Constraining effective field theories with machine learning

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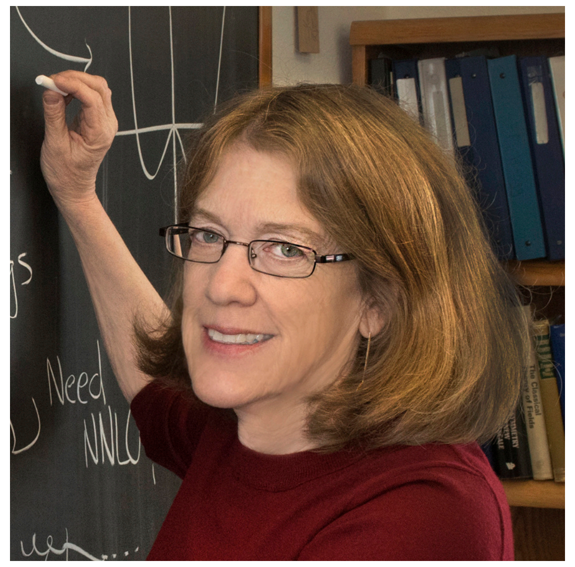
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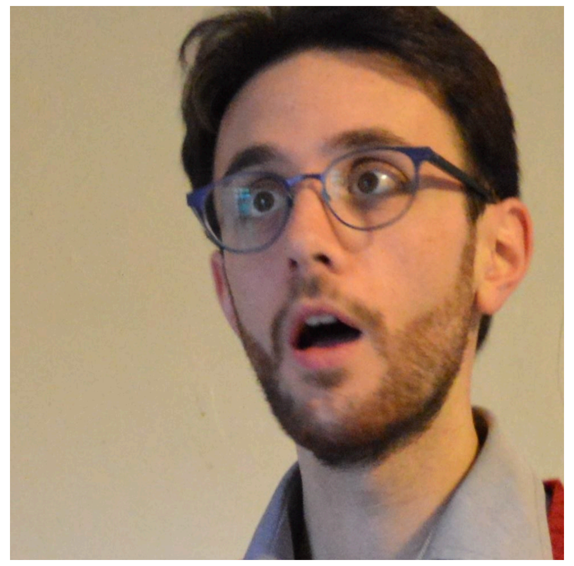

Marco Farina

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

NYU

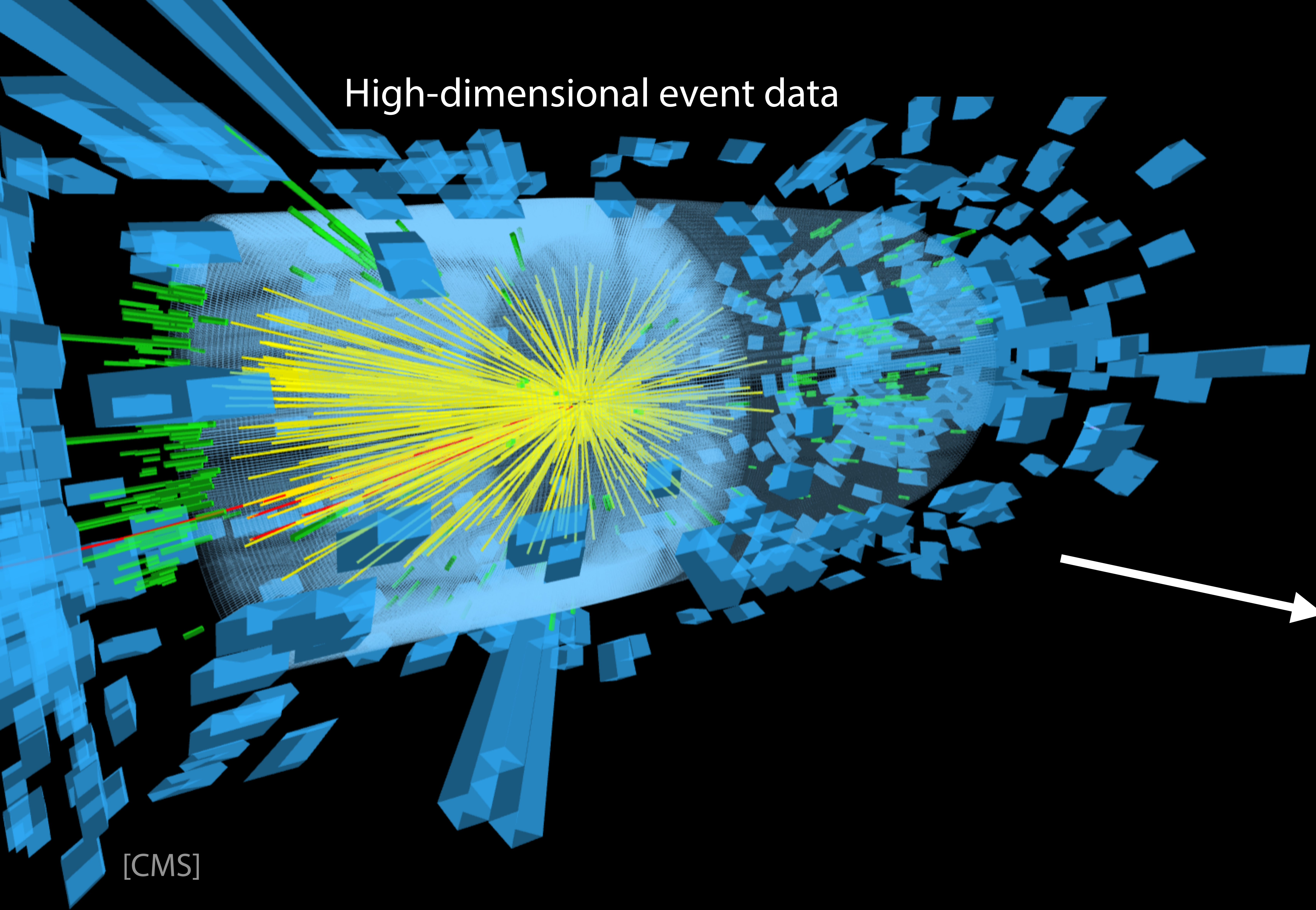
MSDSE
Moore - Sloan
Data Science Environments

dianahep

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

The SCAILFIN Project
scailfin.github.io

High-dimensional event data



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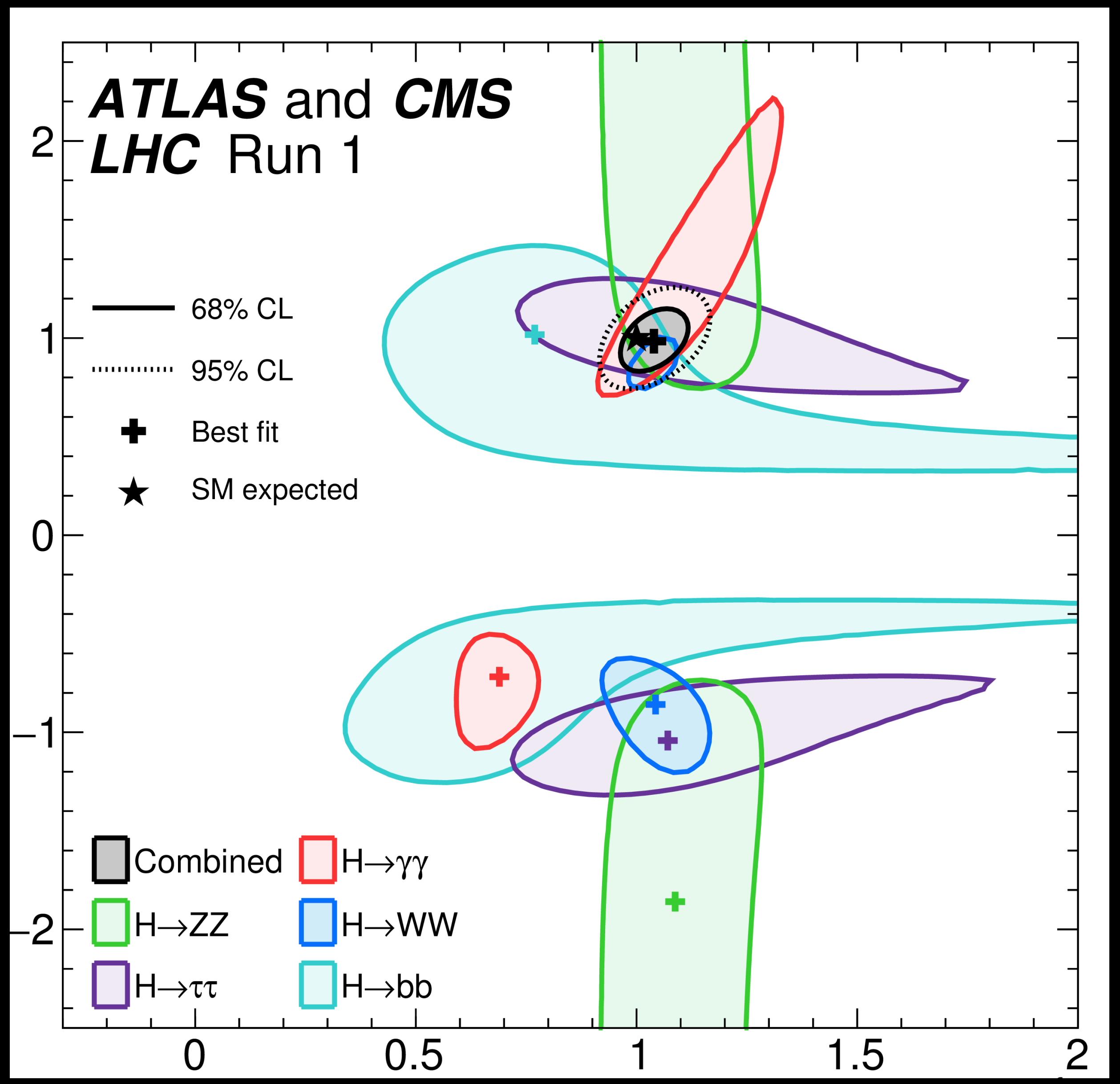
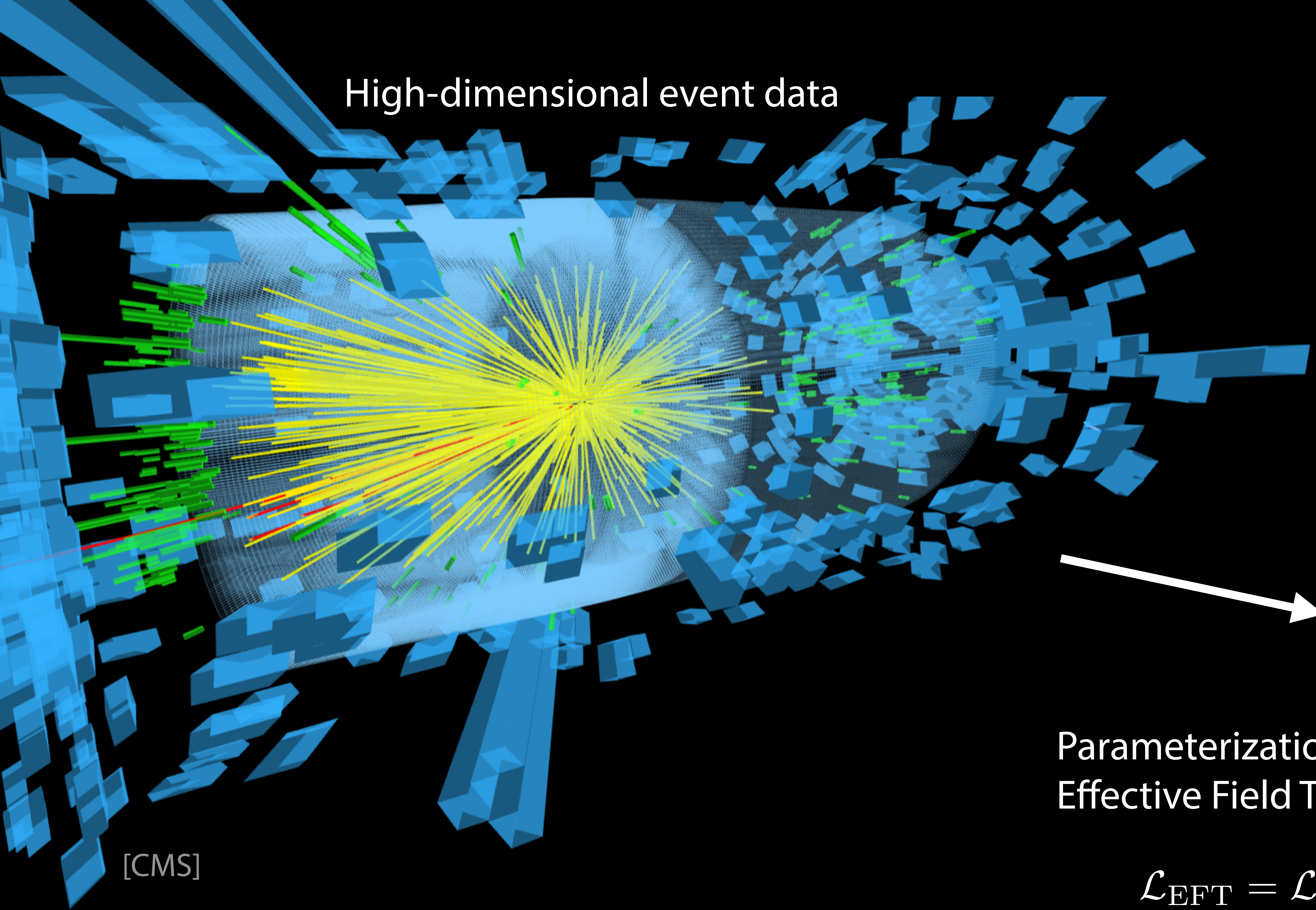


