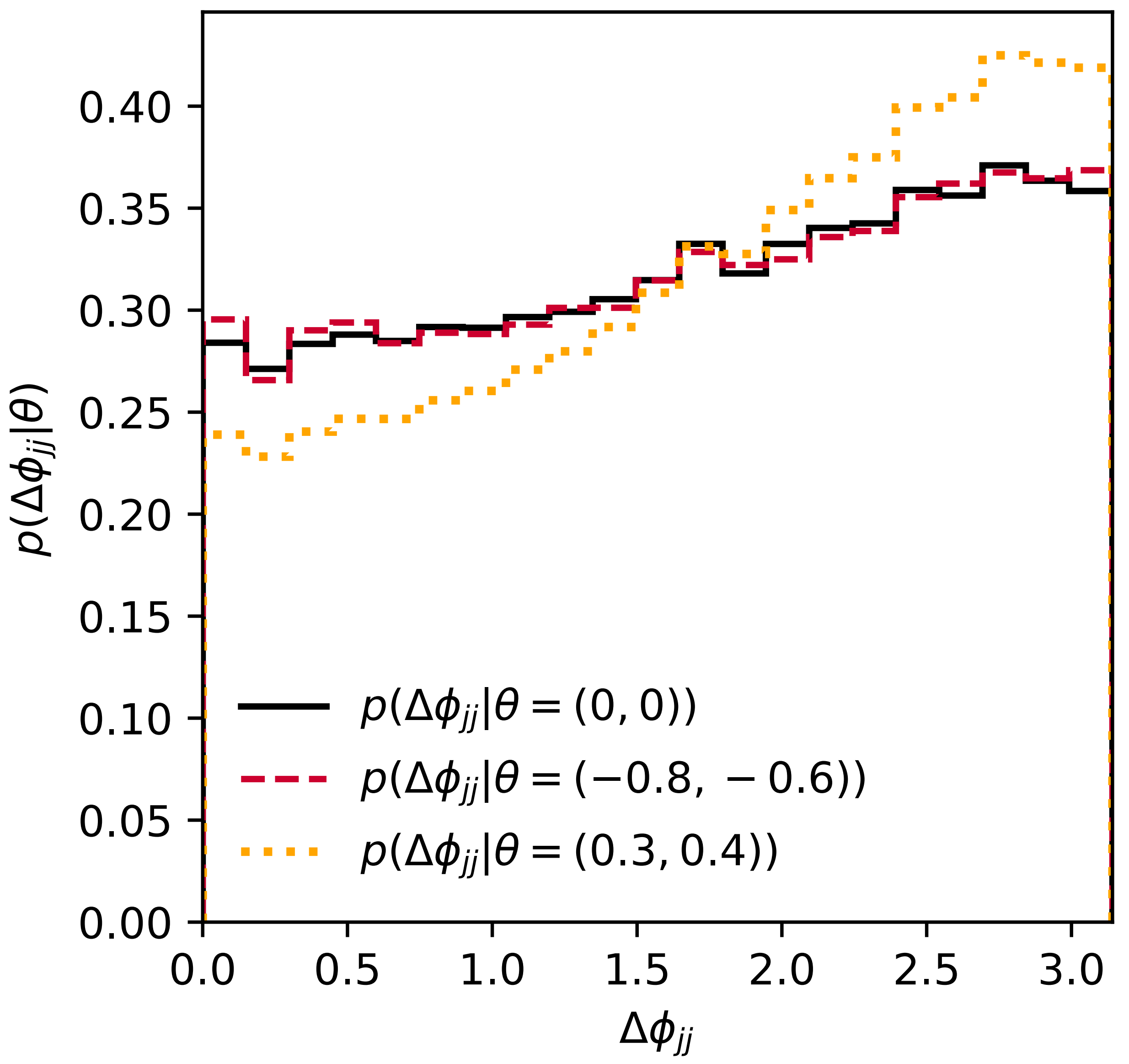
- Simpler & more robust than RASCAL
- Just as powerful close to θ_{ref}, but can lead to suboptimal limits further away

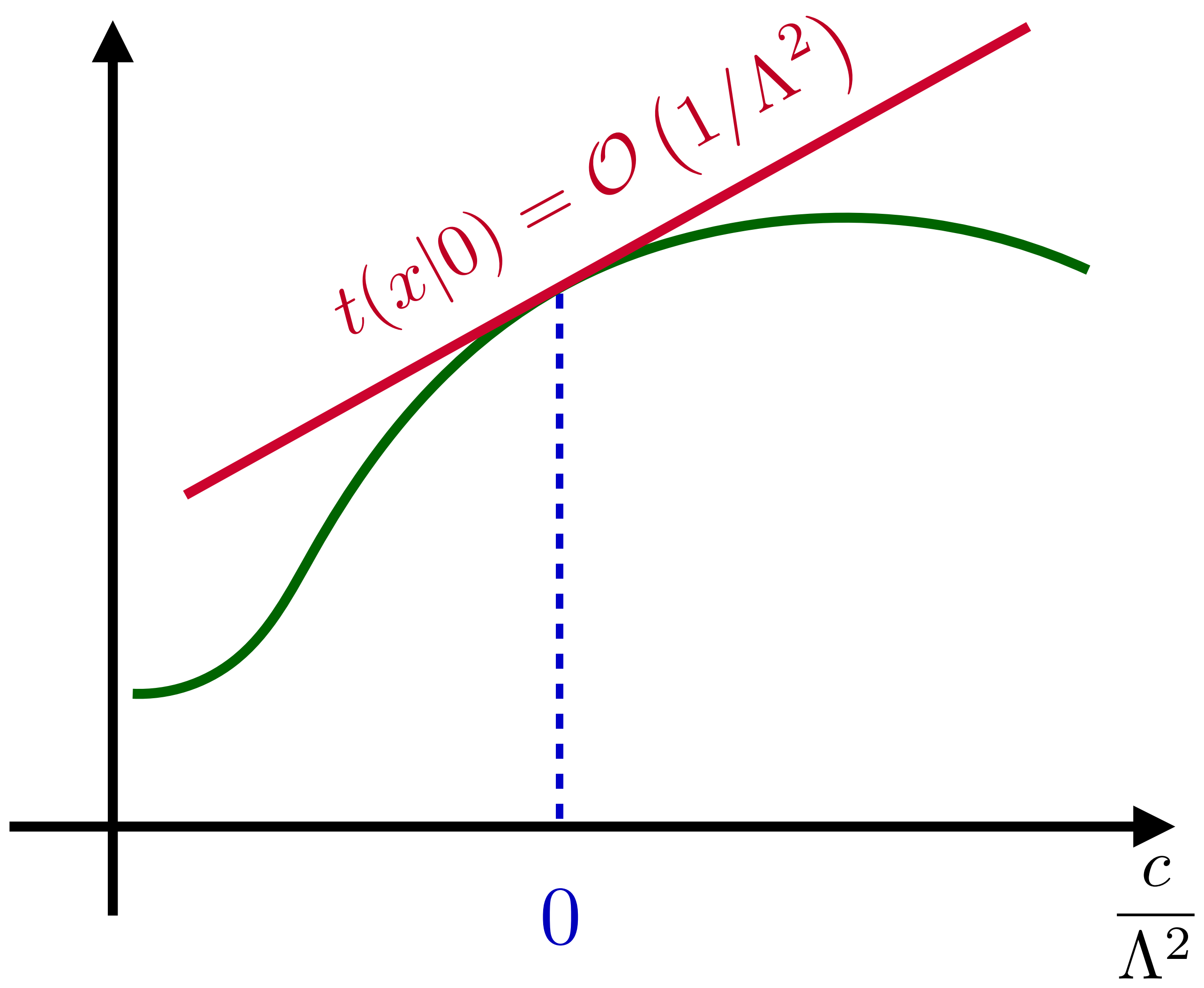
Perfect match for EFT measurements



- Good for subtle kinematic effects
  (Subtle point: Large overlap of kinematic distributions reduces variance of joint likelihood ratio / joint score)

Perfect match for EFT measurements





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  (SMALLY?)

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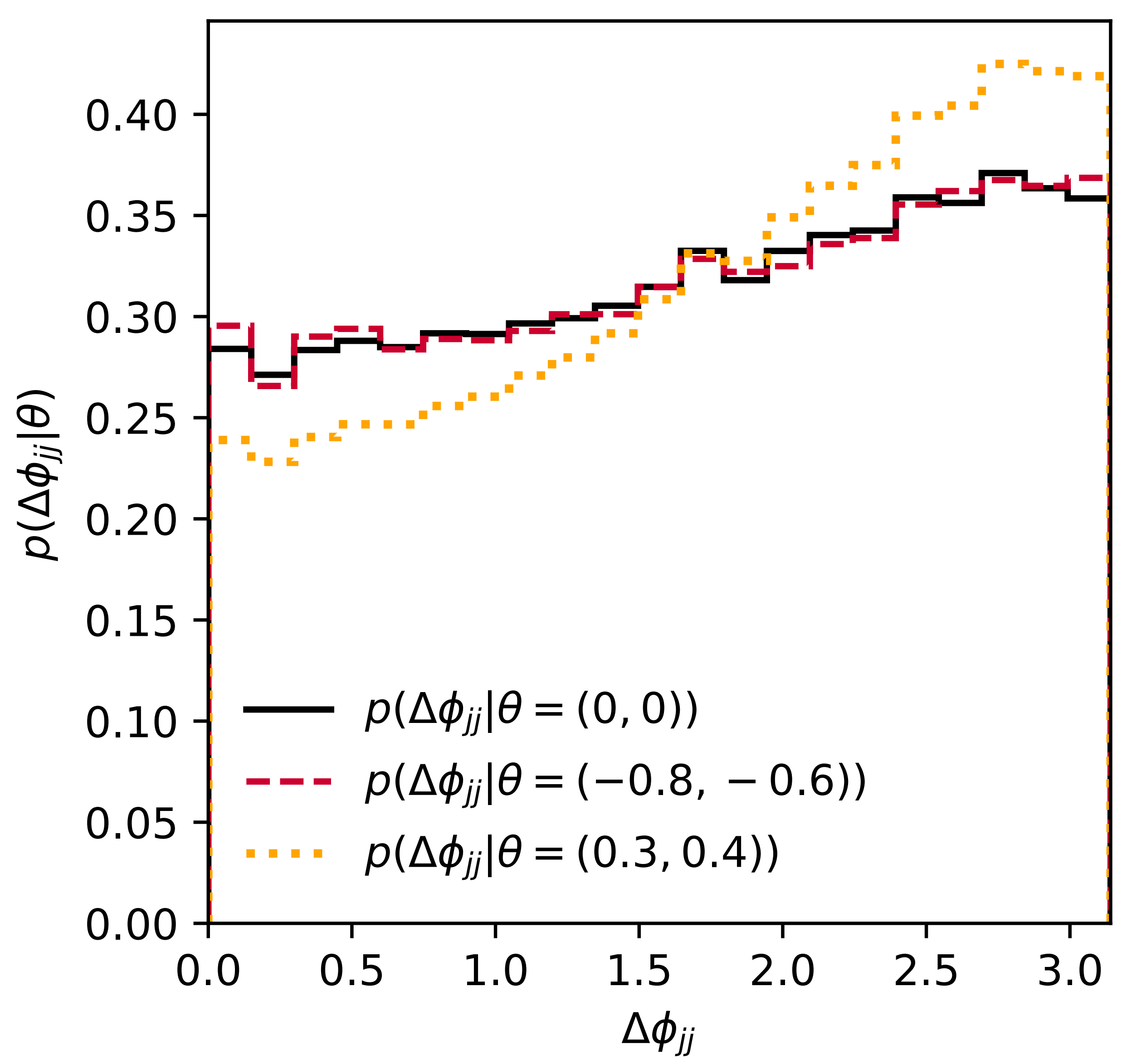
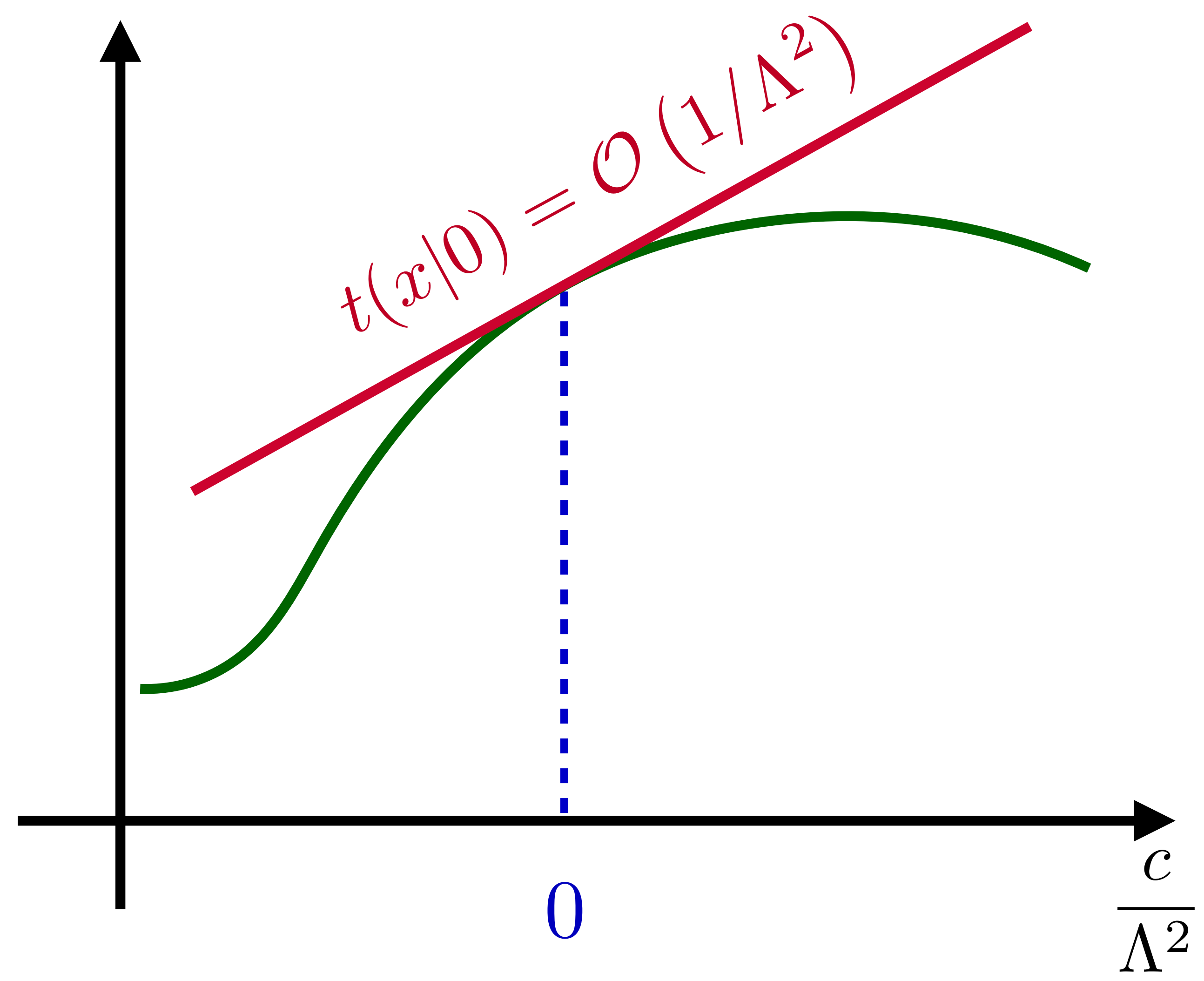
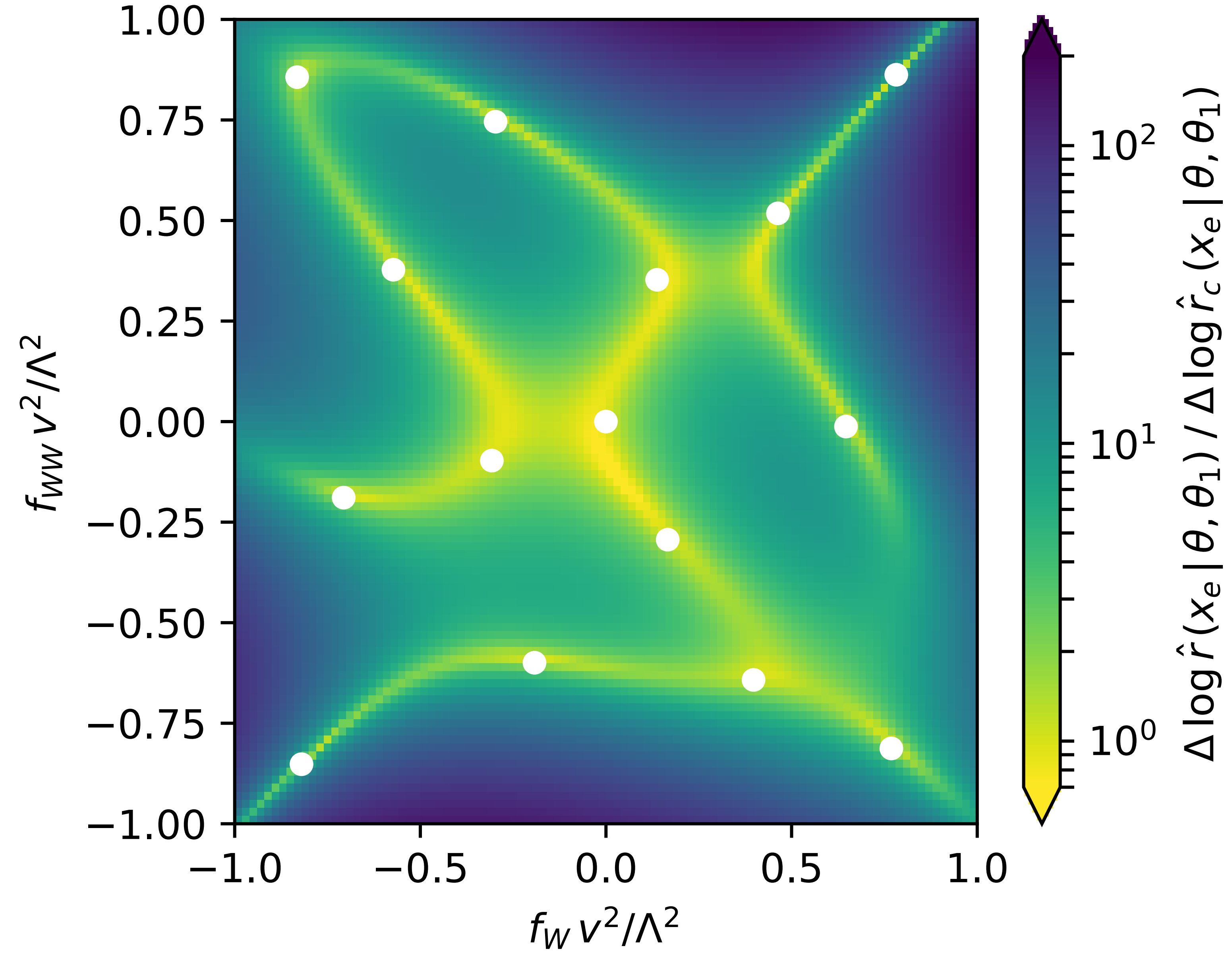