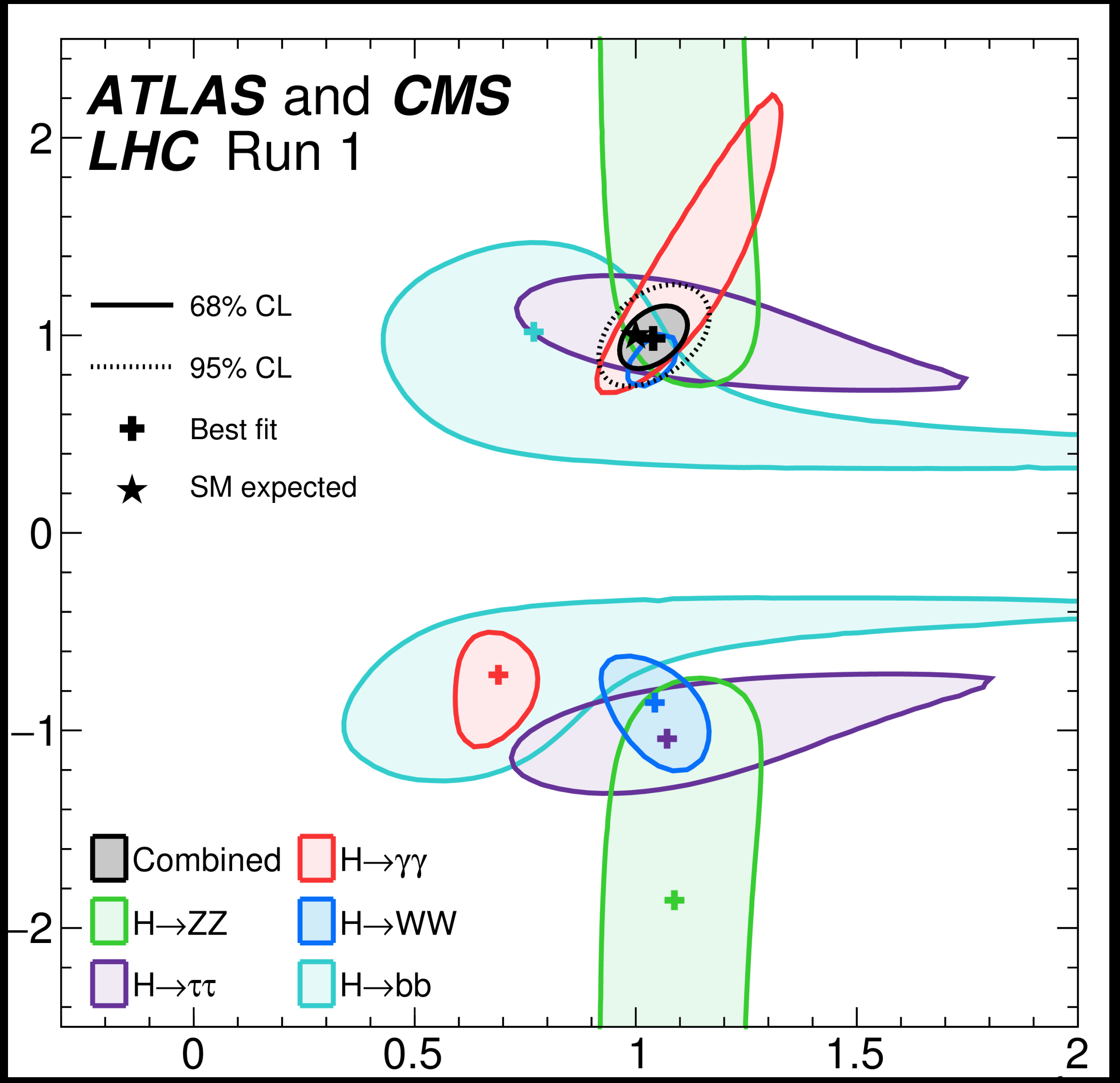
[ATLAS, CMS 1606.02266]

Precision constraints on indirect effects of new physics

High-dimensional event data



[CMS]



[ATLAS, CMS 1606.02266]

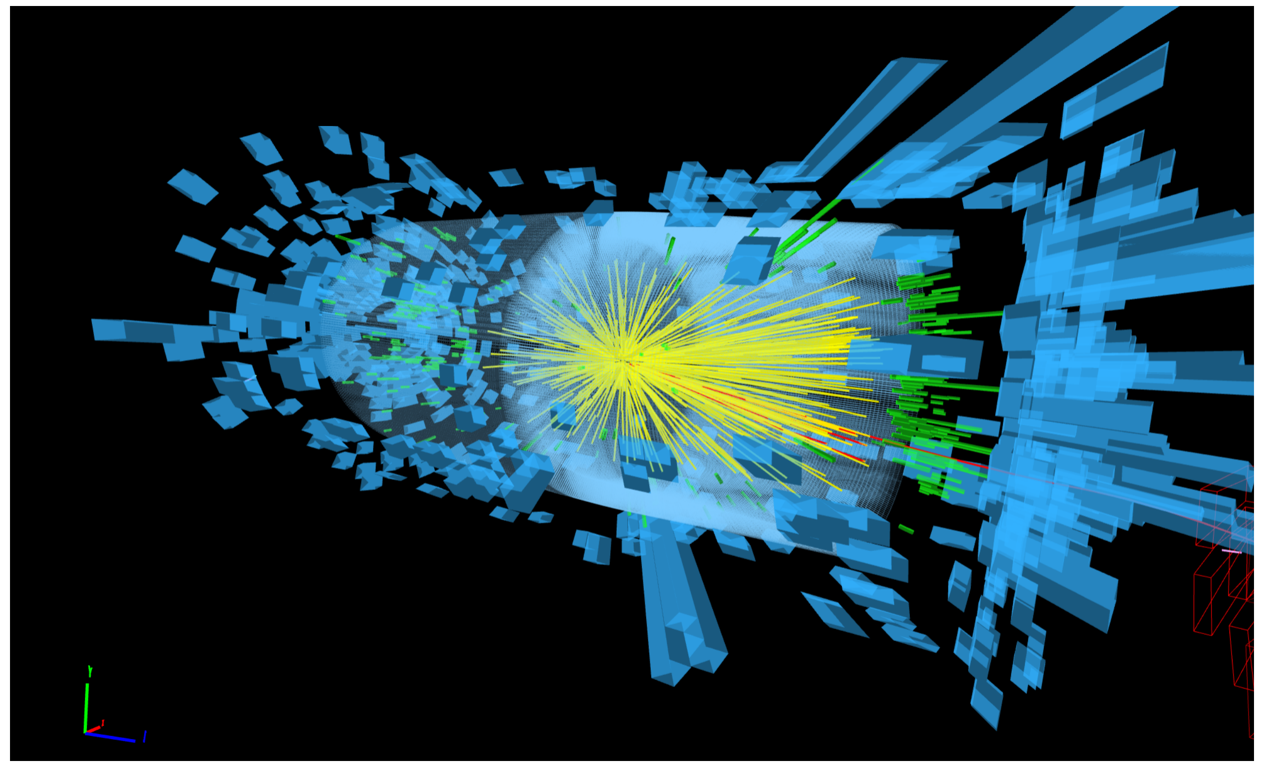
Precision constraints on indirect effects of new physics

Parameterization in Effective Field Theory:

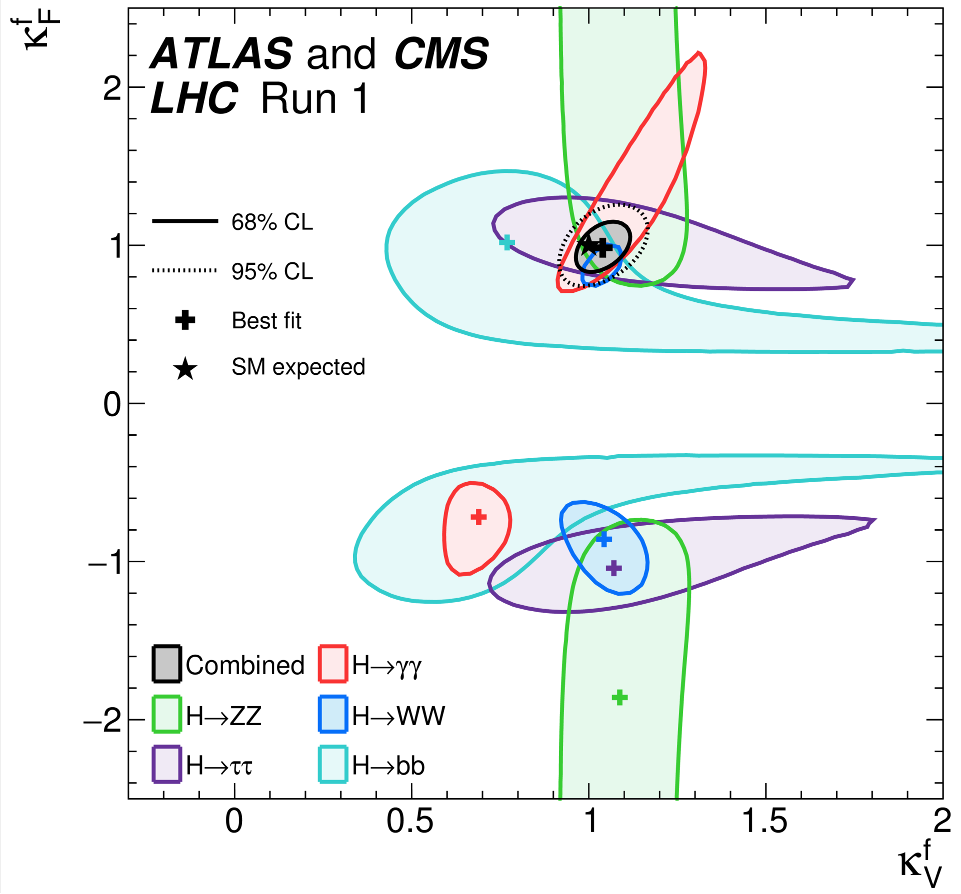
$$\mathcal{L}_{\mathrm{EFT}} = \mathcal{L}_{\mathrm{SM}} + \sum_i \frac{f_i}{\Lambda^2}\,\mathcal{O}_i + \ldots$$