- Good for subtle kinematic effects
  (Subtle point: Large overlap of kinematic distributions reduces variance of joint likelihood ratio / joint score)
- Interference effects can be isolated using SALLY at the SM
  (SMALLY?)
- Morphing techniques allow fast reweighting to any parameter points
  [e.g. ATL-PHYS-PUB-2015-047]

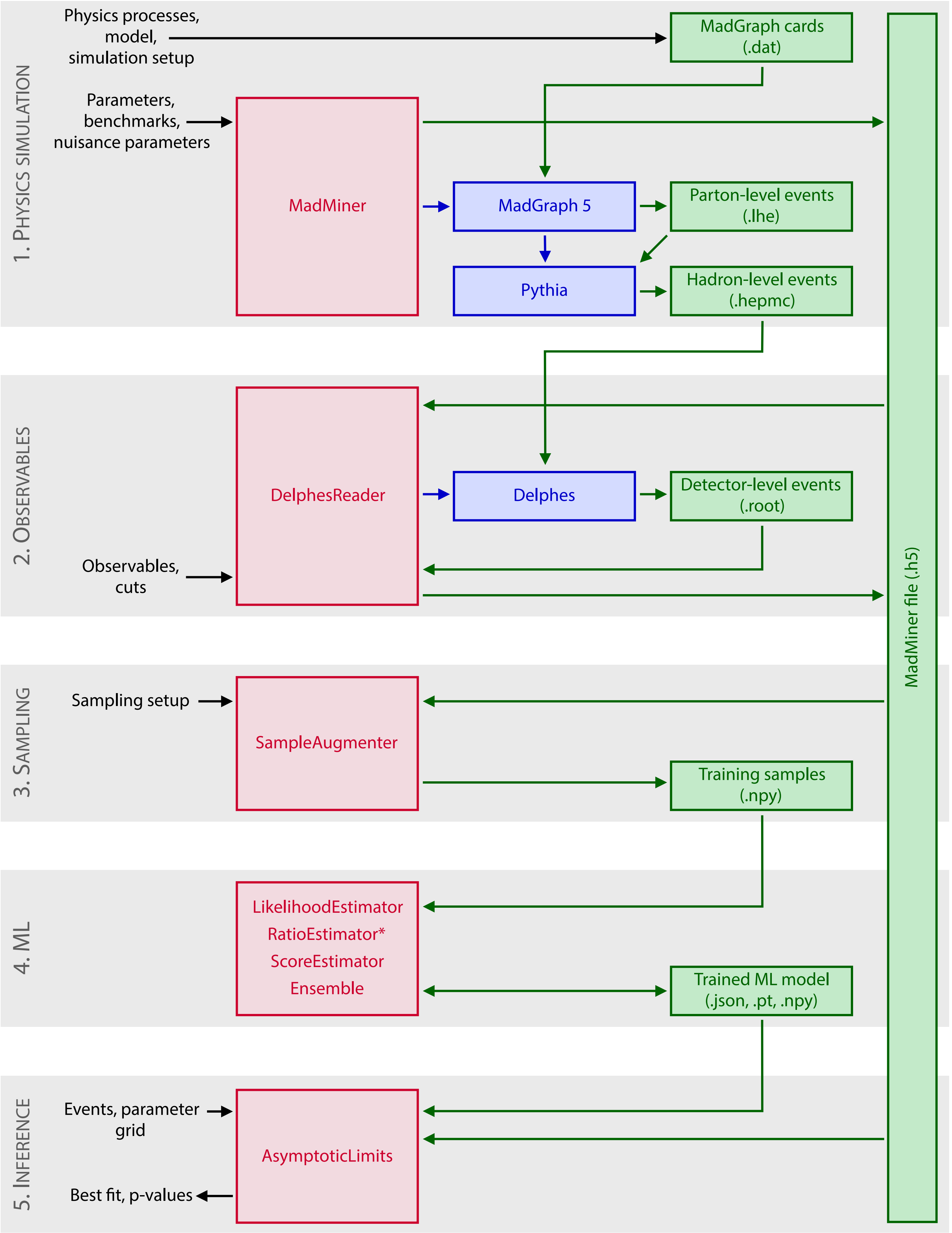
In practice

Automization

[JB, F. Kling, I. Espejo, K. Cranmer doi: 10.5281/zenodo.1489147]

We are developing MadMiner, which makes it straightforward to apply the new techniques to LHC problems

- Out of the box: Pheno-level analyses
  - MadGraph, Pythia, Delphes
  - Systematic uncertainties from PDF / scale variation
- Scalable to state-of-the-art experimental tools
  - Mostly requires bookkeeping of fully differential cross sections
- Modular interface
  - Extensive documentation
  - Embedded into Python / ML ecosystem

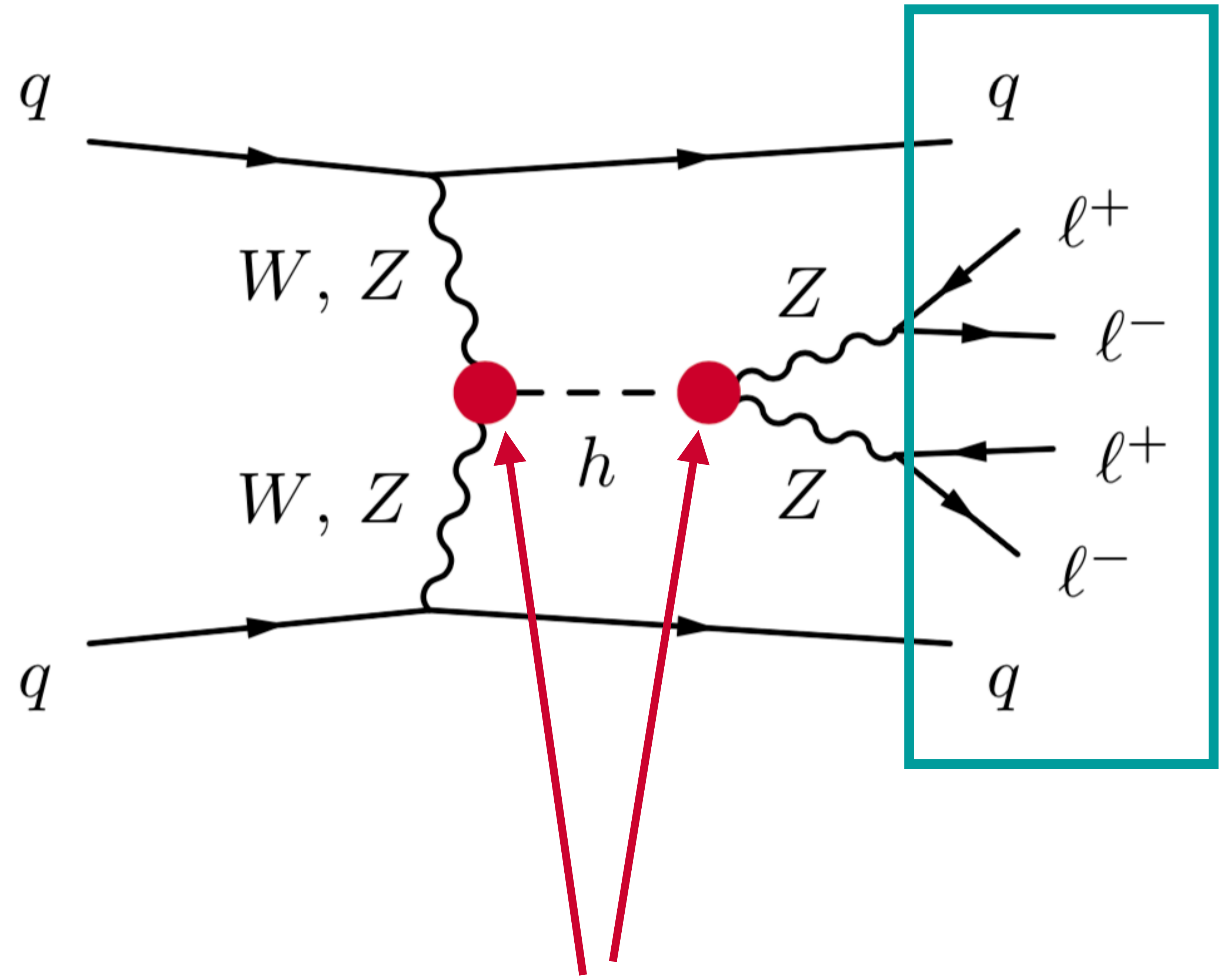


github.com/johannbrehmer/madminer madminer.readthedocs.io `pip install madminer`

Proof of concept: Higgs production in weak boson fusion

[JB, K. Cranmer, G. Louppe, J. Pavez
1805.00013, 1805.00020]

at least 16-dimensional
observable space



Exciting new physics might hide here!
We parameterize it with two EFT coefficients:

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

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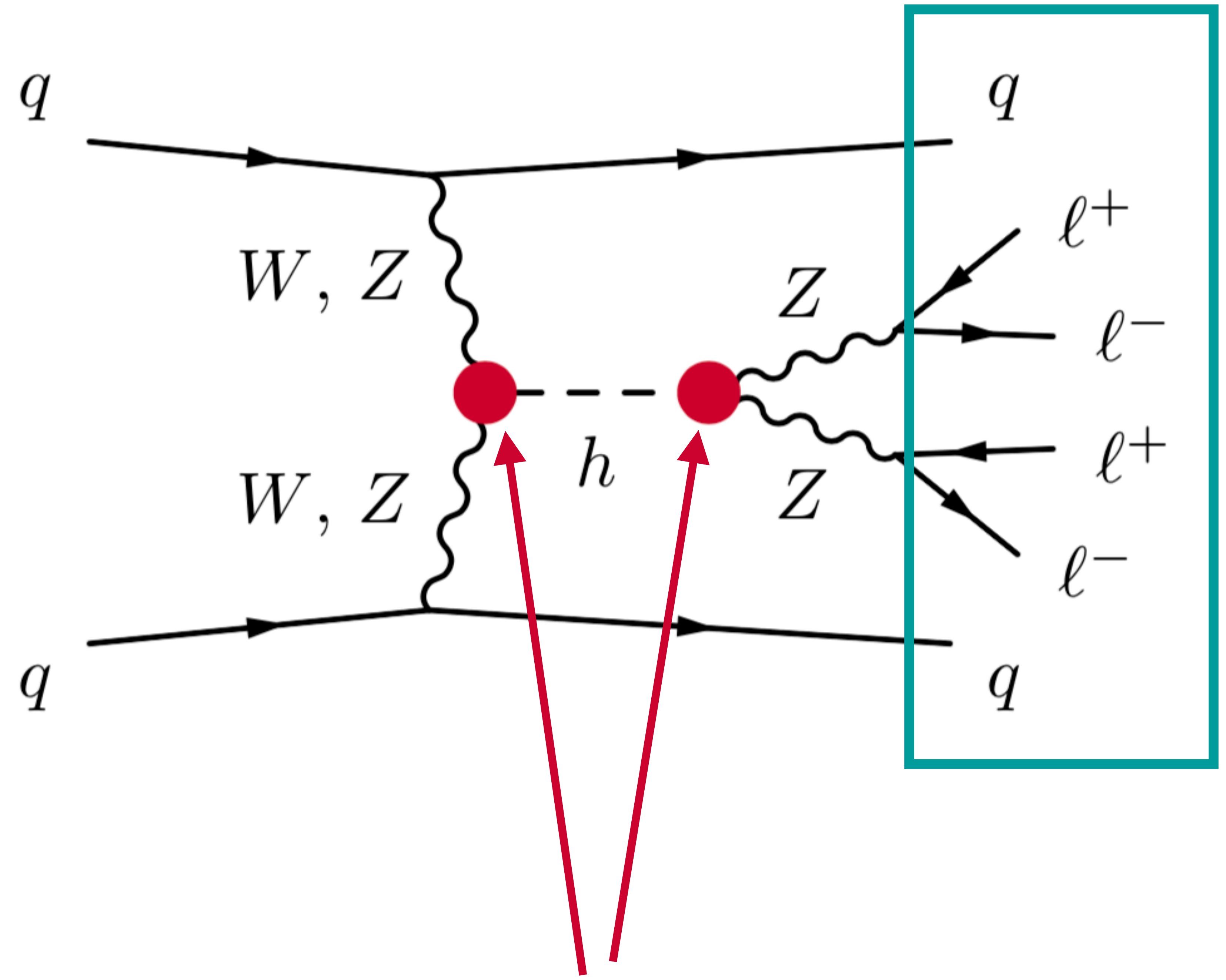