systematic expansion of new physics around Standard Model

10s to 1000s "universal" parameters to measure



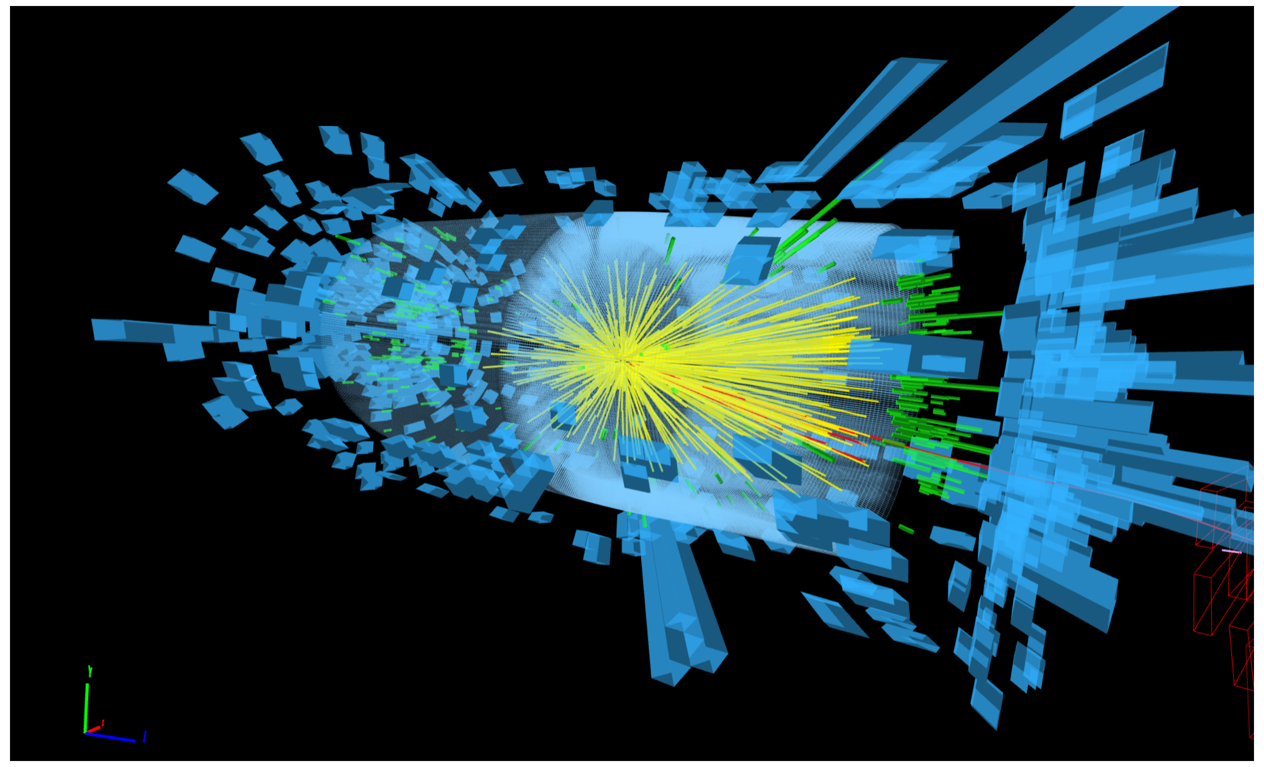
High-dimensional
event data x



Constraints on
parameters θ

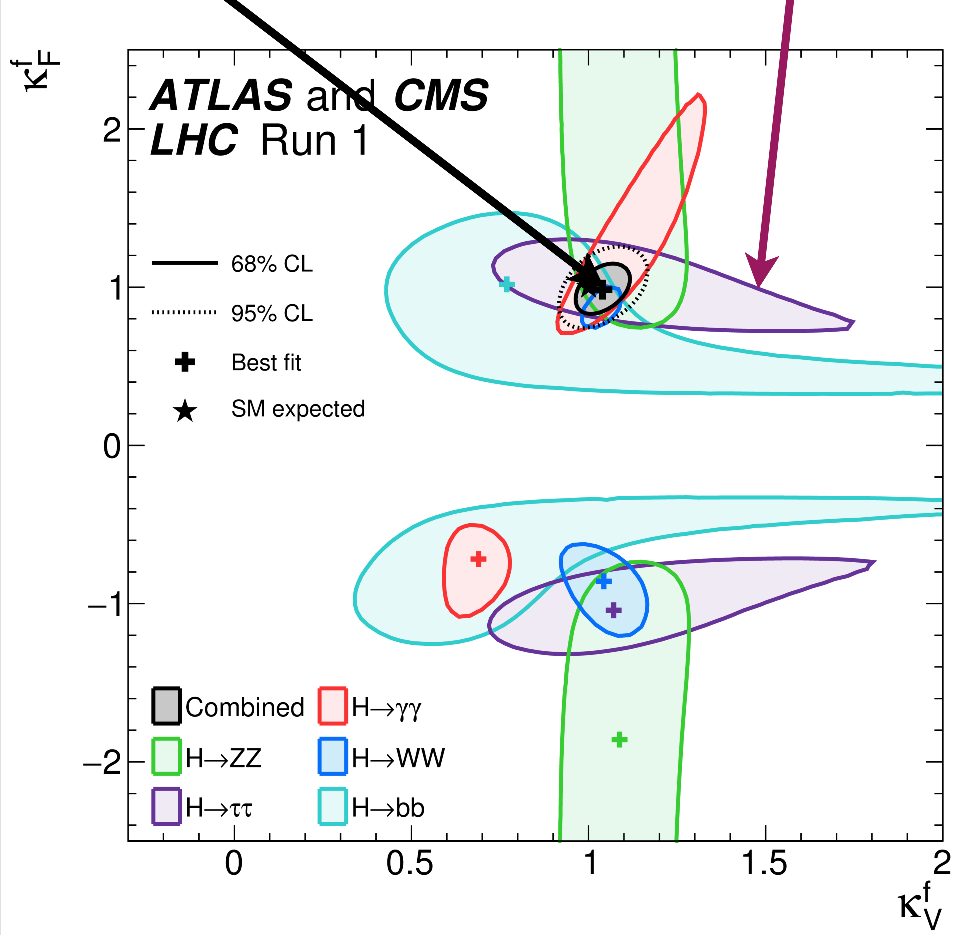
Maximum-likelihood estimator

Confidence limits based on likelihood ratio tests

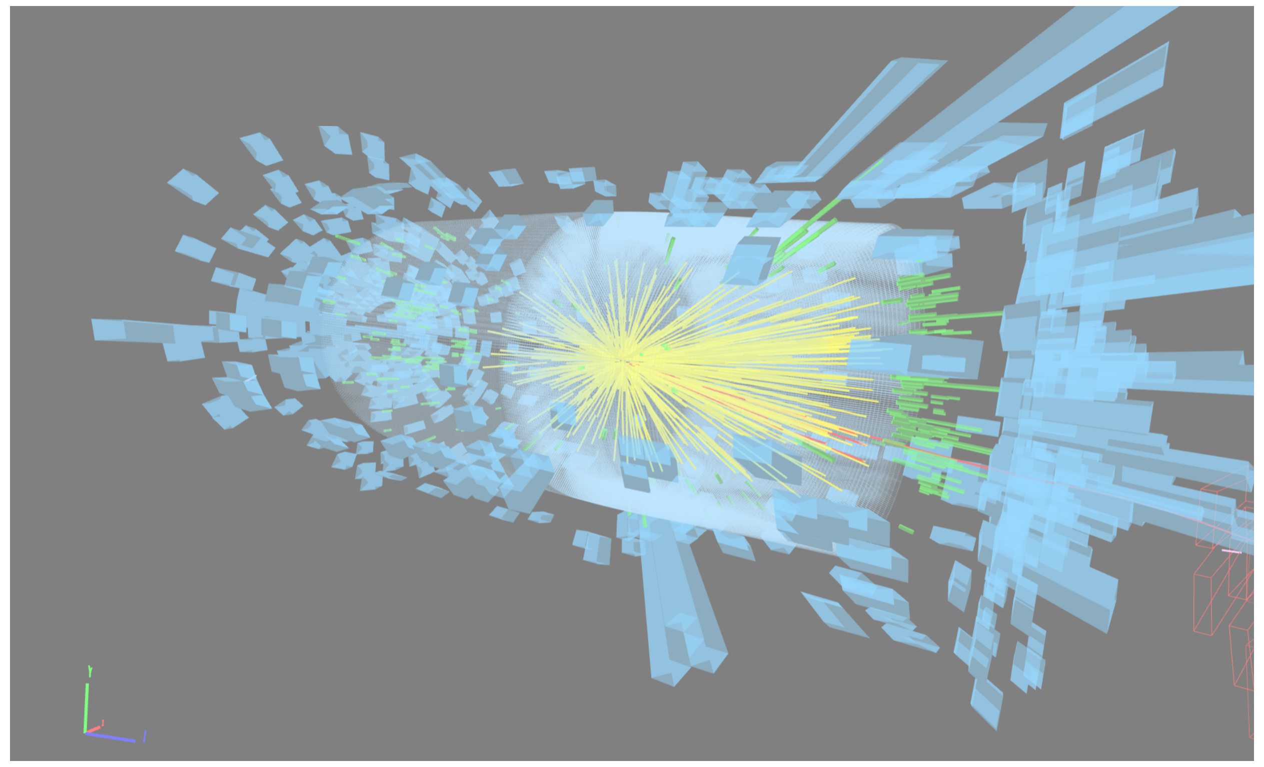


High-dimensional event data x

Likelihood function
$p(x|\theta)$

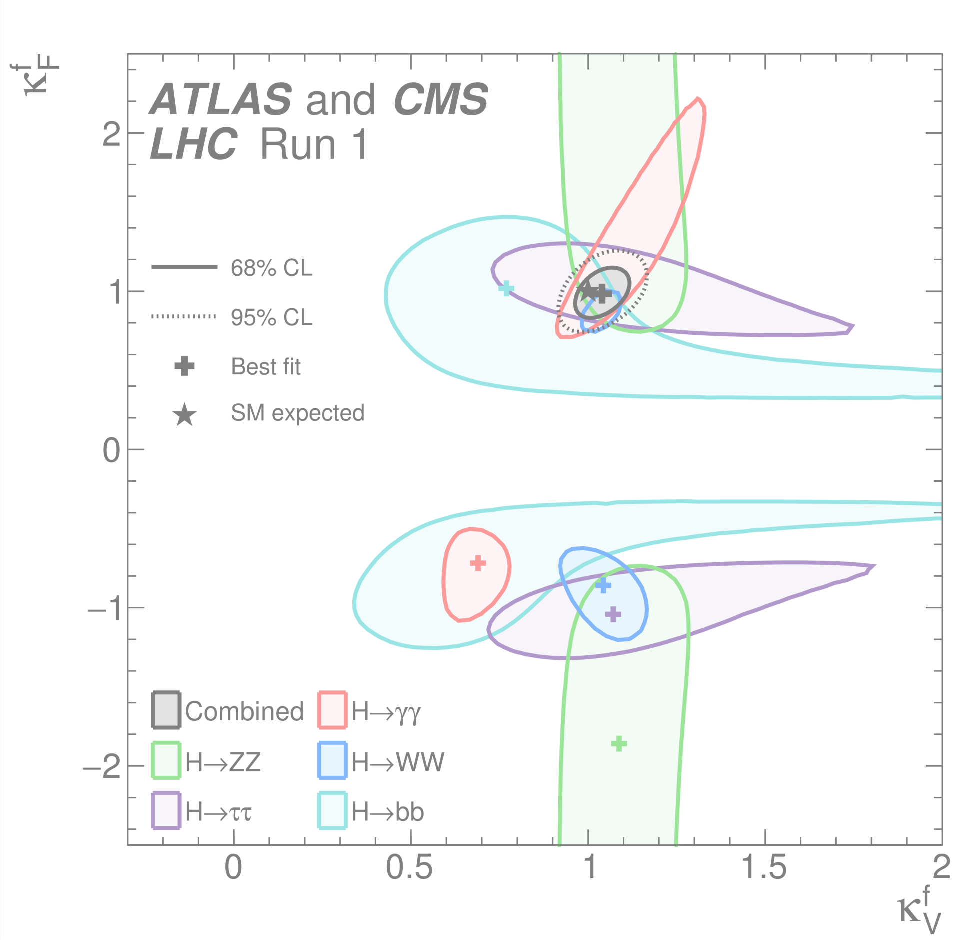


Constraints on parameters θ



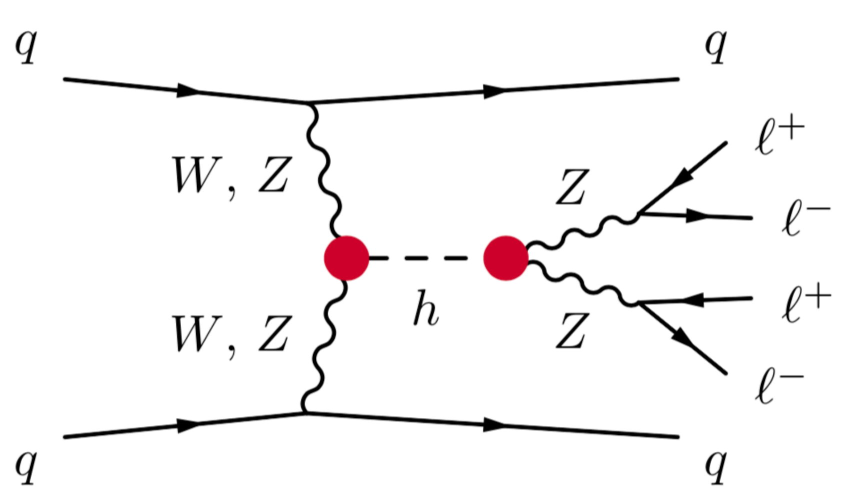
High-dimensional event data x

Likelihood function $p(x|\theta)$

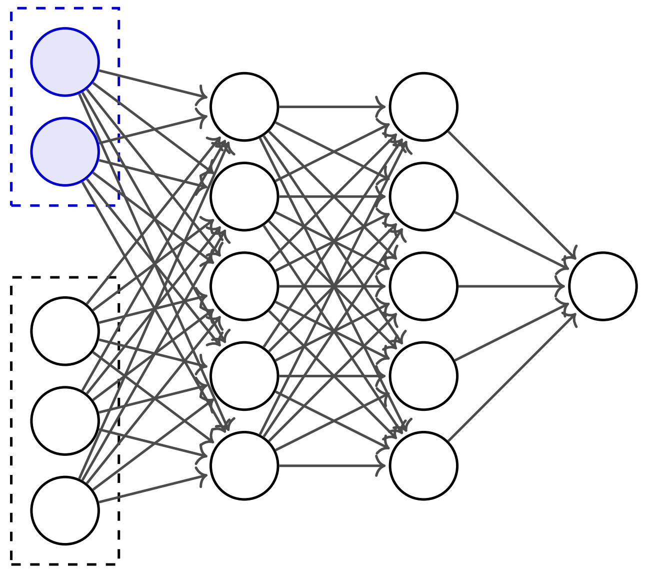


Constraints on parameters θ

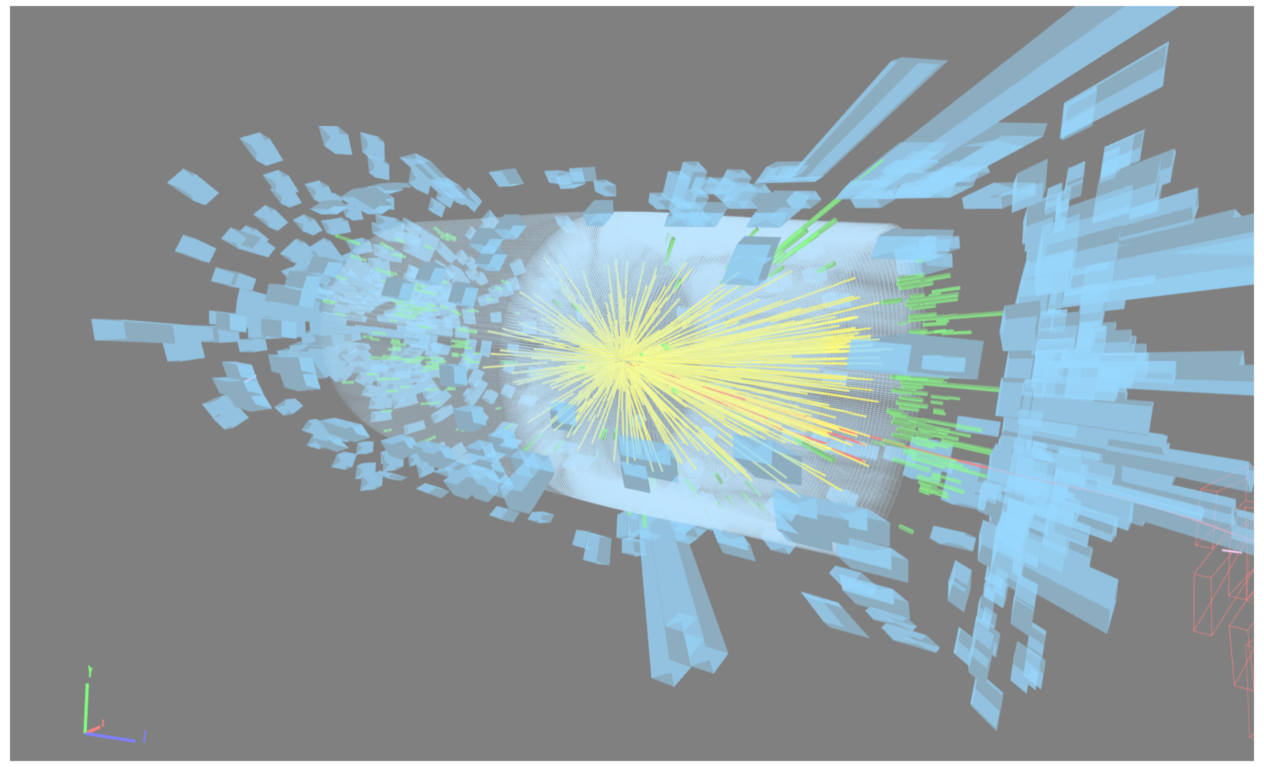
Surprisingly, when we want to use high-dimensional data and have to deal with the detector response, we do not have a good way to calculate the likelihood.



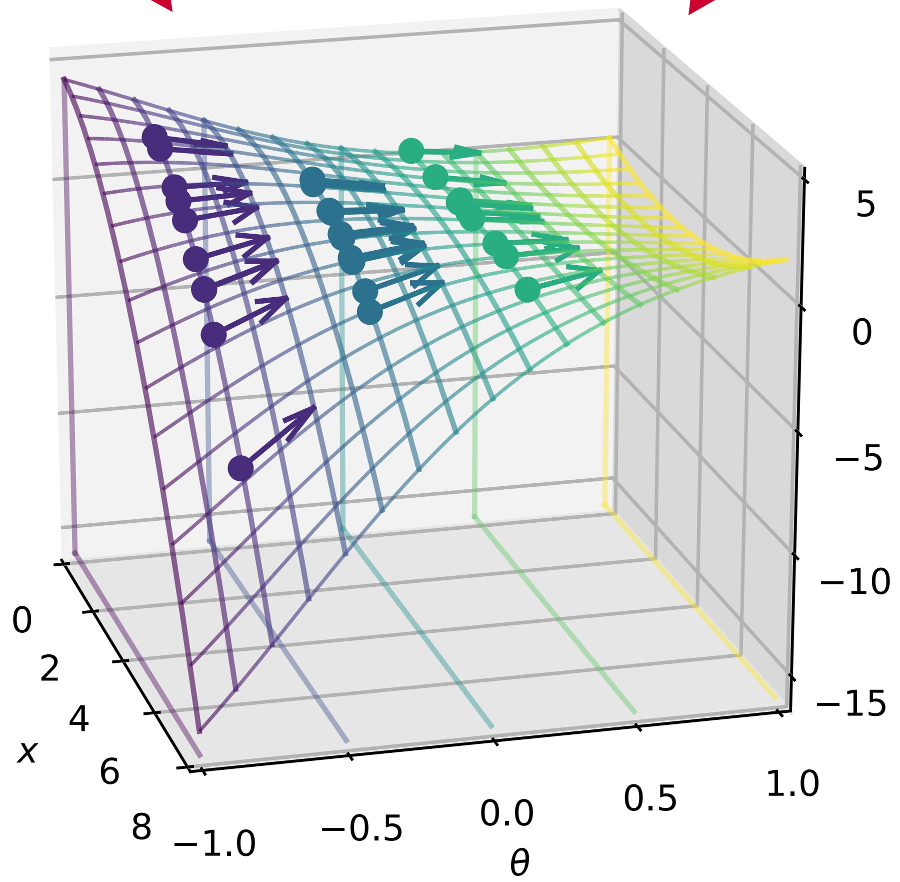
Physics insight:
matrix element information