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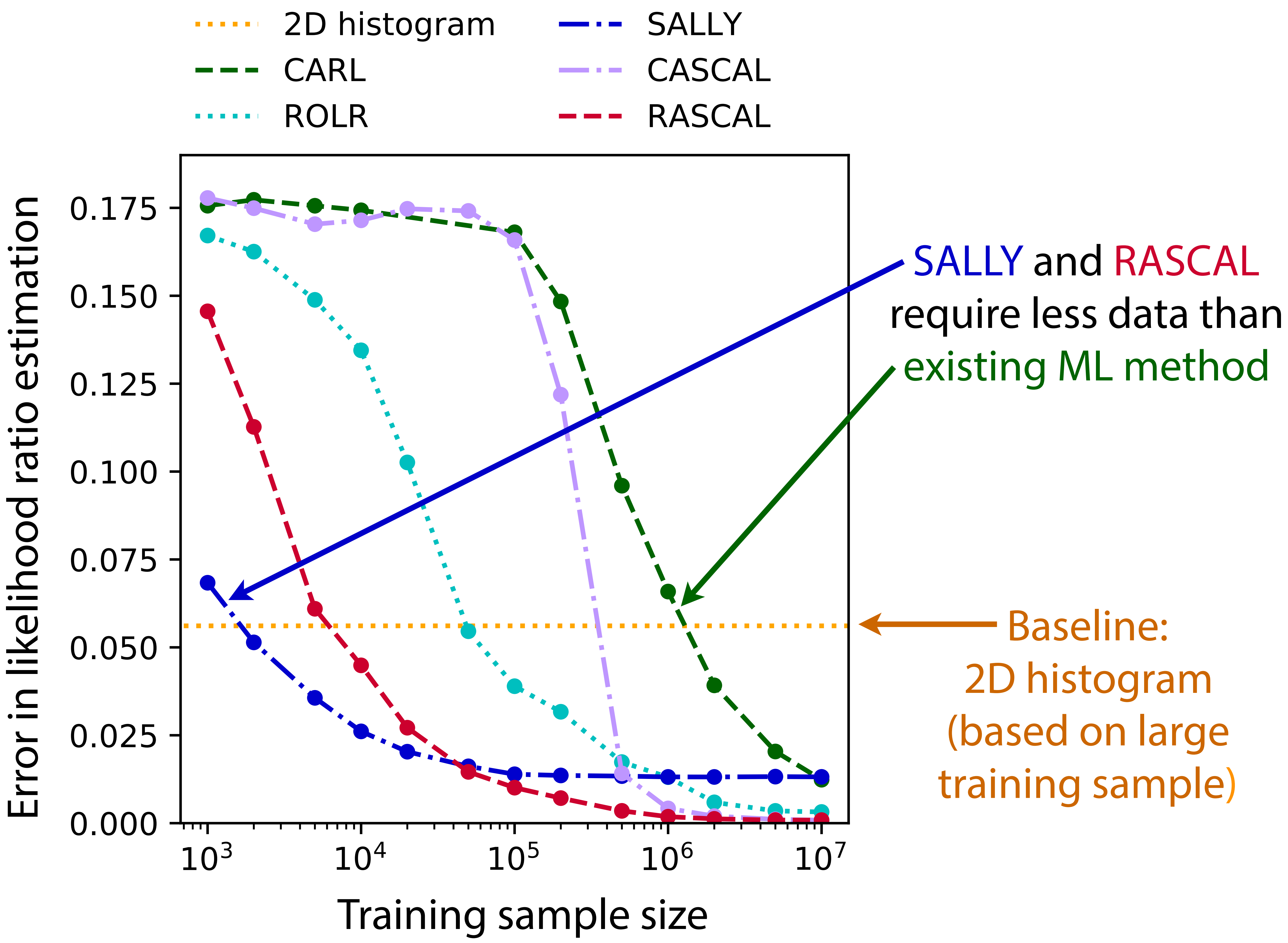
Goal: constrain the two EFT parameters

- new inference methods
- baseline: 2d histogram analysis of jet momenta & angular correlations

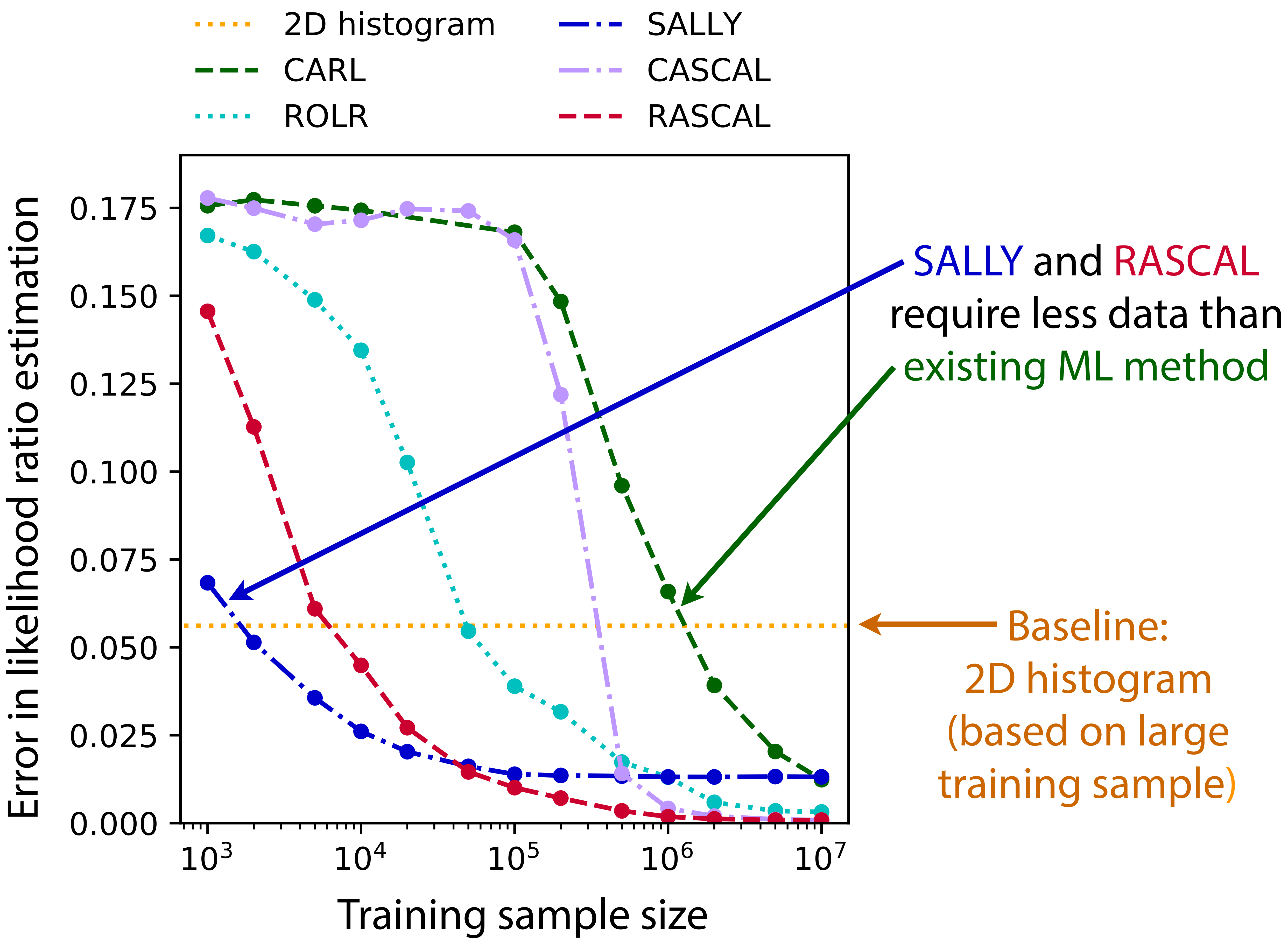
Two scenarios:

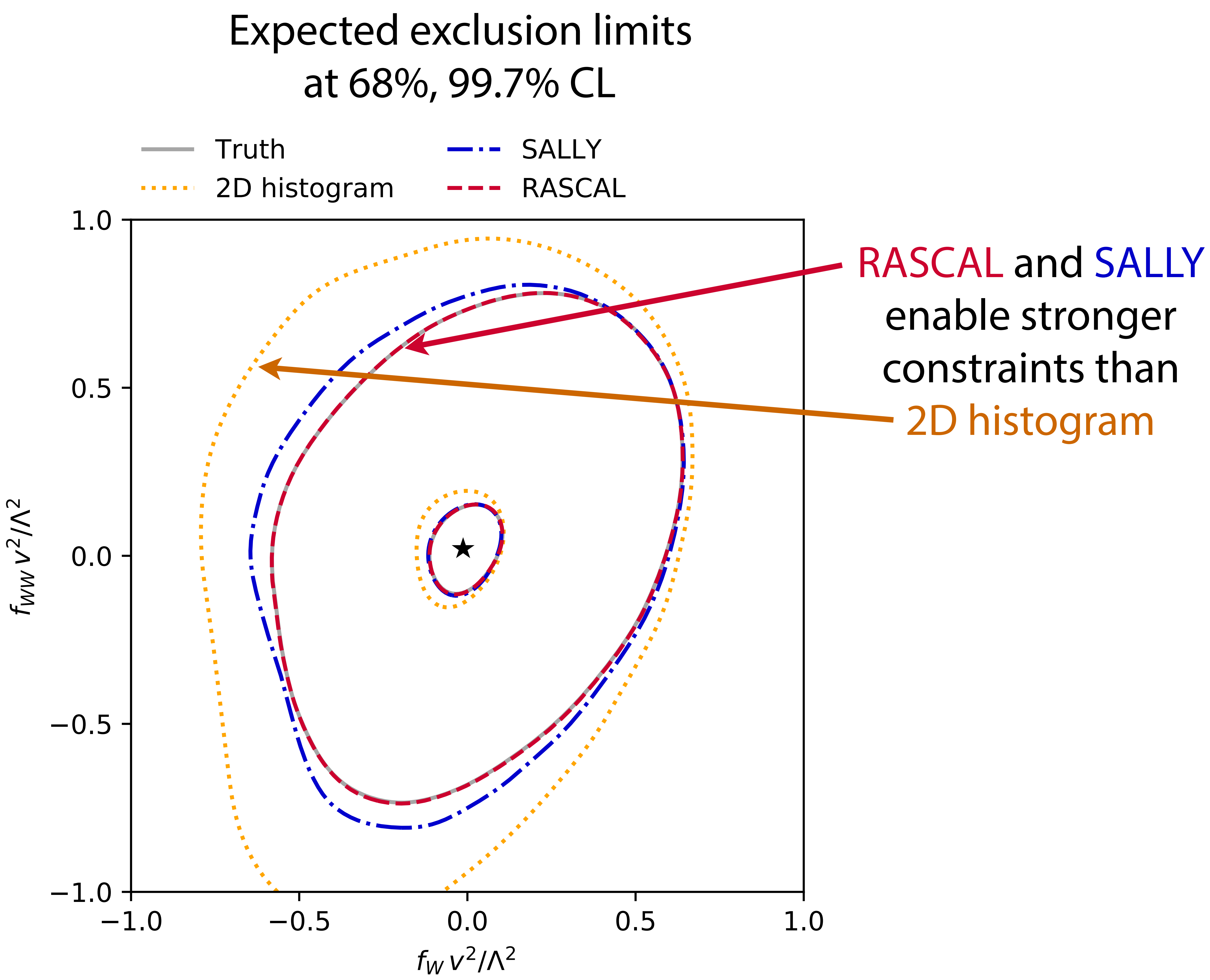
- Simplified setup in which we can compare to true likelihood
- "Realistic" simulation with approximate detector effects

Stronger constraints with less training data



Stronger constraints with less training data





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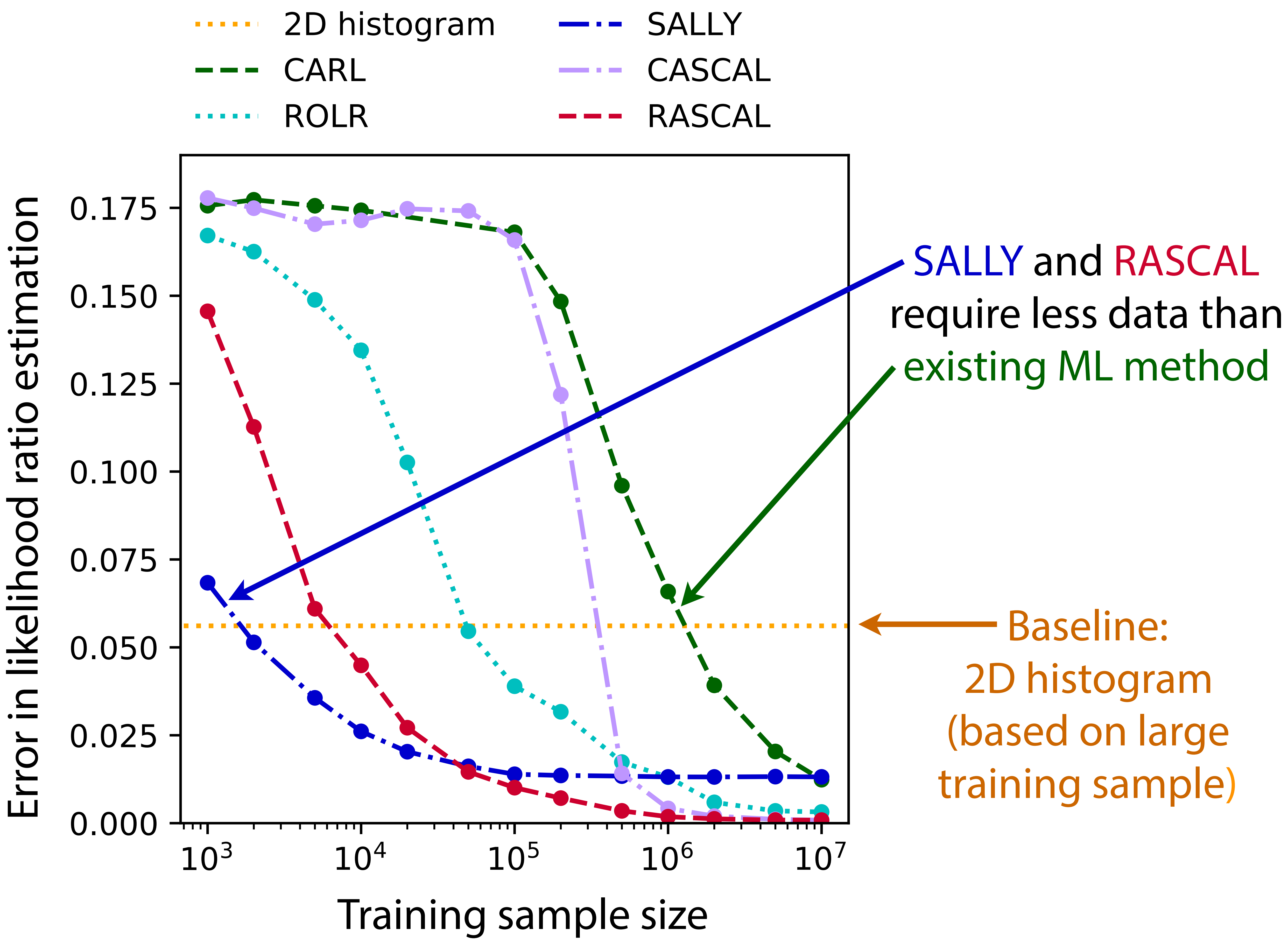
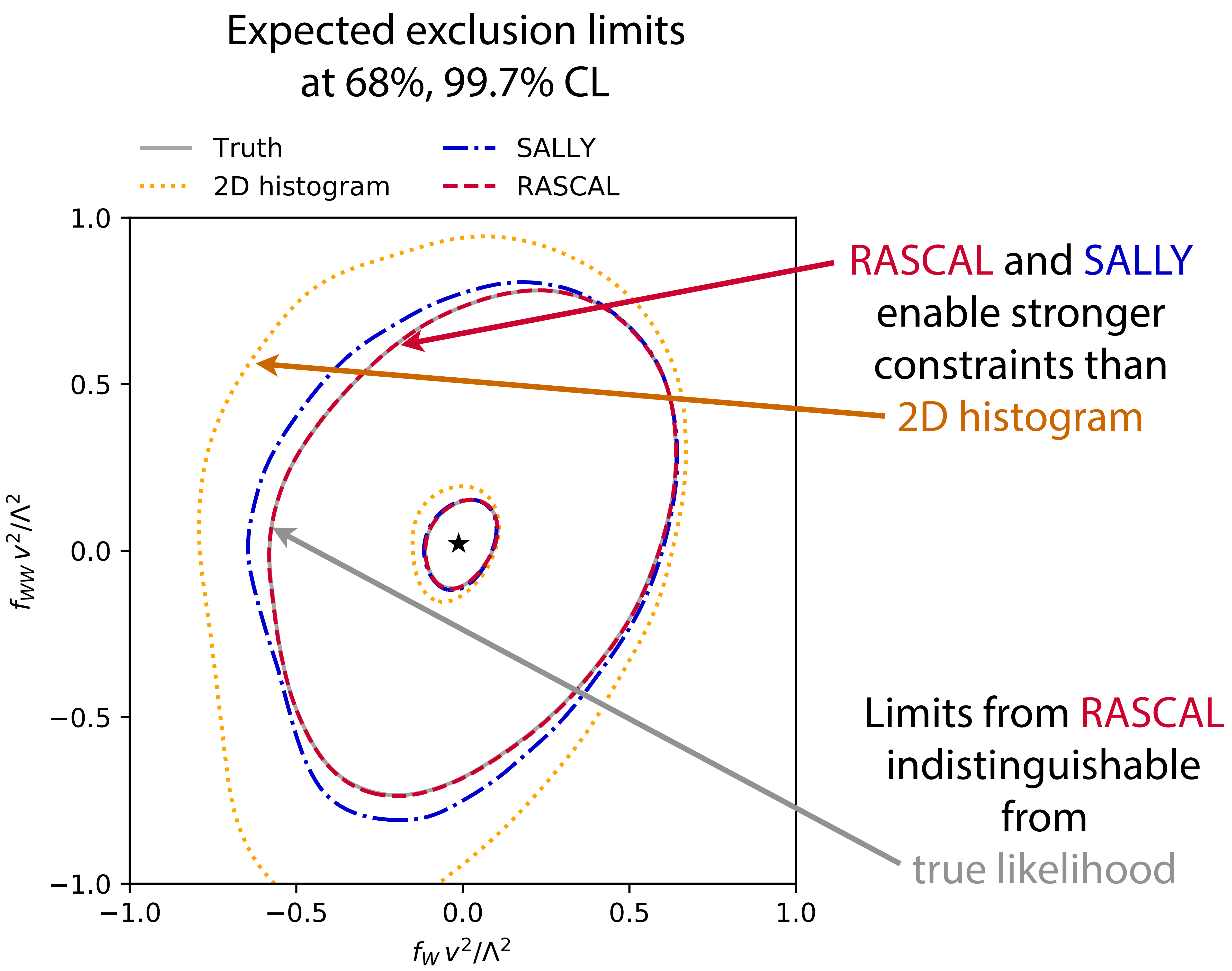


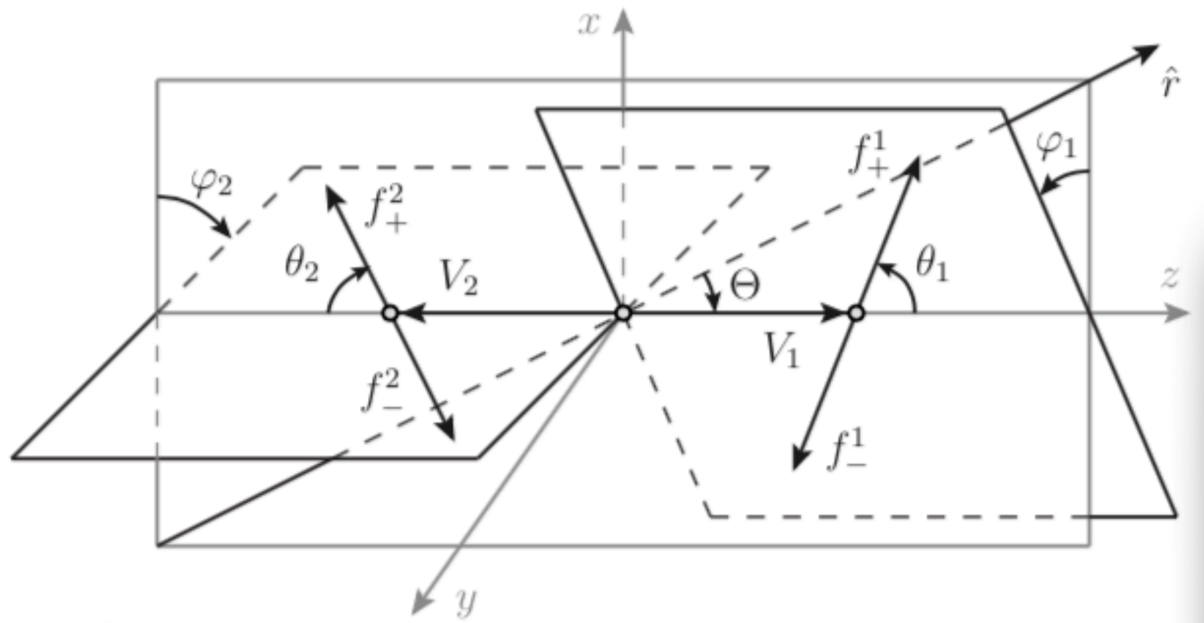


Dibosons

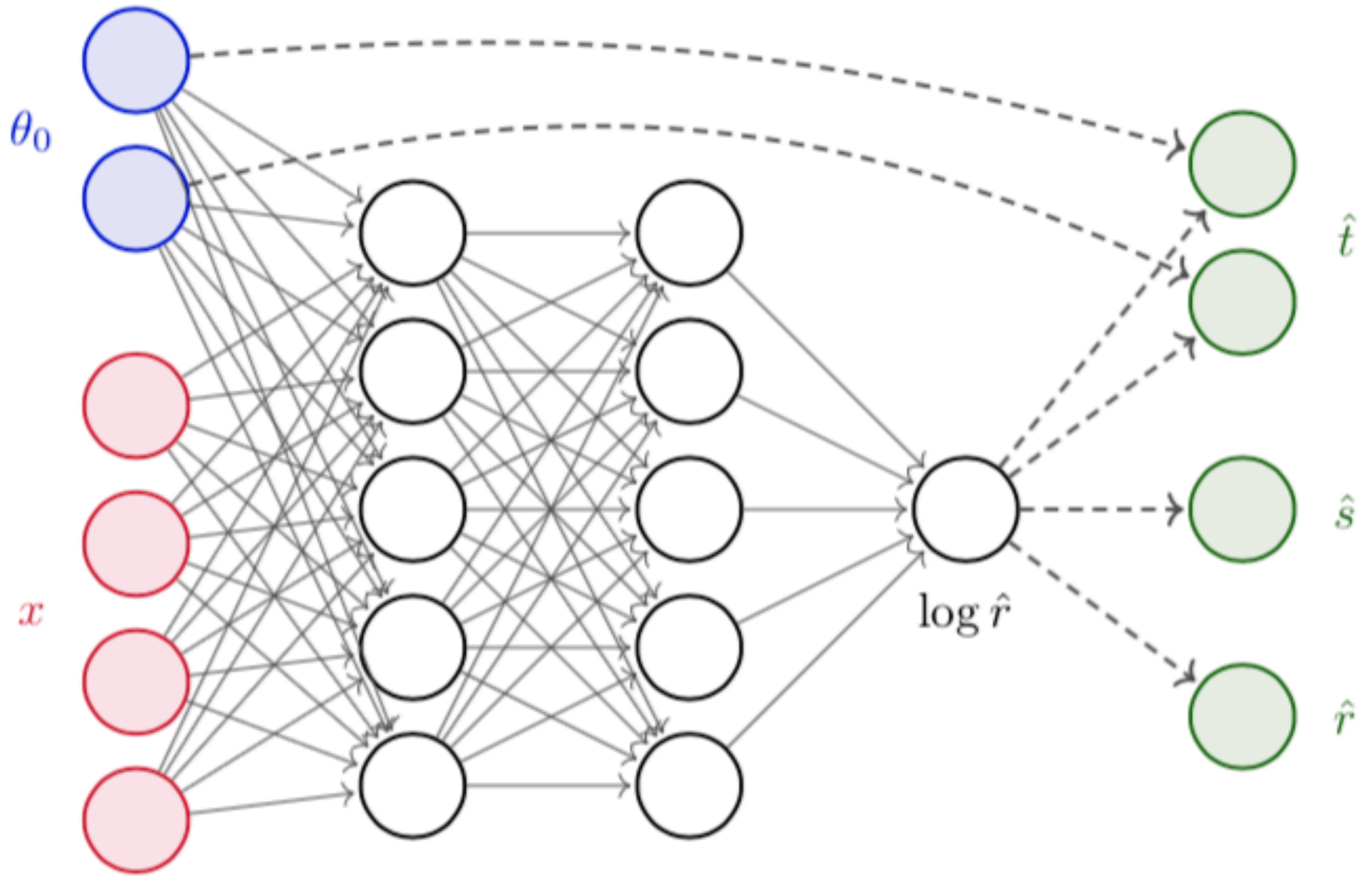
Transverse DiBosons

[Panico, Riva, AW, 2017]

Measuring diboson diff. cross-sections is not enough



Can we get this done by a Machine? (in real world)



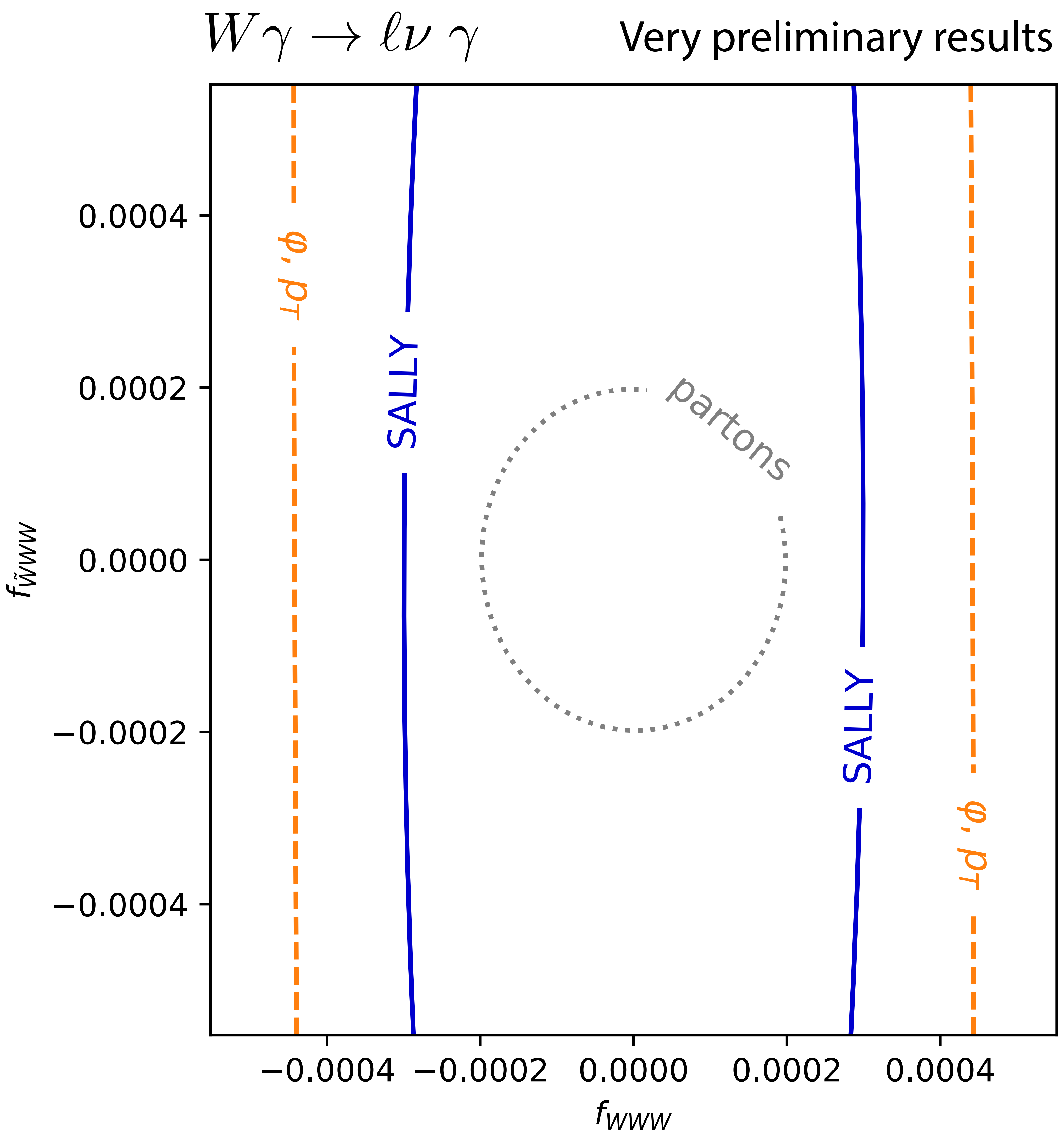
Cranmer et.al., 2018

[from A. Wulzer's talk]

Dibosons

[JB, K. Cranmer, M. Farina, F. Kling, D. Pappadopulo, J. Ruderman in progress]

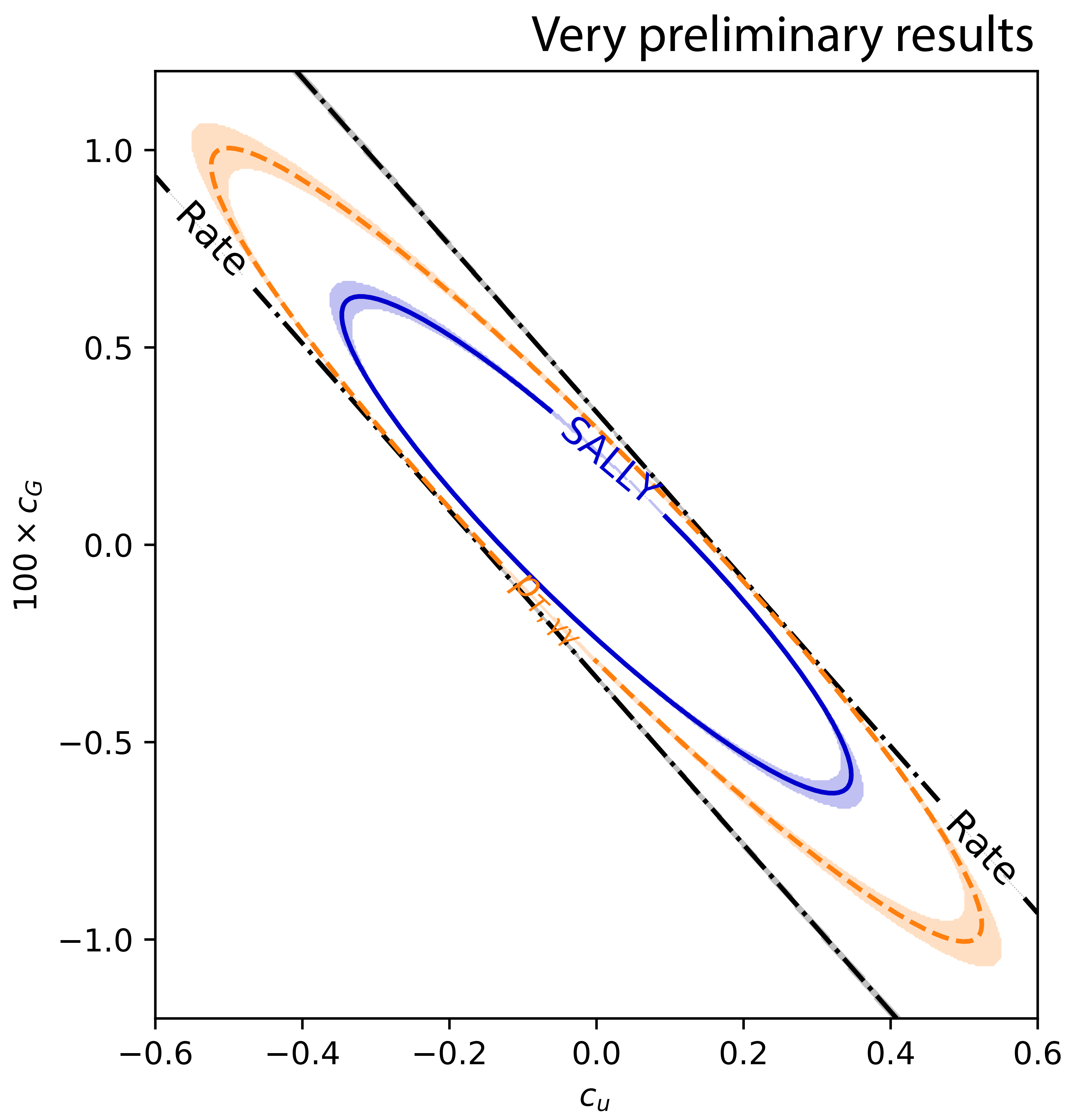
Yes.