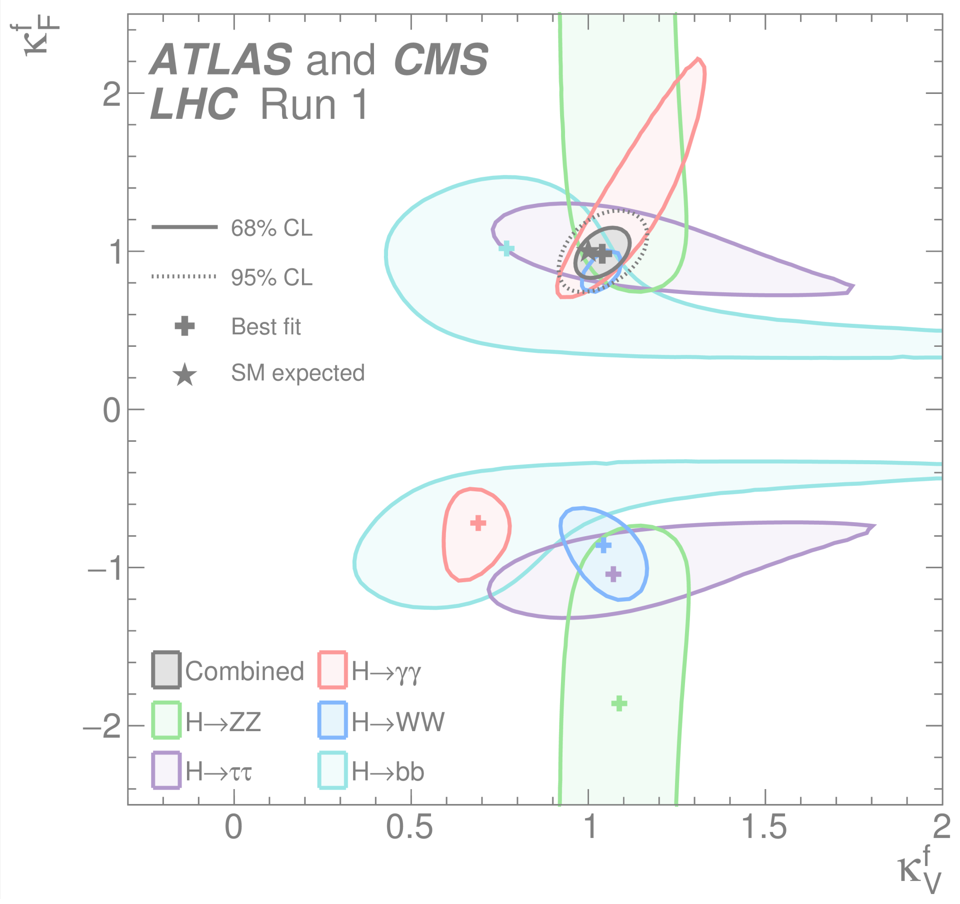
Machine learning



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

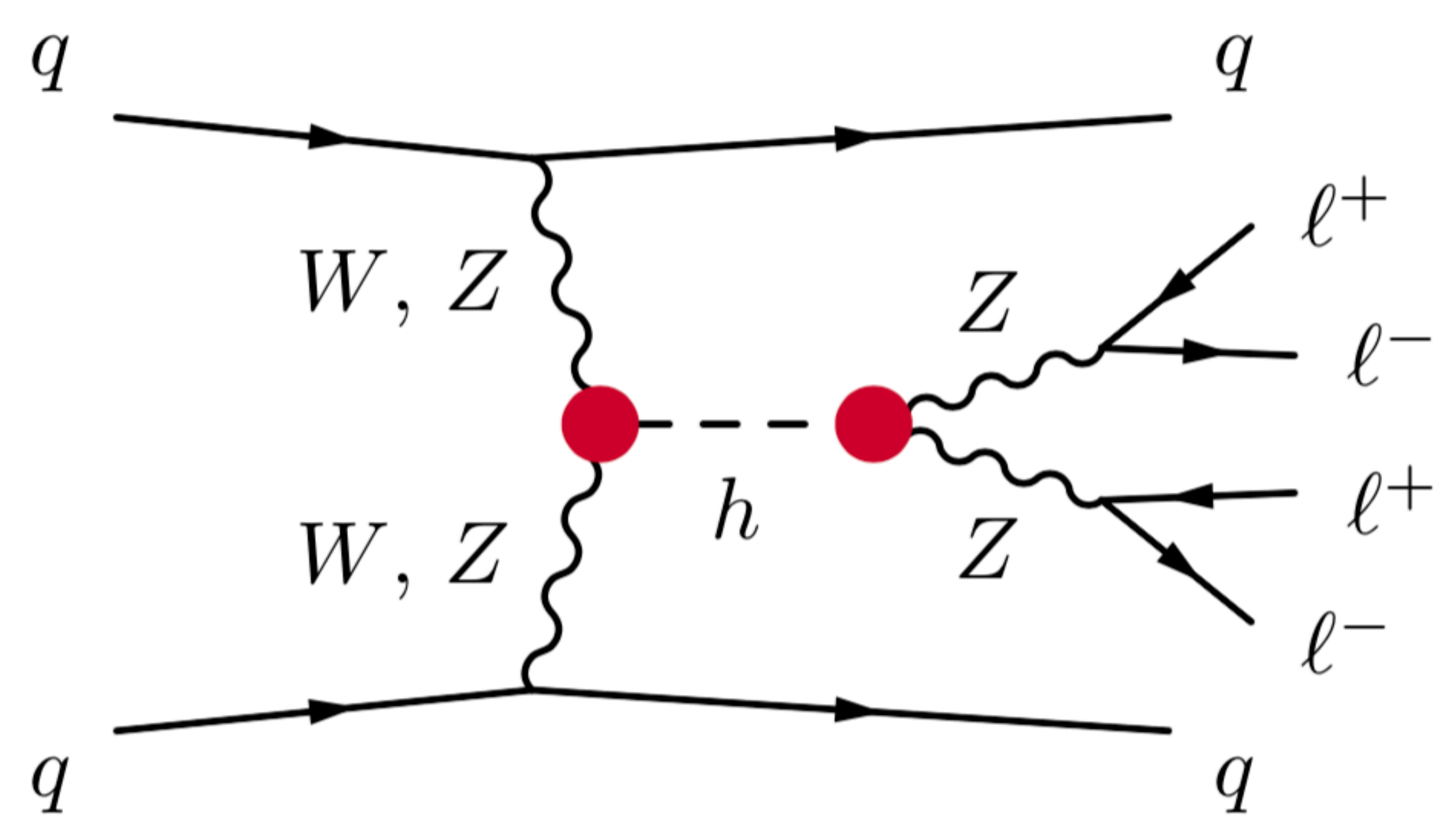
Modelling particle physics processes

Latent variables

Parton-level momenta

Theory parameters

$z_p \longleftarrow \theta$

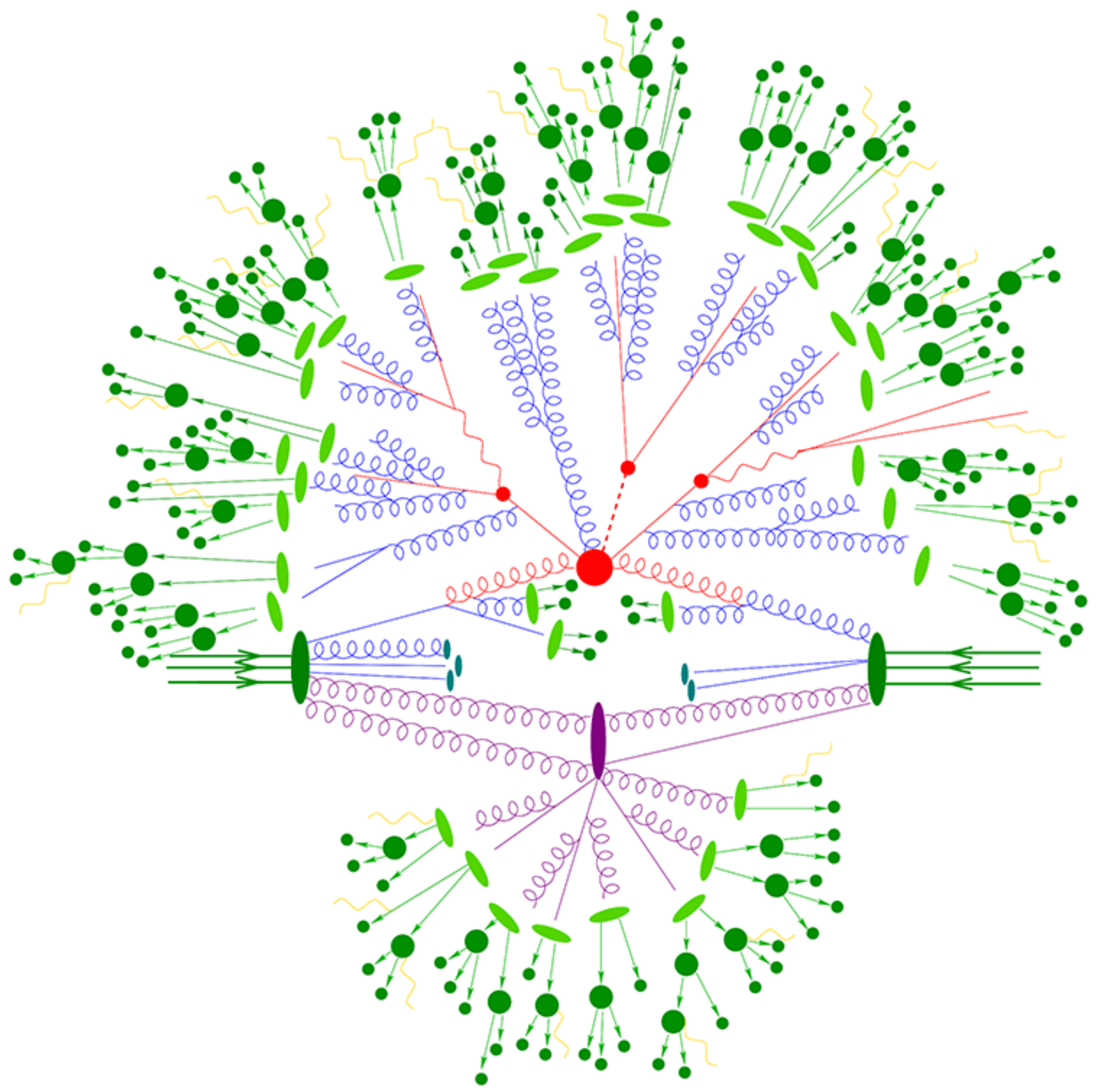


Evolution

Modelling particle physics processes

Latent variables

Shower splittings		Parton-level momenta		Theory parameters
z_s	$\leftarrow$	z_p	$\leftarrow$	θ



[F. Krauss]