Higgs measurements

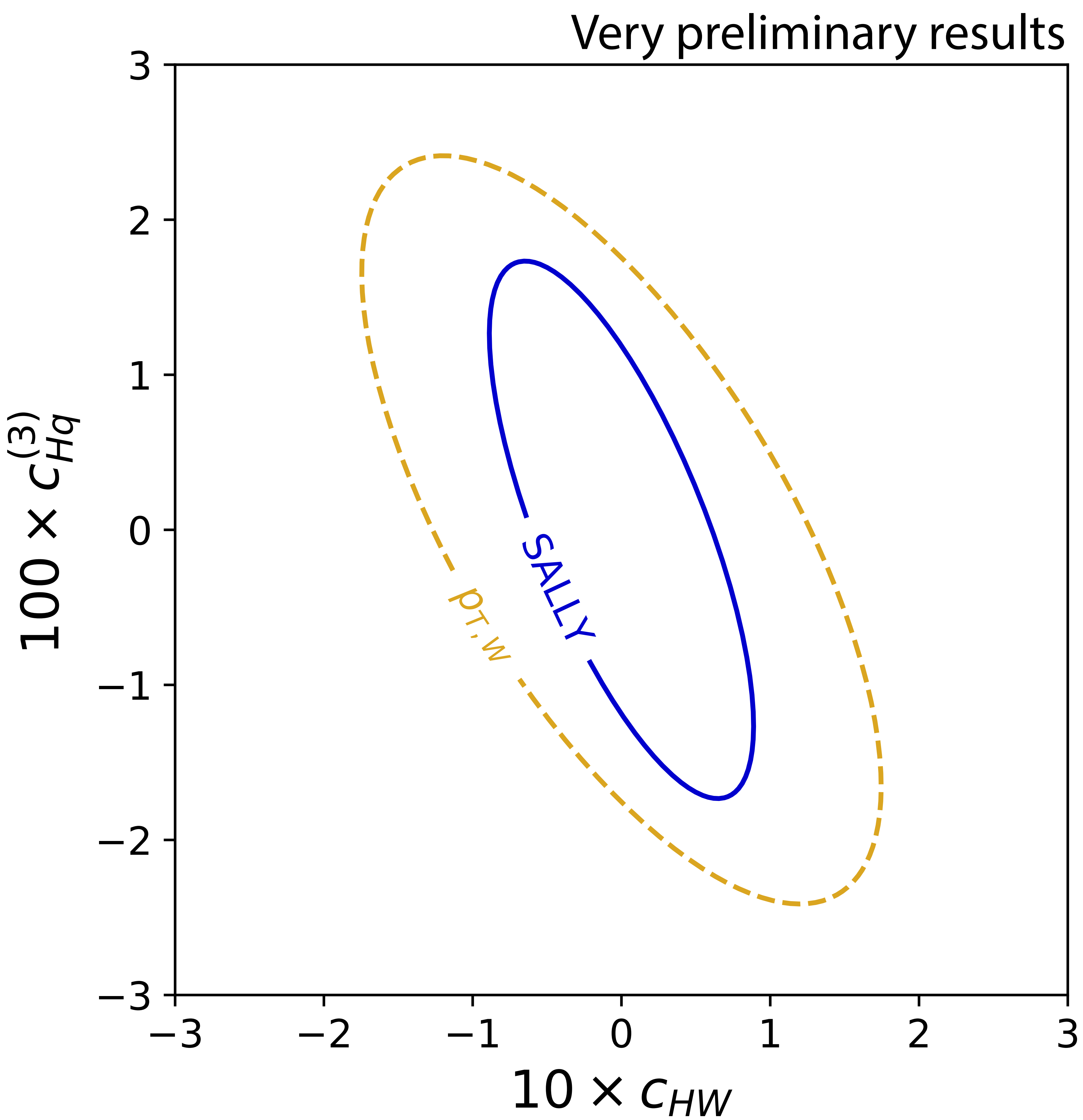
$$t\bar{t}\,h \to (b\ell^+\nu)\,(b\ell^-\bar{\nu})\,(\gamma\gamma)$$

[JB, F. Kling, I. Espejo, K. Cranmer in progress]

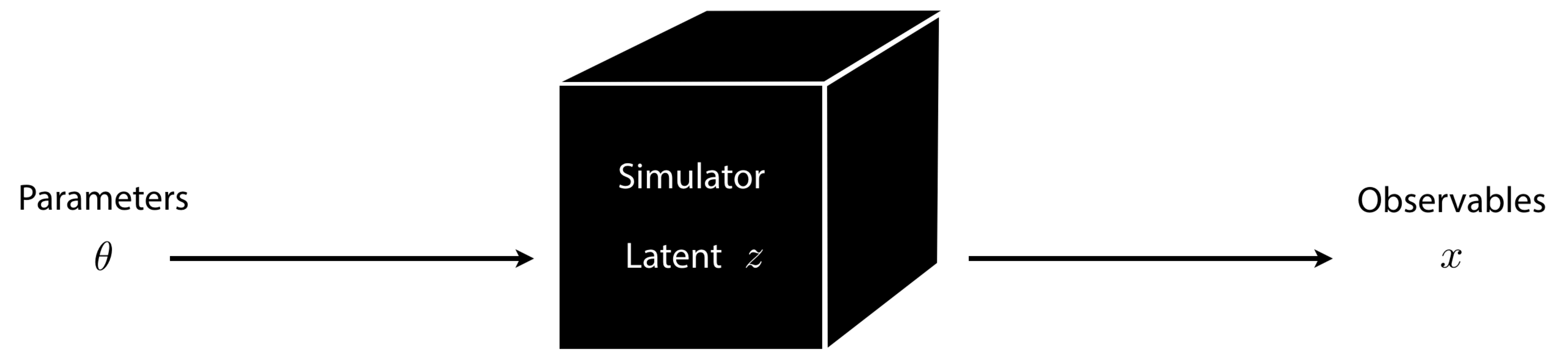


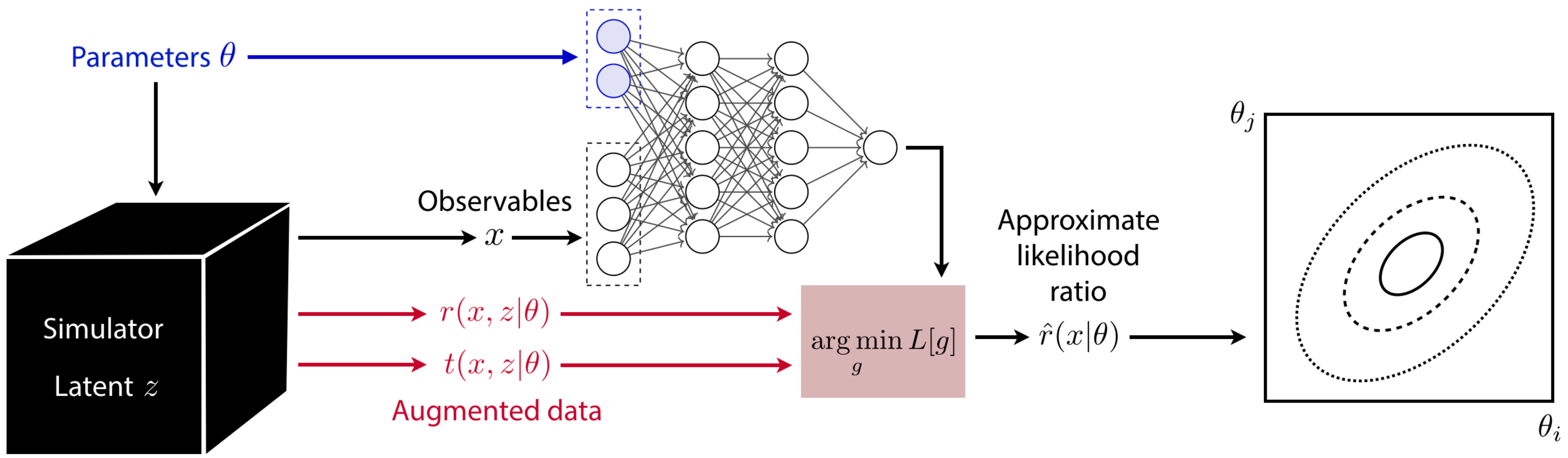
$$Wh \to (\ell\nu)(b\bar{b})$$

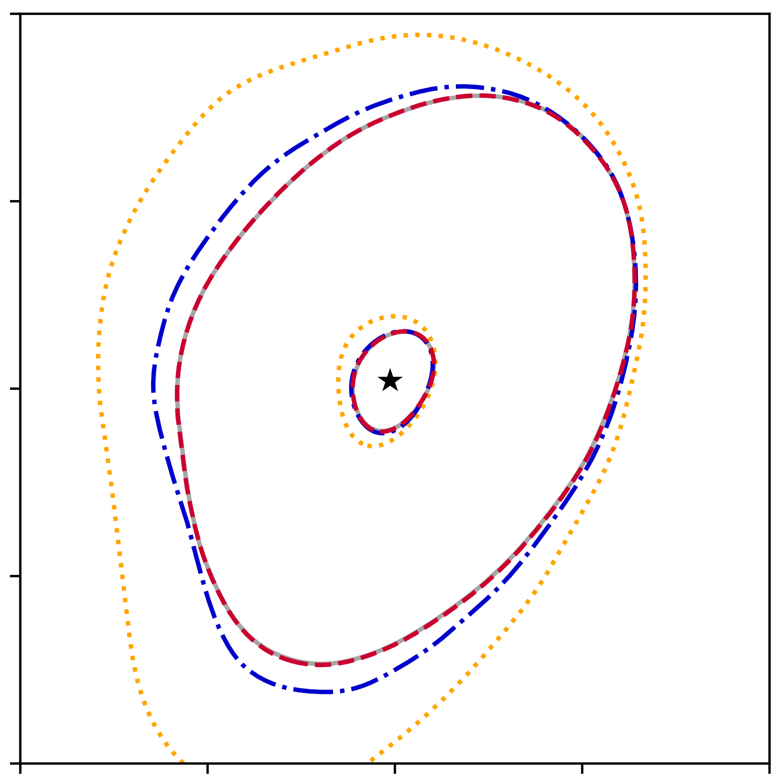
[JB, S. Dawson, S. Homiller, F. Kling, T. Plehn in progress]



A new approach to LHC measurements







- LHC measurements with high-dimensional observations have "likelihood-free" structure
- New multivariate inference techniques: Leverage information in matrix elements + power of machine learning to…
  - estimate the full likelihood function
  - learn optimal summary statistics
- First tests show potential to substantially increase sensitivity to new physics
  - Ideal for EFT measurements

References


Kyle Cranmer


Gilles Louppe


Juan Pavez


Markus Stoye


Felix Kling


Irina Espejo

JB, KC, GL, JP:	Constraining Effective Field Theories with Machine Learning	[PRL, 1805.00013]
JB, KC, GL, JP:	A Guide to Constraining Effective Field Theories with Machine Learning	[PRD, 1805.00020]
JB, GL, JP, KC:	Mining gold from implicit models to improve likelihood-free inference	[1805.12244]
MS, JB, GL, JP, KC:	Likelihood-free inference with an improved cross-entropy estimator	[1808.00973]
JB, FK, IE, KC:	MadMiner: An inference toolkit for particle physics	[doi: 10.5281/zenodo.1489147]

Bonus material

Solve it by approximating the integral

- Problem: high-dim. integral over shower / detector trajectories

$$p(x|\theta) = \int \mathrm{d}z_d \int \mathrm{d}z_s \int \mathrm{d}z_p \; p(x|z_d)\, p(z_d|z_s)\, p(z_s|z_p)\, p(z_p|\theta)$$

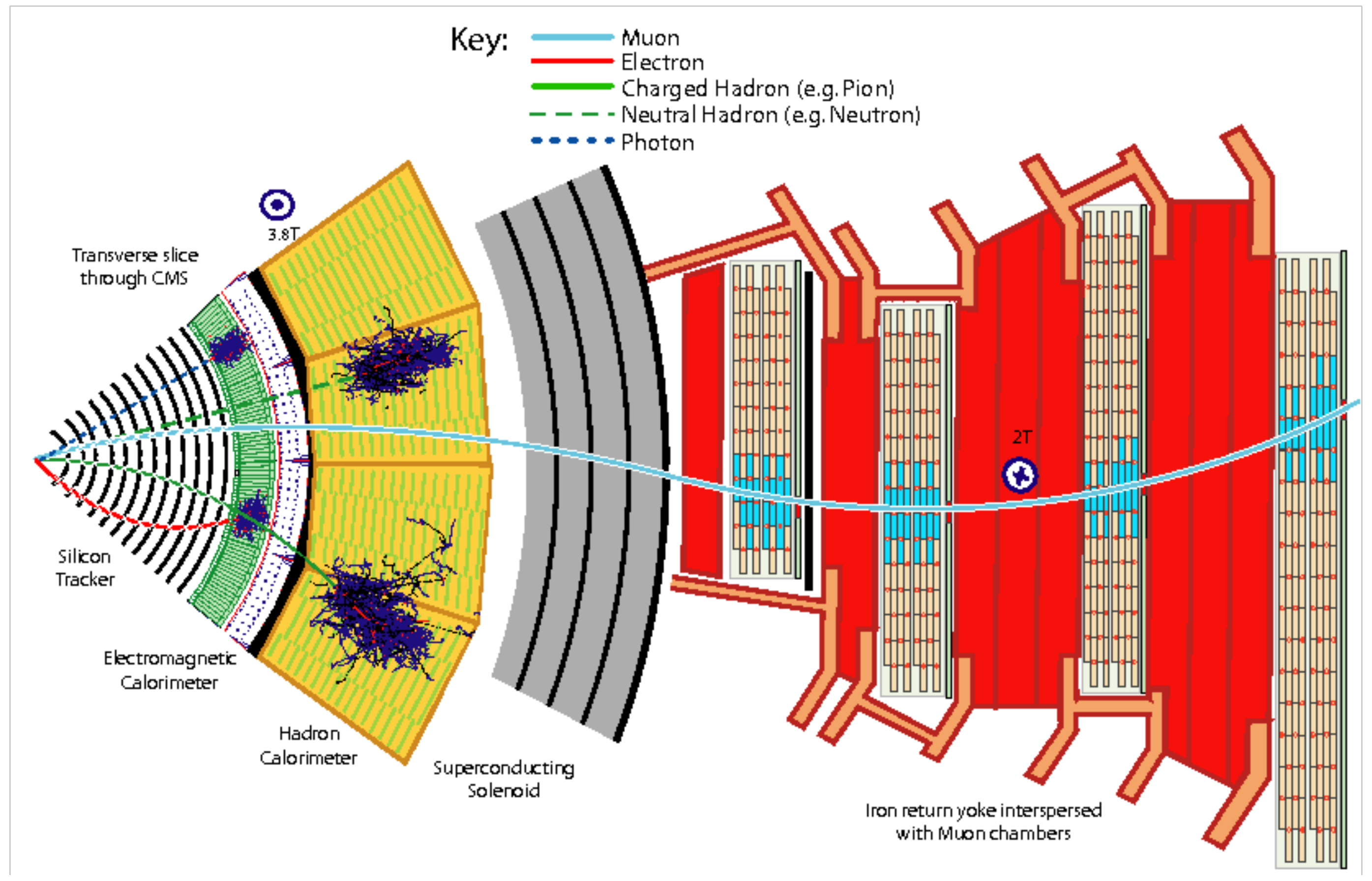
- Matrix Element Method: [K. Kondo 1988]
  - approximate shower + detector effects into transfer function $\hat{p}(x|z_p)$
  - explicitly calculate remaining integral

$$\hat{p}(x|\theta) = \int \mathrm{d}z_p \; \hat{p}(x|z_p)\, p(z_p|\theta)$$

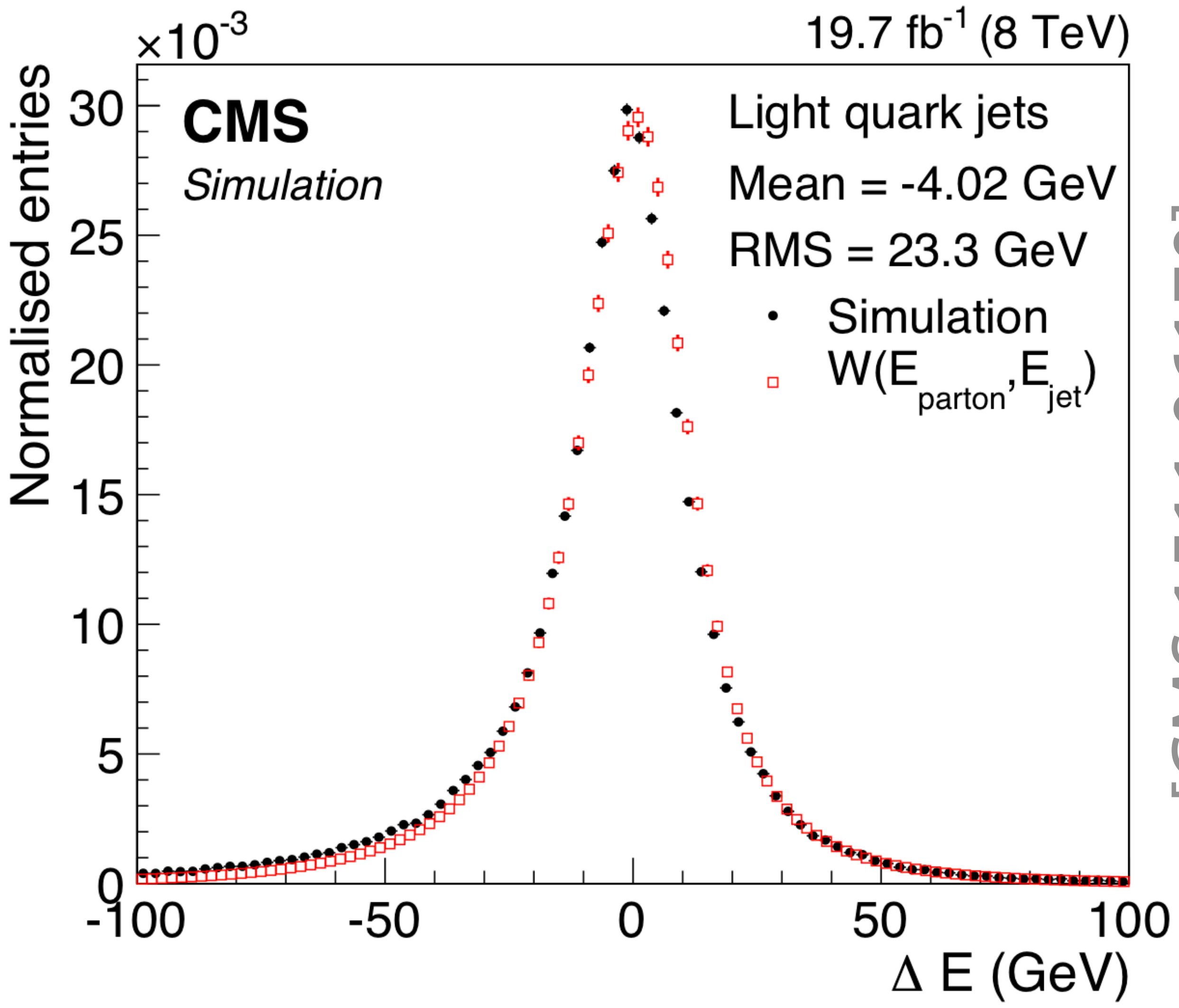
  - Shower / Event Deconstruction [D. E. Soper, M. Spannowsky 1102.3480, 1402.1189] extend explicit calculation to the shower

⇒ Uses matrix-element information, no summary statistics necessary, but:

- ad-hoc transfer functions (what about extra radiation?)
- evaluation still requires calculating an expensive integral



[CMS]



[CMS 1511.06170]

Solve it with machine learning classifiers

[K. Cranmer, J. Pavez, G. Louppe 1506.02169]

Solve it with machine learning classifiers

[K. Cranmer, J. Pavez, G. Louppe 1506.02169]

[M. Yao, idea for analogy: K. Cranmer]

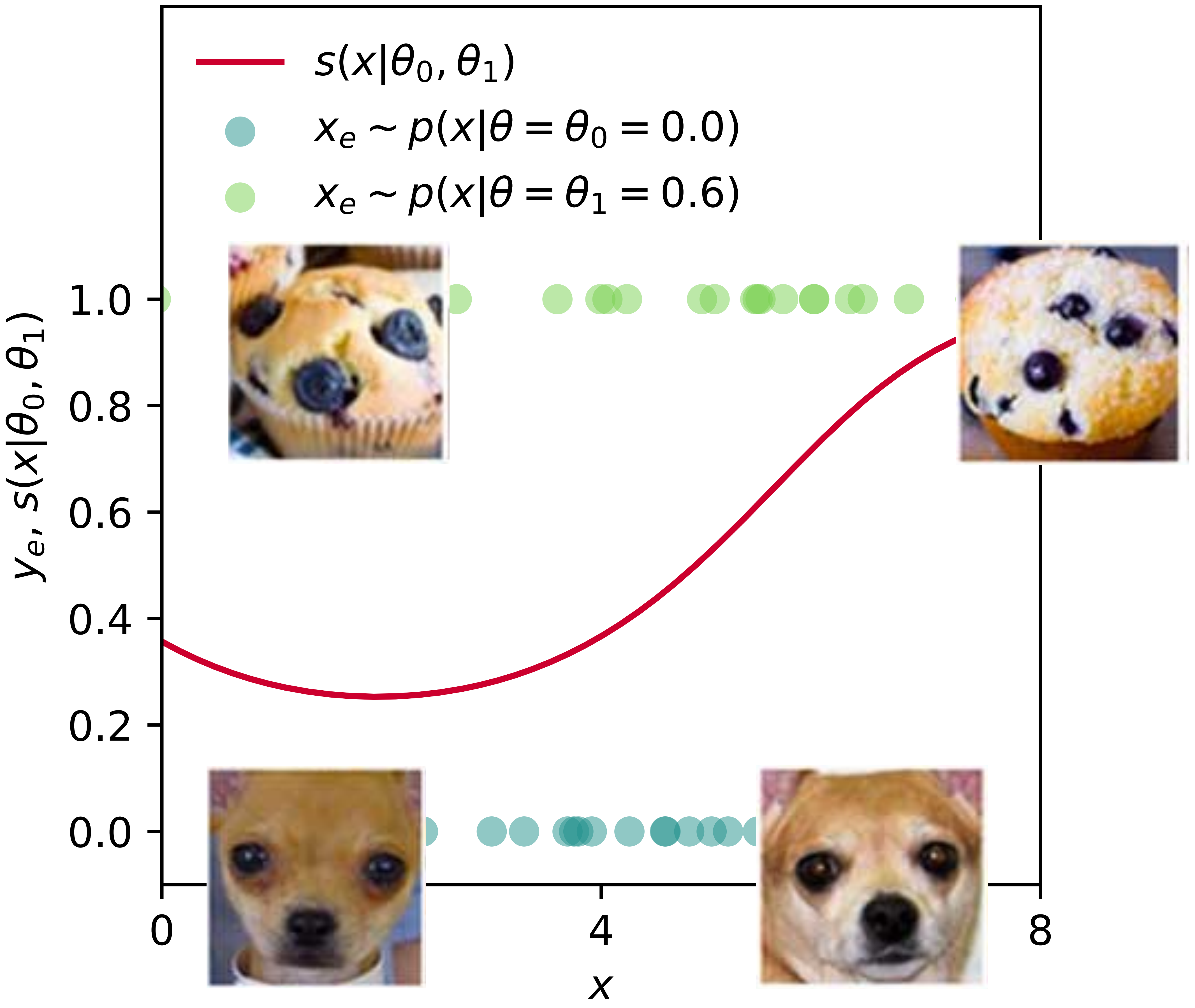
Solve it with machine learning classifiers

[K. Cranmer, J. Pavez, G. Louppe 1506.02169]

- Train neural network (BDT, …) to tell $x \sim p(x|\theta_0)$ from $x \sim p(x|\theta_1)$
- Classifier output $\hat{s}(x)$ is closer to 0 for θ_0-like events (closer to 1 for θ_1-like events)
- CARL: Transform classifier output function $\hat{s}(x)$ into estimator for the likelihood ratio

$$r(x) \equiv p(x|\theta_0)/p(x|\theta_1)$$

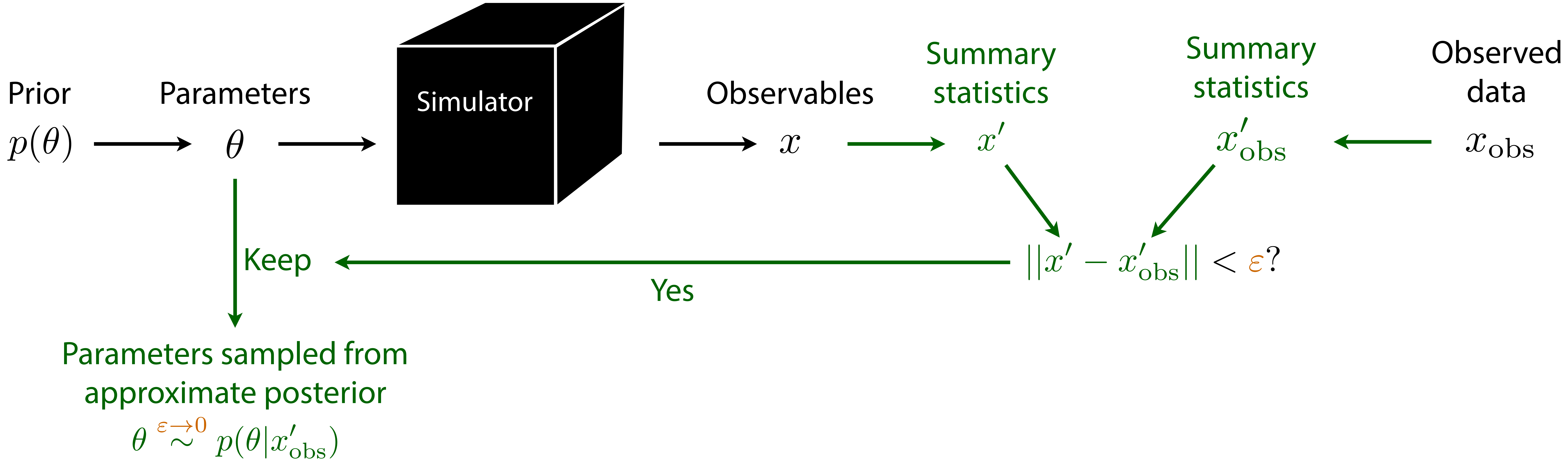
(calibrate estimator with histograms of NN output)



⇒ No summary statistics necessary, very fast evaluation… but may require large training samples

Approximate Bayesian Computation (ABC)

[D. Rubin 1984]



- How to choose x'?
- How to choose ε?
- No tractable posterior
- Need to run new simulations for new data or new prior

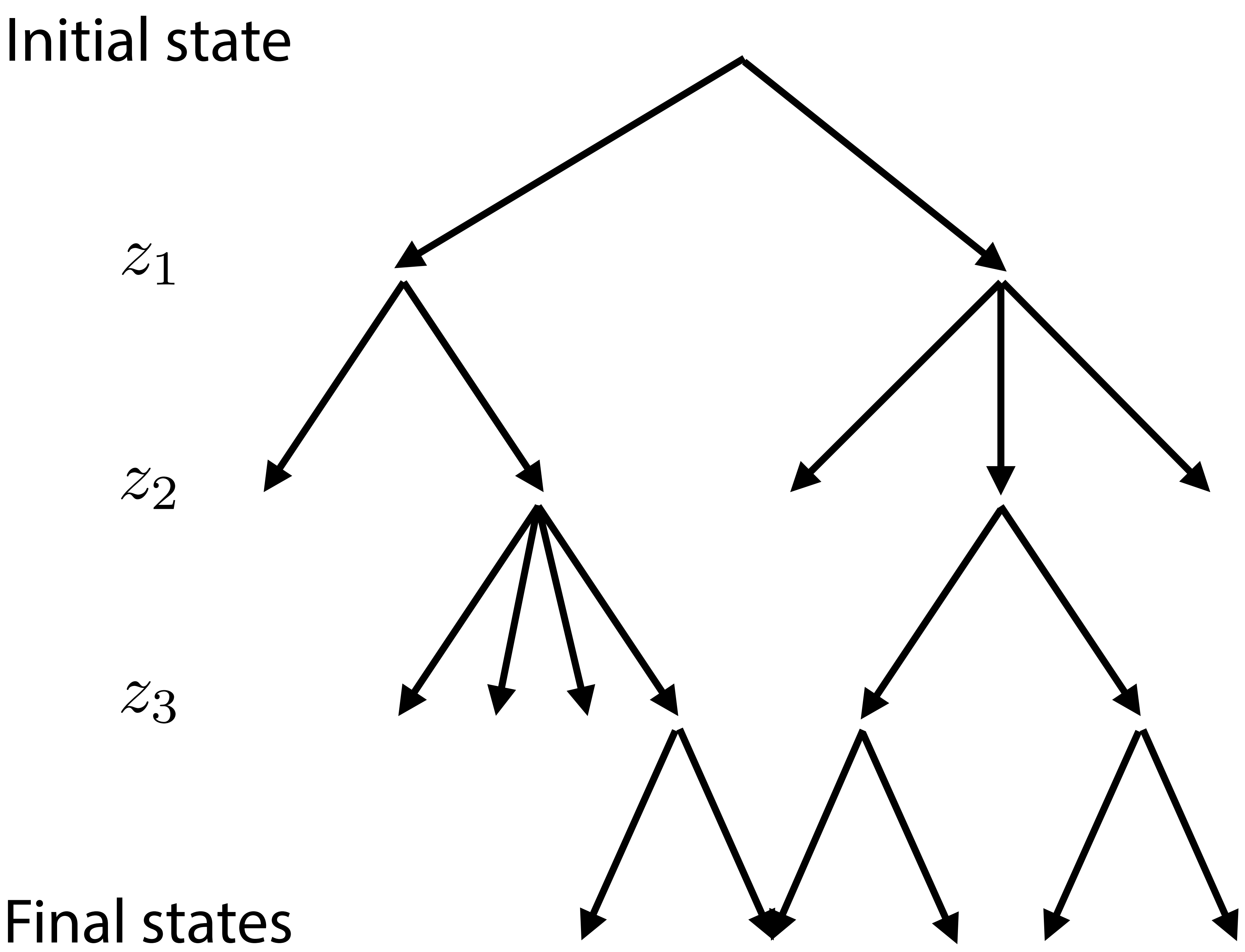
"Curse of dimensionality"

Precision vs efficiency tradeoff

Extracting the joint likelihood ratio from any simulation

- Computer simulation typically evolve along a tree-like structure of successive random branchings
- The probabilities of each branching $p_i(z_i|z_{i-1},\theta)$ are often clearly defined in the code:

```
if random() > 0.1 + 2.5 * model_parameter:
    do_one_thing()
else:
    do_another_thing()
```