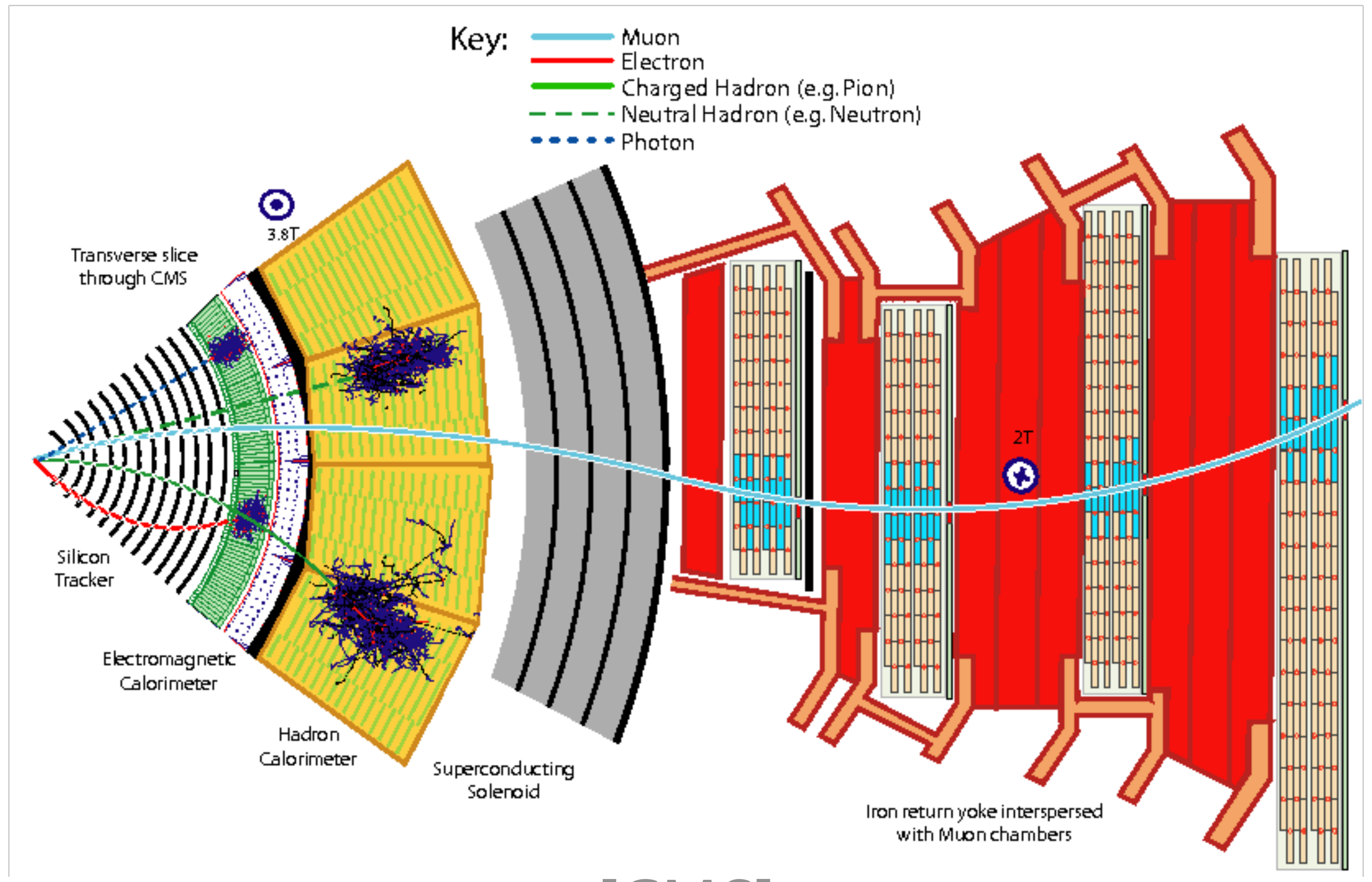
Evolution

Modelling particle physics processes

Latent variables

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

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



[CMS]

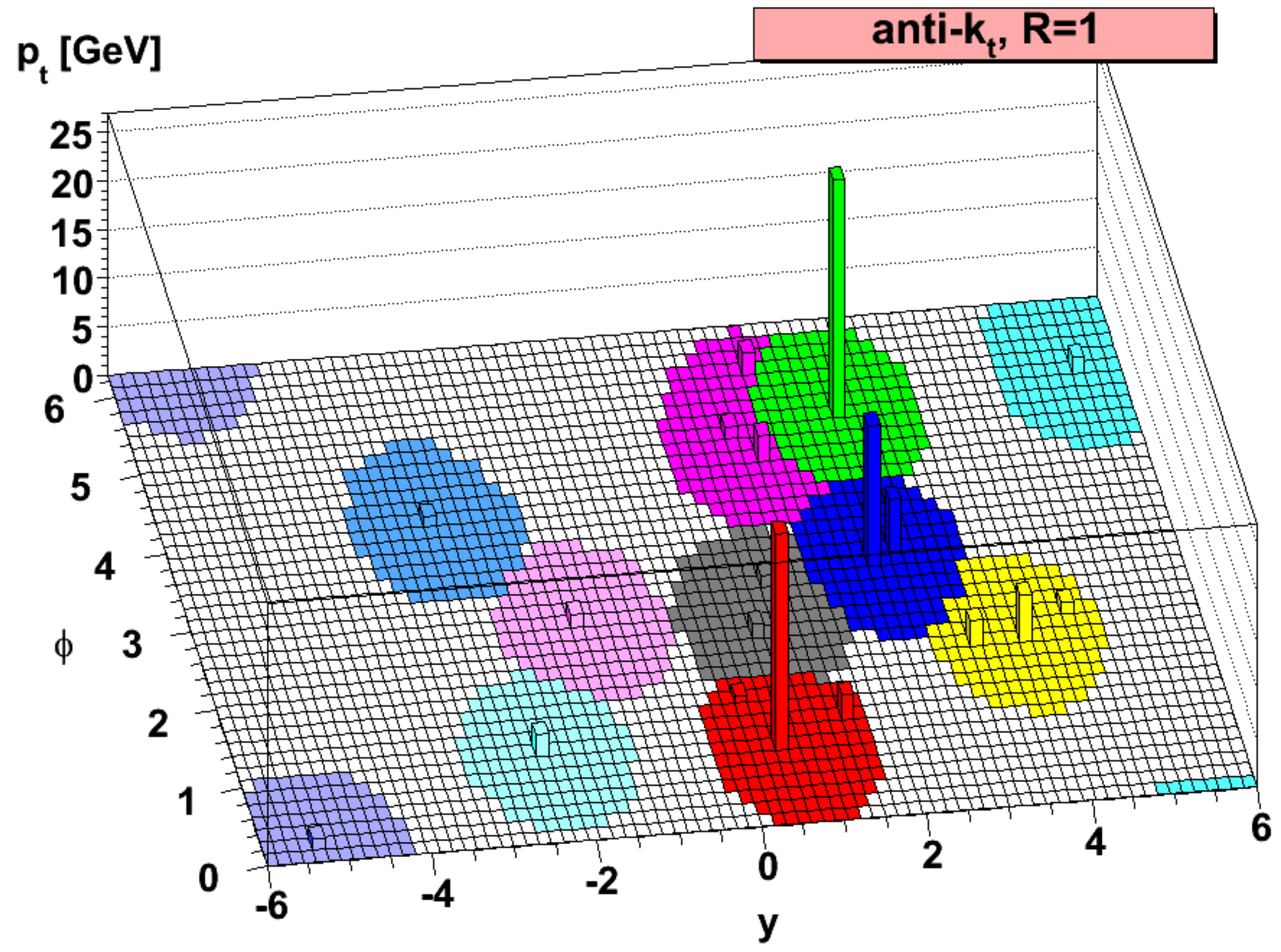
Evolution

Modelling particle physics processes

Latent variables

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

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



[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

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

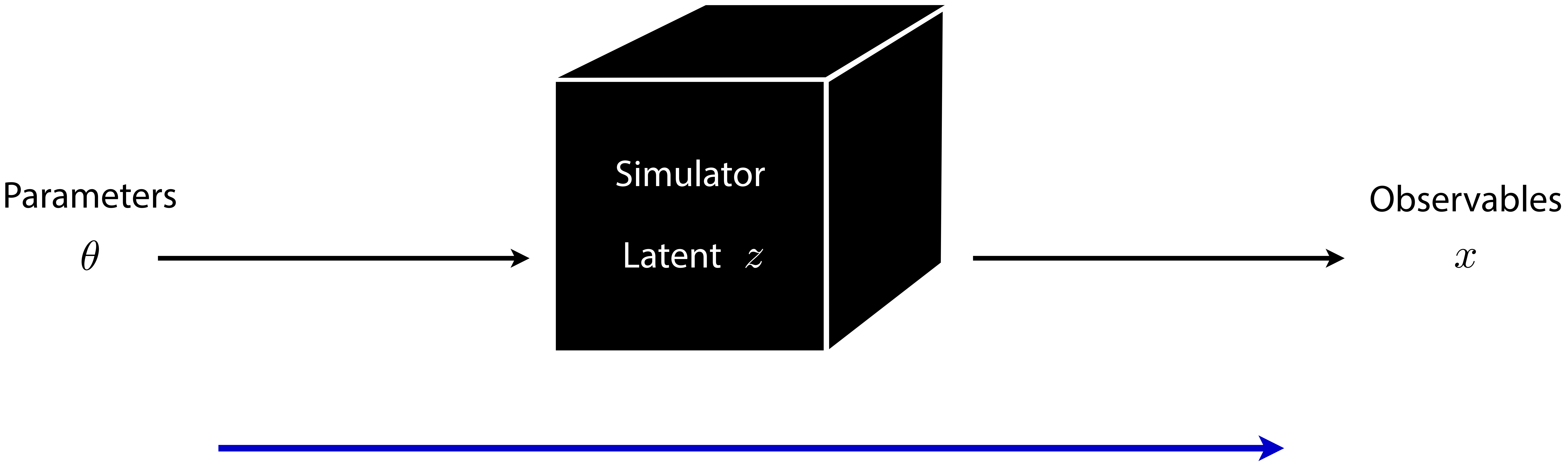
It's infeasible to calculate the integral over this enormous space!

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

$\longrightarrow$

Inference

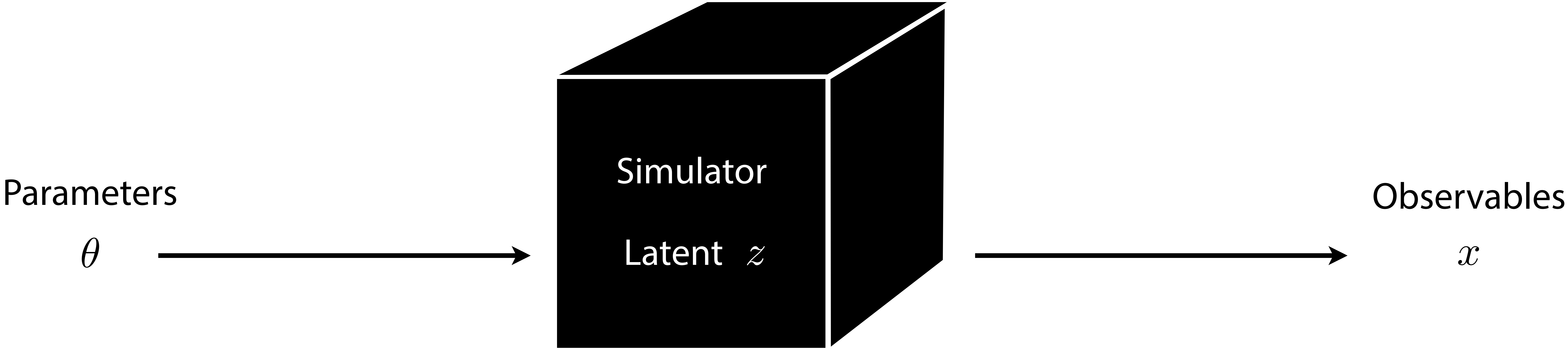
Likelihood-free inference / implicit models



Prediction:

- Well-understood mechanistic model
- Simulator can generate samples

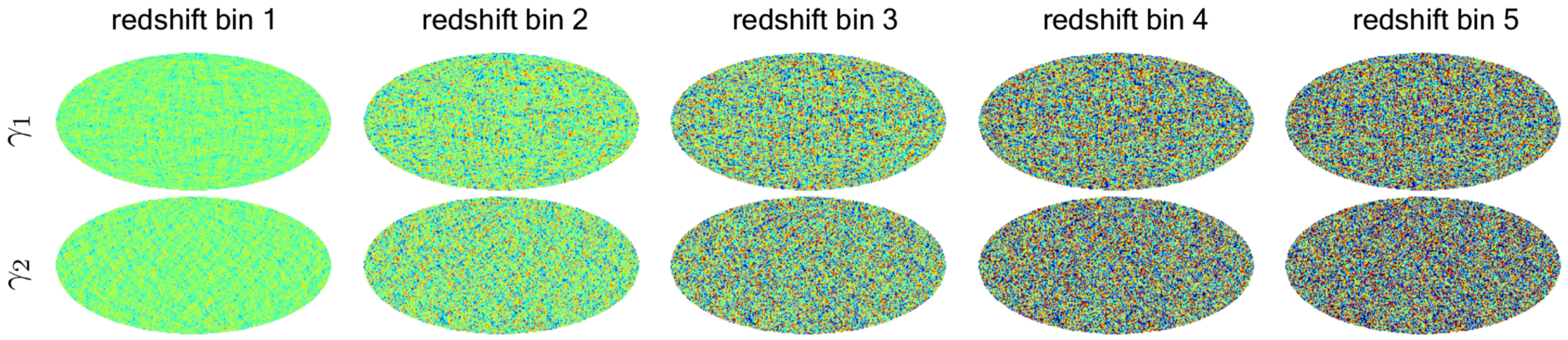
Likelihood-free inference / implicit models



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

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

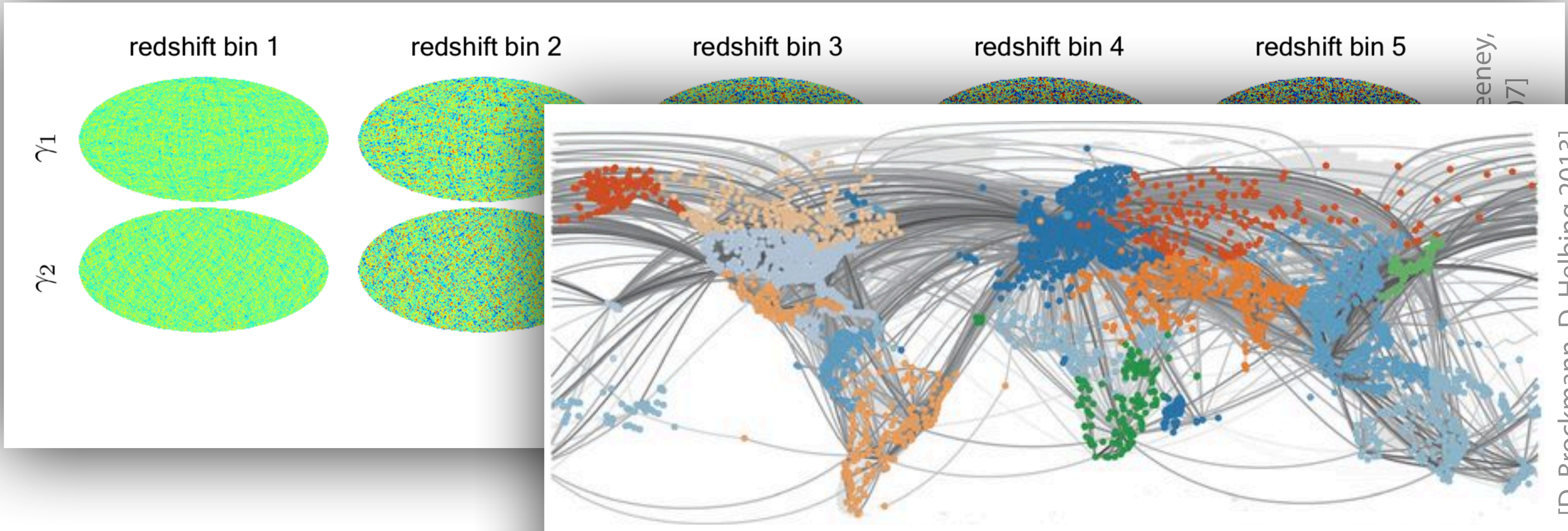
A thriving research field



Cosmology

[J. Alsing, T. Charnock, S. Feeney, B. Wandeelt 1903.00007]

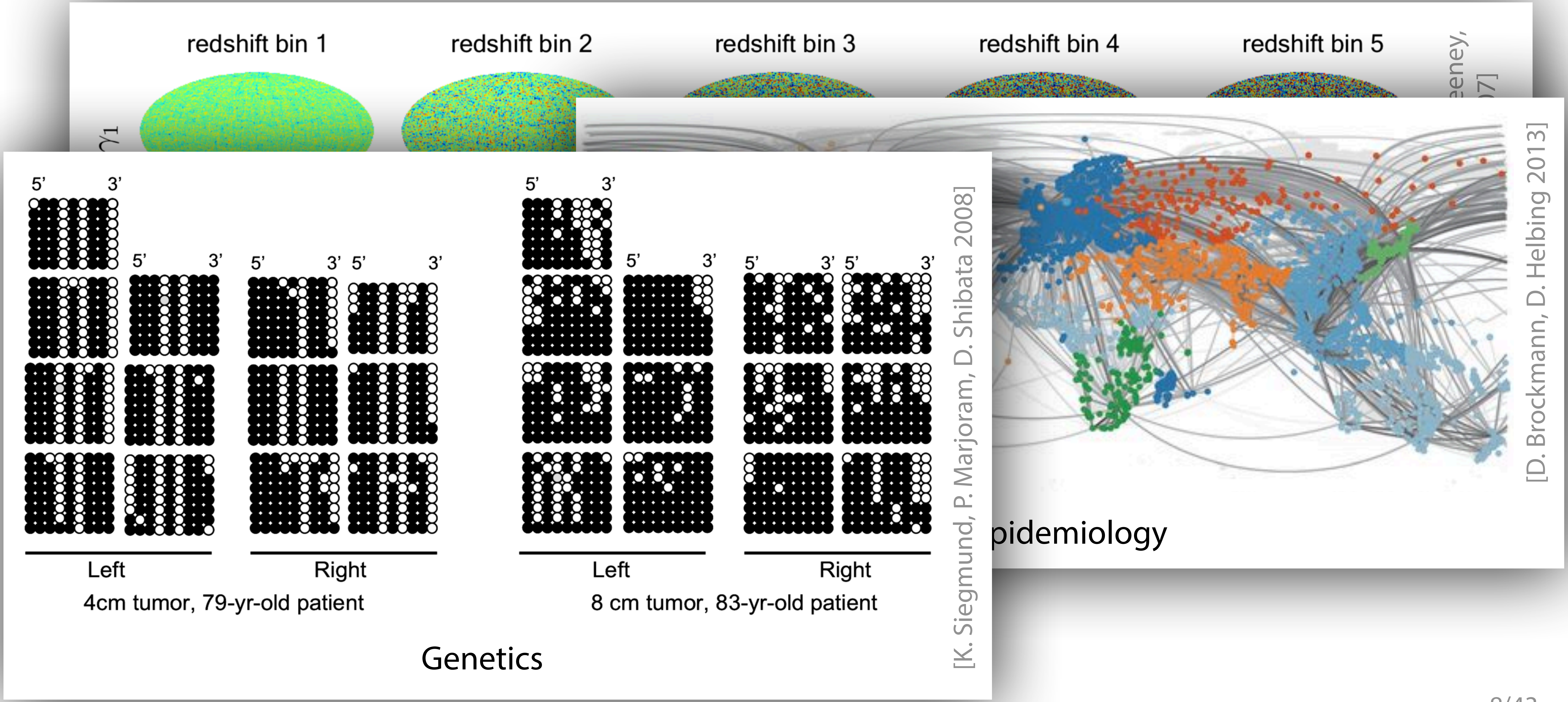
A thriving research field



Epidemiology

[D. Brockmann, D. Helbing 2013]

A thriving research field



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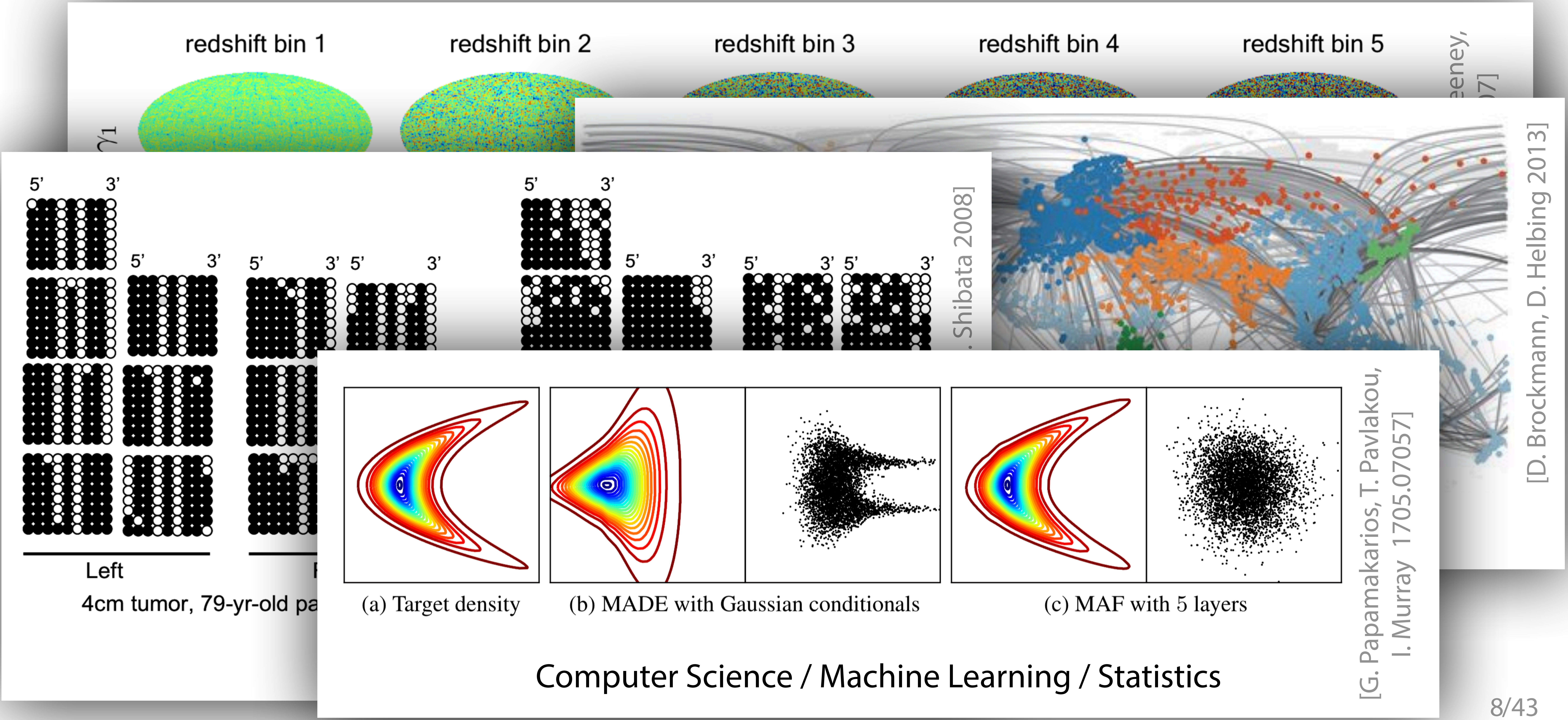
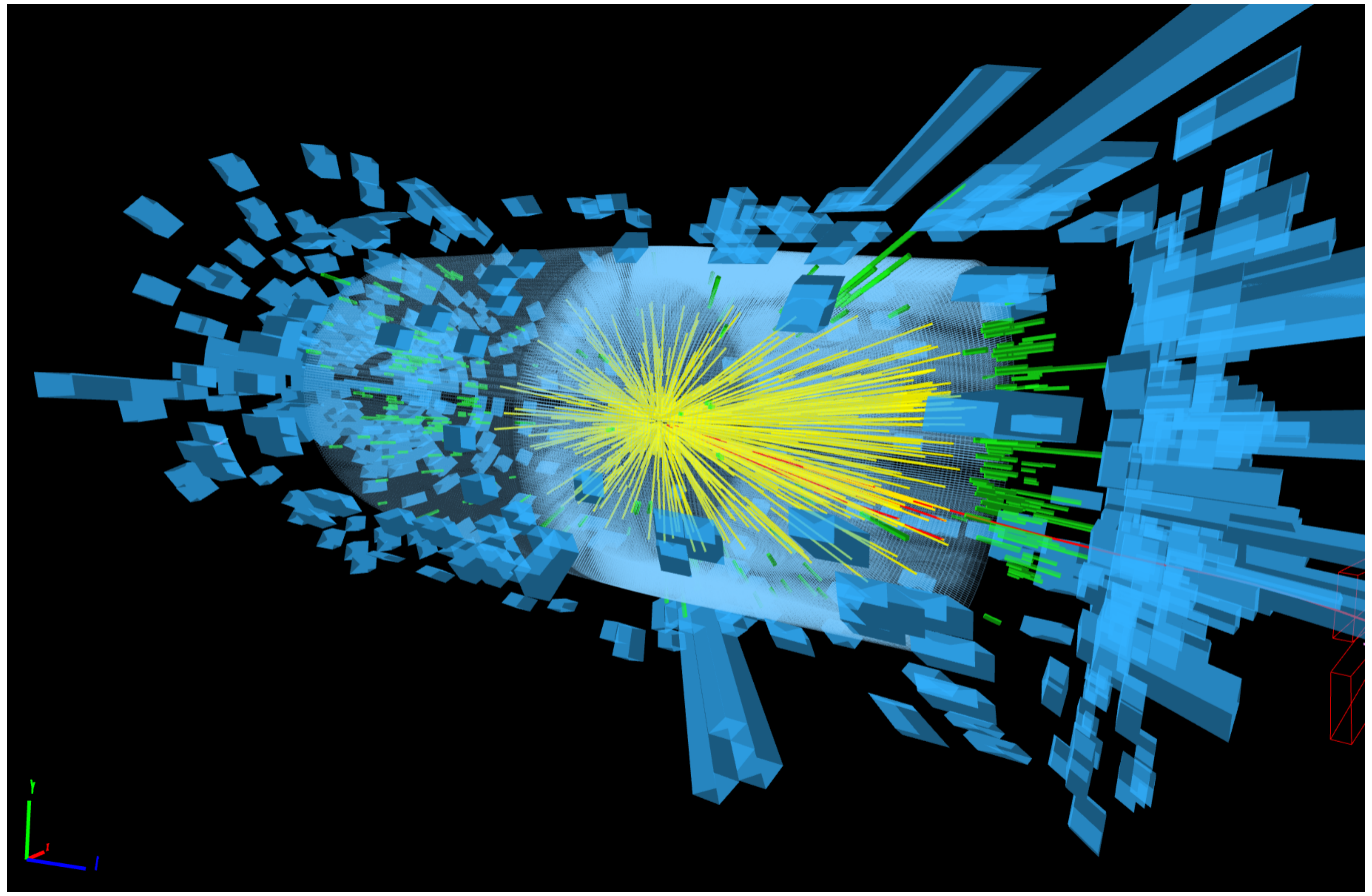