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```
if random() > 0.1 + 2.5 * model_parameter:
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```
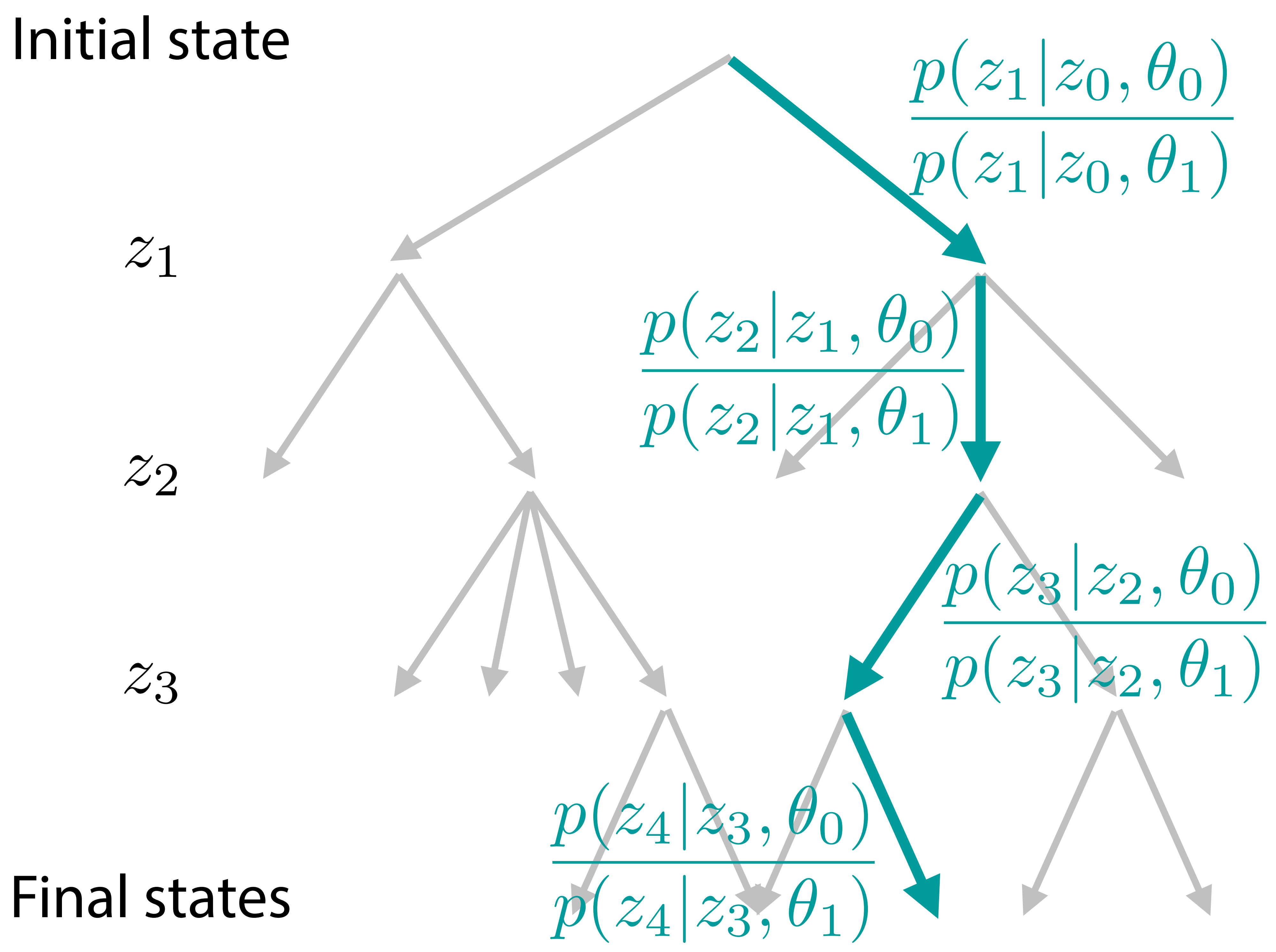

- For each run of the simulator, we can calculate the probability of the chosen path for different values of the parameters, and the "joint likelihood ratio":

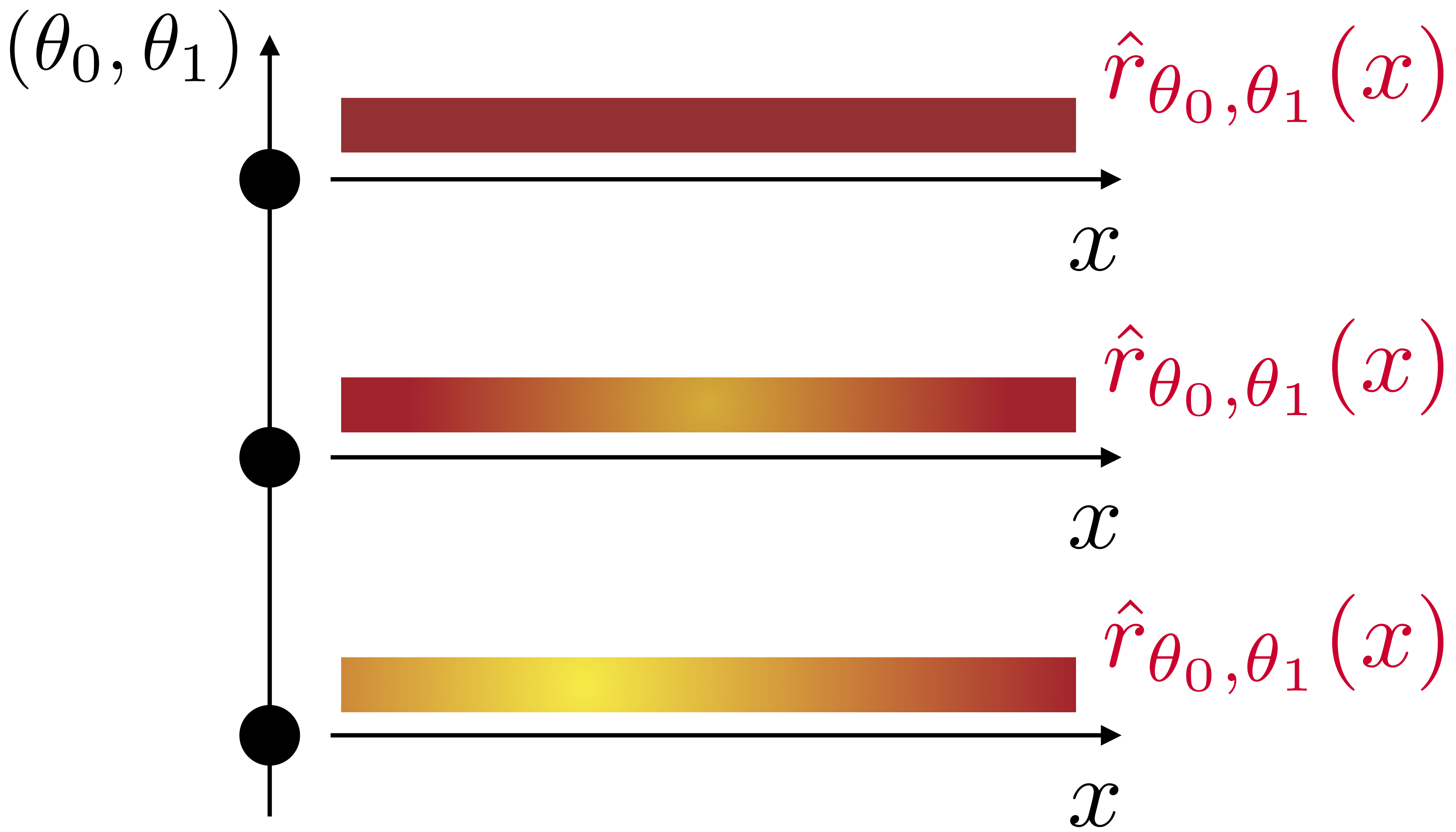
$$r(x,z|\theta_0,\theta_1) = \frac{p(x,z|\theta_0)}{p(x,z|\theta_1)} = \prod_i \frac{p(z_i|z_{i-1},\theta_0)}{p(z_i|z_{i-1},\theta_1)}$$



Two types of likelihood ratio estimators

A) Point by point:

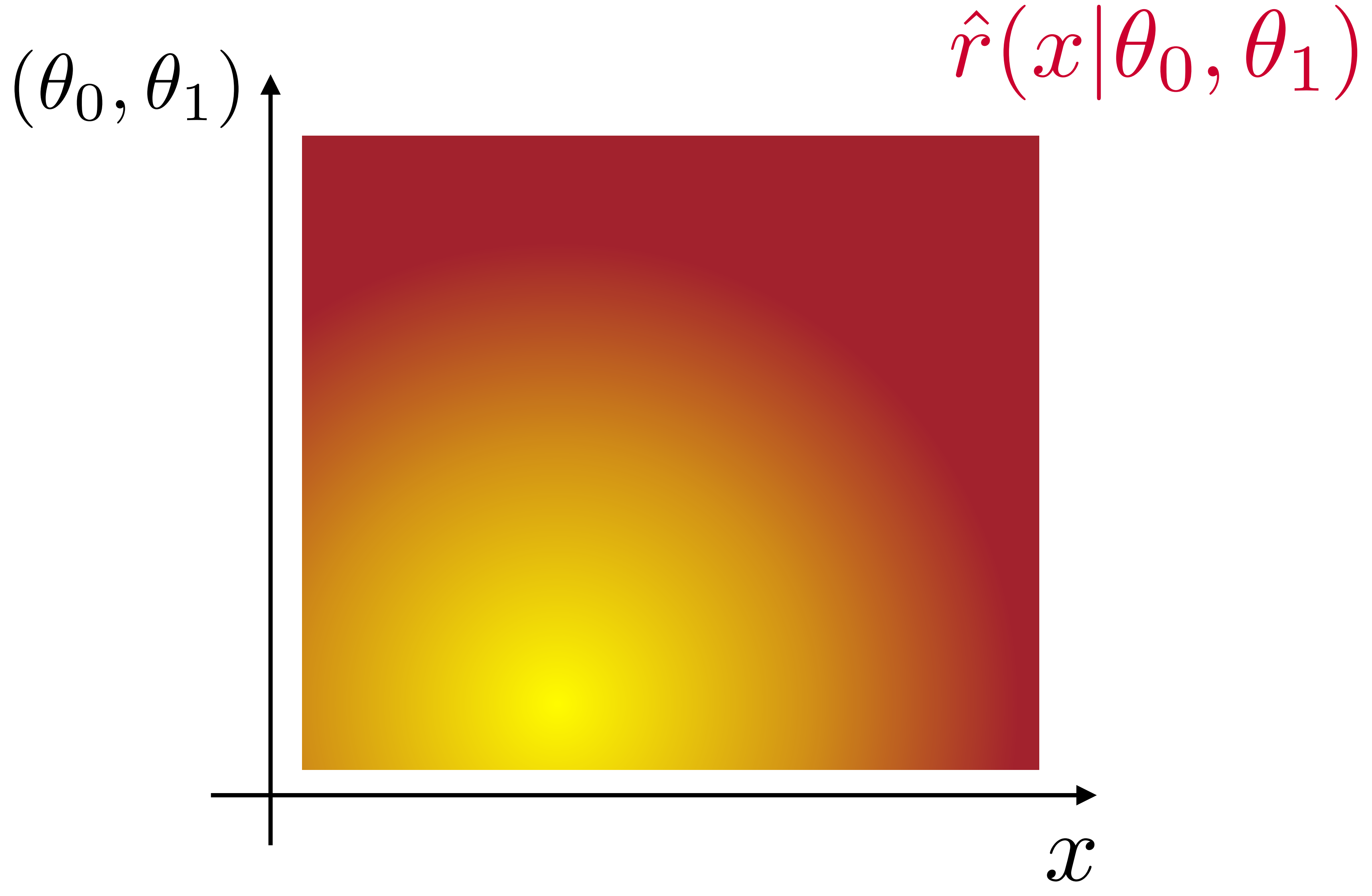
- first, define grid of parameter points $\{(\theta_0, \theta_1)\}$
- for each combination (θ_0, θ_1) , create separate estimator $\hat{r}_{\theta_0,\theta_1}(x)$
- final results can be interpolated between grid points

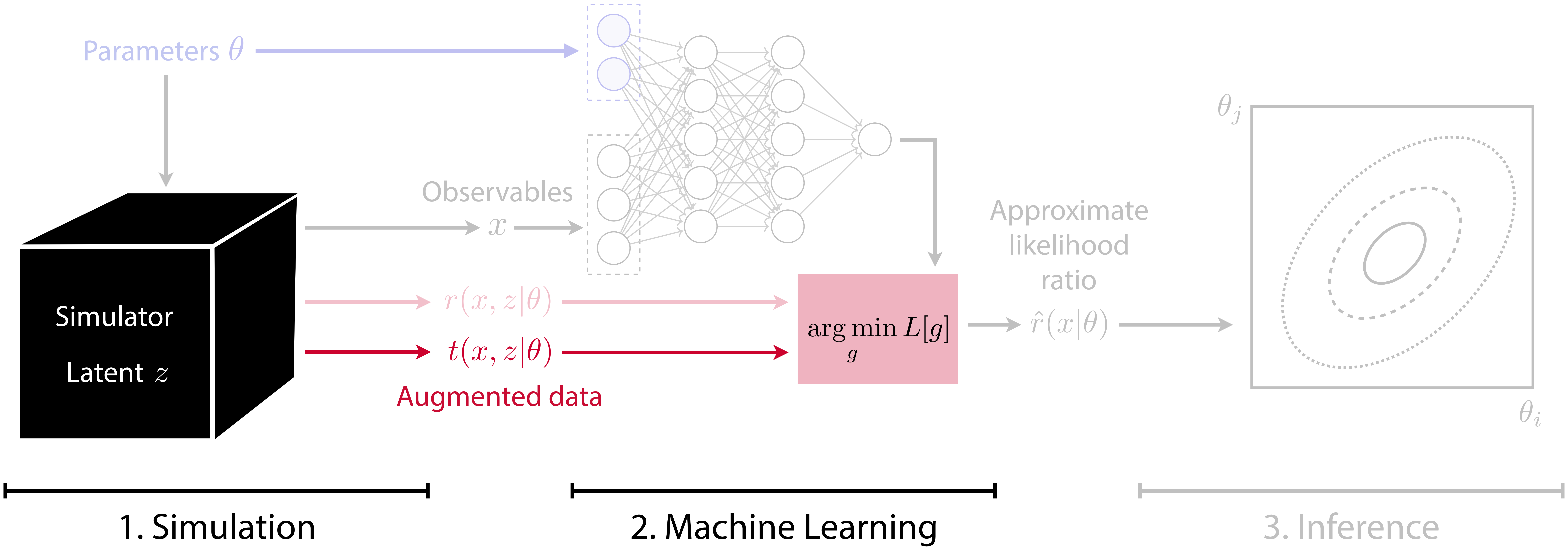


B) Parameterized:

[K. Cranmer, J. Pavez, G. Louppe 1506.02169; P. Baldi et al. 1601.07913]

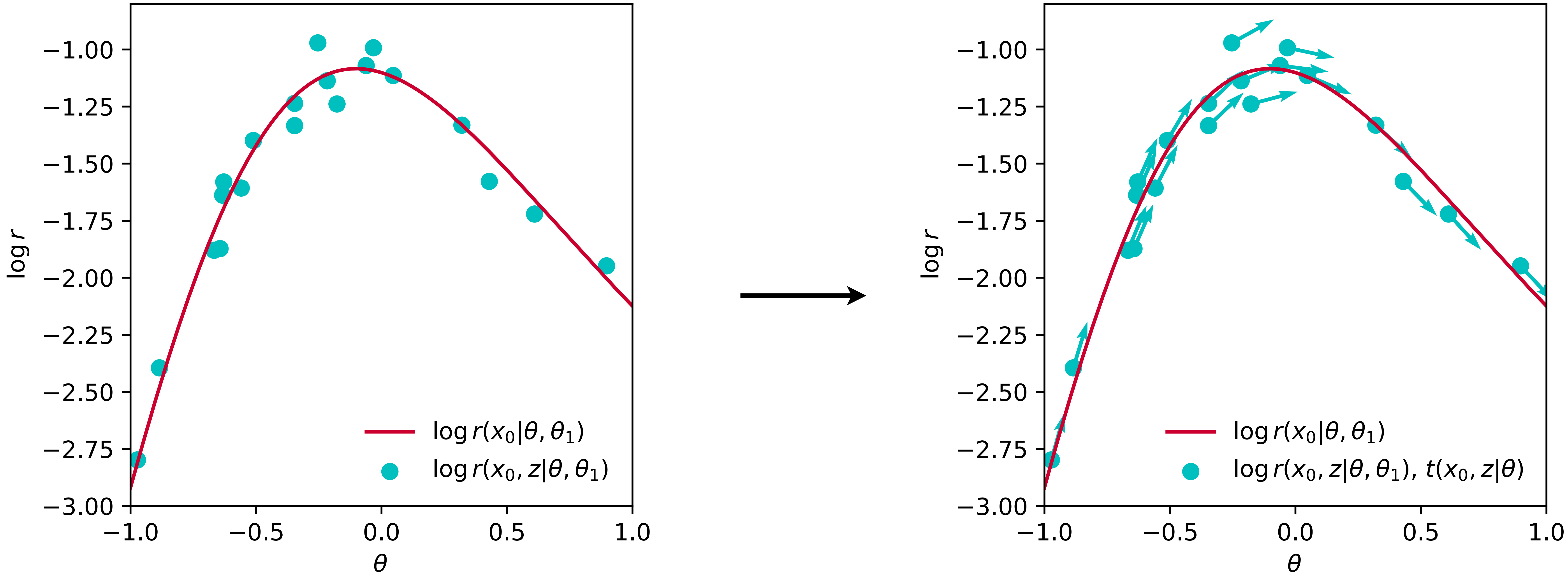
- create one estimator $\hat{r}(x|\theta_0, \theta_1)$ that is a function of θ_0 and θ_1
- no further interpolation necessary
- “borrows information” from close points




Parameters θ
Observables x
Simulator
Latent z
$r(x, z|\theta)$
$t(x, z|\theta)$
Augmented data
$\arg\min_g L[g]$
Approximate likelihood ratio
$\hat{r}(x|\theta)$
θ_j
θ_i
1. Simulation
2. Machine Learning
3. Inference

One more piece: the score

- Knowing derivative often helps fitting:



- In our case, the relevant quantity is the score $t(x|\theta_0) \equiv \nabla_\theta \log p(x|\theta)\Big|_{\theta_0}$.
  - The score itself is intractable. But…

Learning the score

Similar to the joint likelihood ratio, from the simulator we can extract the joint score

$$t(x, z|\theta_0) \equiv \nabla_\theta \log p(x, z_d, z_s, z_p|\theta)\Big|_{\theta_0}$$

We want the score

$$t(x|\theta_0) \equiv \nabla_\theta \log p(x|\theta)\Big|_{\theta_0}$$

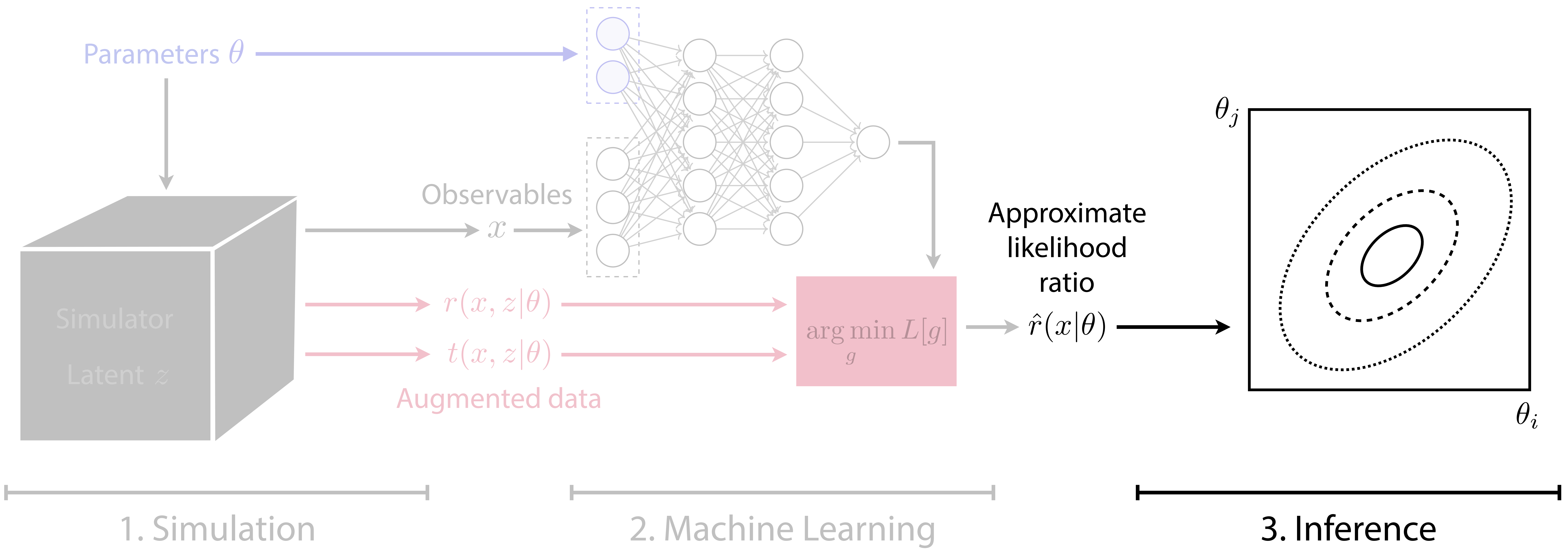
Given $t(x, z|\theta_0)$,
we define the functional

$$L_t[\hat{t}(x|\theta_0)] = \int \mathrm{d}x \int \mathrm{d}z \;\; p(x, z|\theta_0) \left[\left(\hat{t}(x|\theta_0) - t(x, z|\theta_0)\right)^2\right].$$

One can show it is minimized by

$$t(x|\theta_0) = \underset{\hat{t}(x|\theta_0)}{\arg\min}\, L_t[\hat{t}(x|\theta_0)]\,.$$

Again, we implement this minimization through machine learning.



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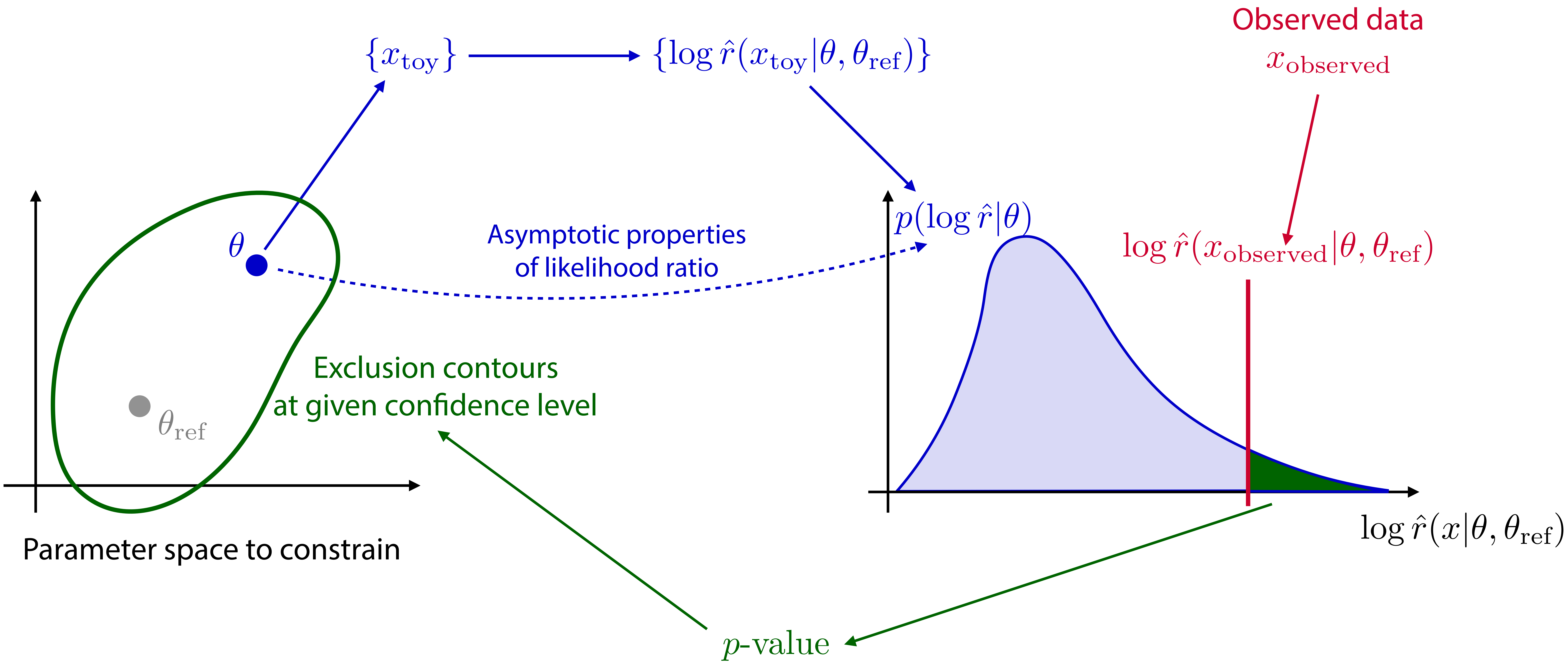
Limit setting (frequentist)



A family of new inference techniques

Method	Simulate	Extract $r(x,z)$	Extract $t(x,z)$	NN estimates	Asympt. exact	Generative
ROLR	$\theta_0 \sim \pi(\theta), \theta_1$	✓		$\hat{r}(x\|\theta_0,\theta_1)$	✓	
CASCAL	$\theta_0 \sim \pi(\theta), \theta_1$		✓	$\hat{r}(x\|\theta_0,\theta_1)$	✓	
ALICE	$\theta_0 \sim \pi(\theta), \theta_1$		✓	$\hat{r}(x\|\theta_0,\theta_1)$	✓	
RASCAL	$\theta_0 \sim \pi(\theta), \theta_1$	✓	✓	$\hat{r}(x\|\theta_0,\theta_1)$	✓	
ALICES	$\theta_0 \sim \pi(\theta), \theta_1$	✓	✓	$\hat{r}(x\|\theta_0,\theta_1)$	✓	
SCANDAL	$\theta \sim \pi(\theta)$		✓	$\hat{p}(x\|\theta)$	✓	✓
SALLY	θ_{ref}		✓	$\hat{t}(x\|\theta_{\text{ref}})$	in local approx.	
SALLINO	θ_{ref}		✓	$\hat{t}(x\|\theta_{\text{ref}})$	in local approx.	

Performance gains with cross-entropy-based loss

[M. Stoye, JB, K. Cranmer, G. Louppe, J. Pavez 1808.00973]

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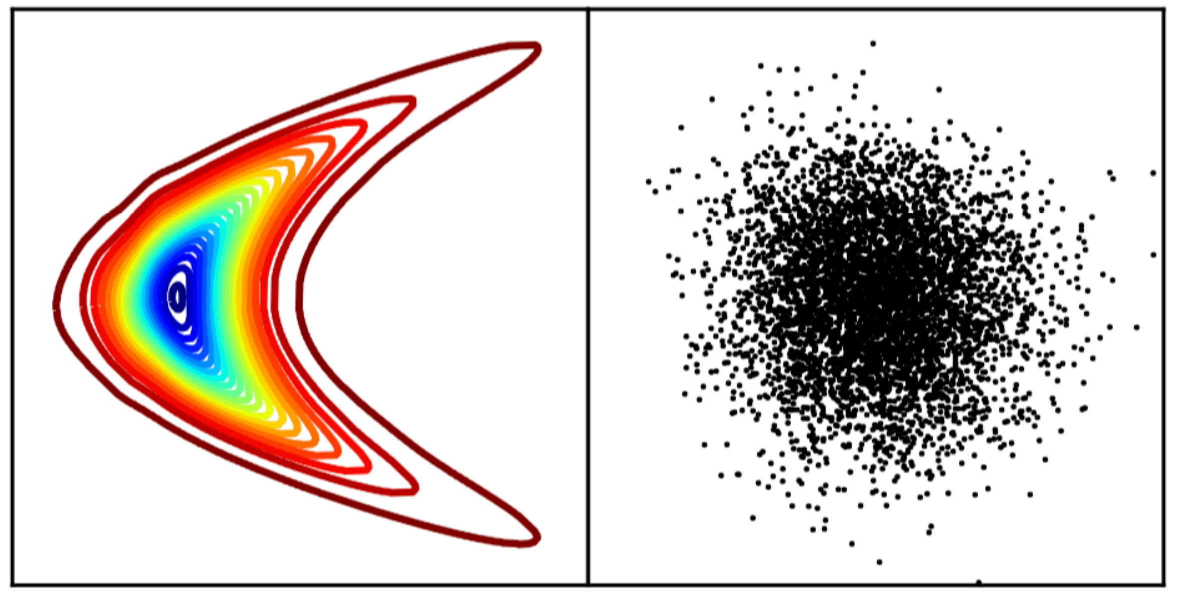
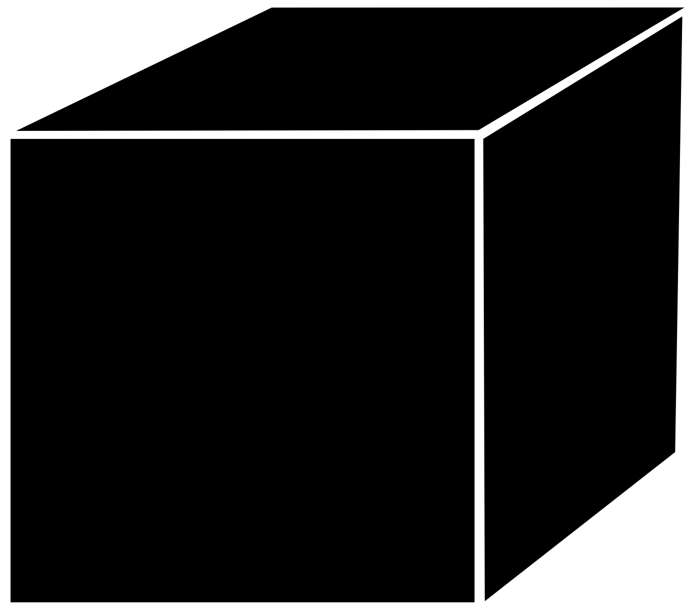


Combination with state-of-the-art conditional neural density estimators, e.g. normalizing flows

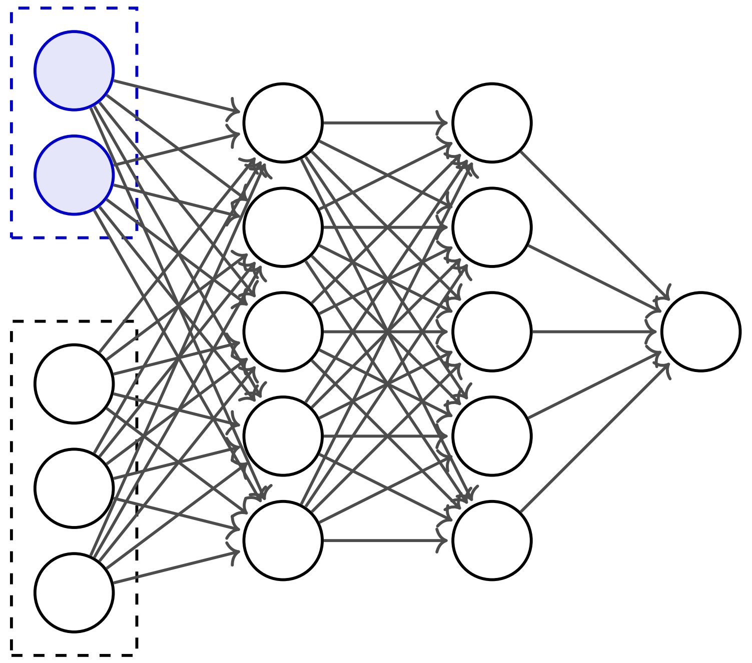
[everything by G. Papamakarios: G. Papamakarios, T. Pavlakou, I. Murray 1705.07057; G. Papamakarios, D. Sterratt, I. Murray 1805.07226; …]

Systematics



Don't fully trust the simulator?

- Nuisance parameters to model systematic uncertainties
- Methods learn dependence both on parameters of interest and nuisance parameters. Then we can construct profile likelihood and "nuisance-hardened" score
  [P. de Castro, T. Dorigo 1806.04743;
  J. Alsing, B. Wandelt 1903.01473]
- Alternatively: Robustness to nuisance with adversarial training
  [G. Louppe, M. Kagan, K. Cranmer 1611.01046]



Don't blindly trust the neural network?

- Diagnostic cross checks: known expectation values, "critic" tests
- Calibration / Neyman construction with toys:
  badly trained network can lead to suboptimal limits, but not to wrong limits

WBF Higgs to four leptons with detector effects