Why has that not stopped us before?

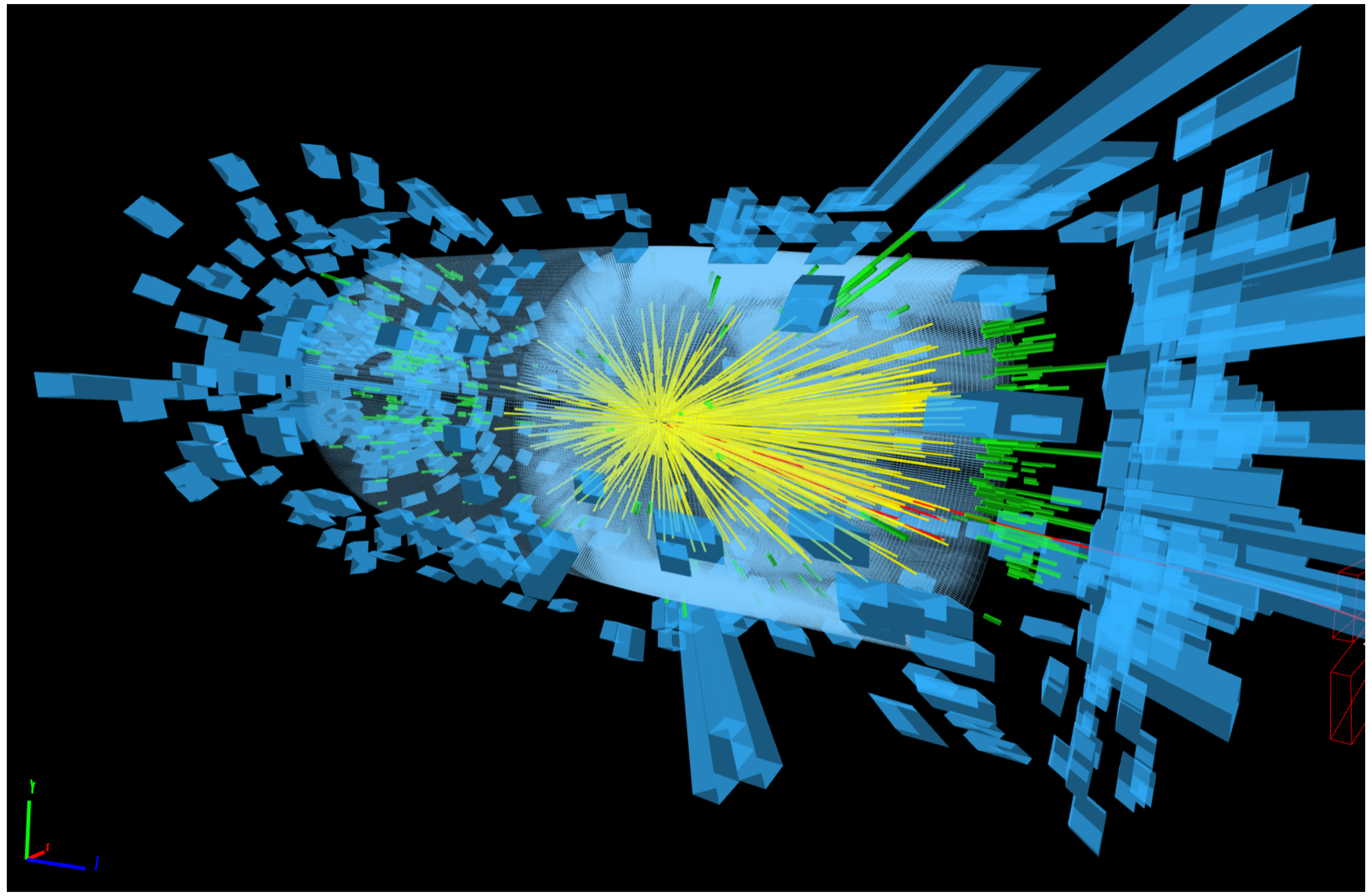
Solve it with summary statistics

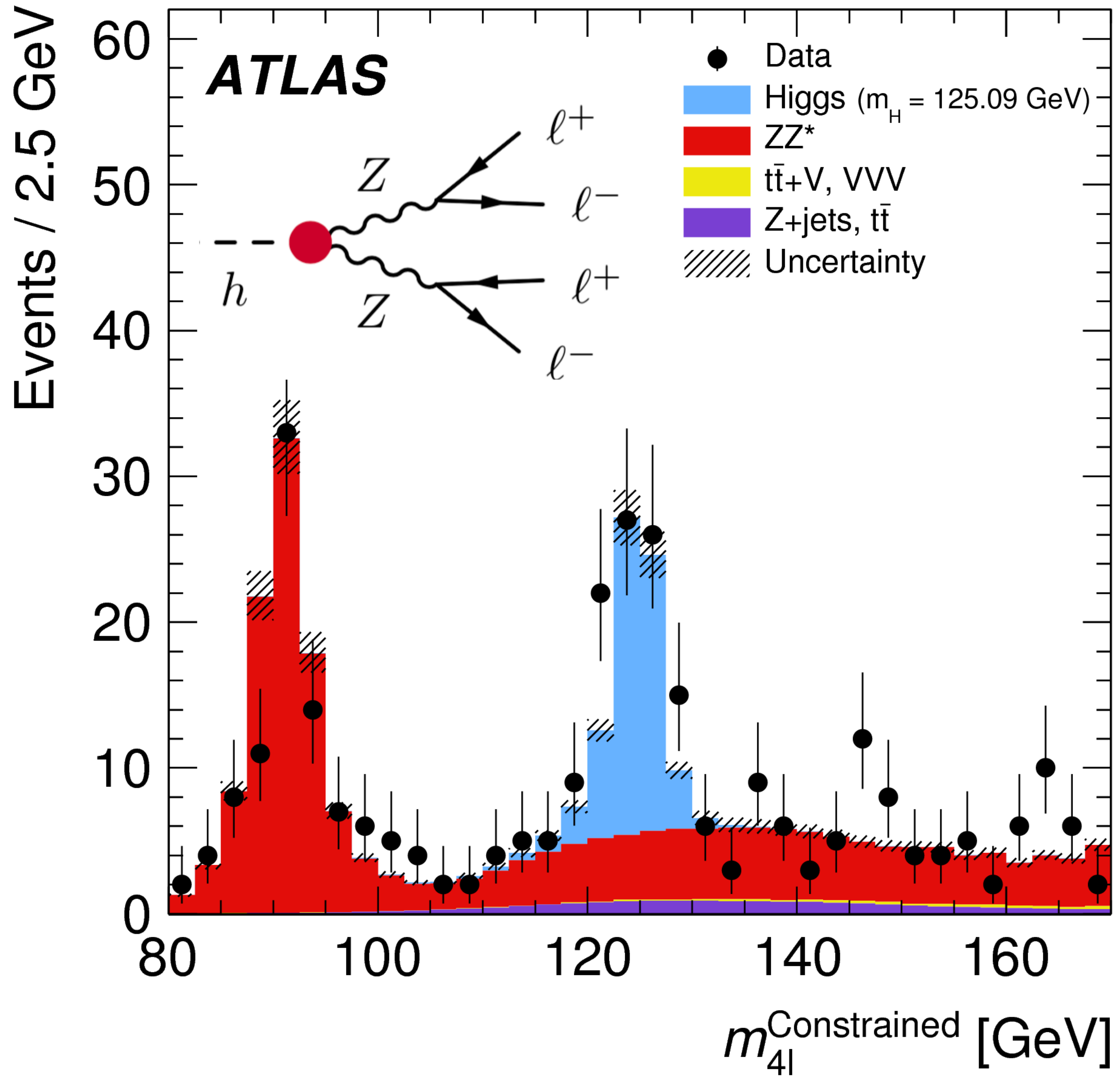


High-dimensional event data x

$p(x|\theta)$ 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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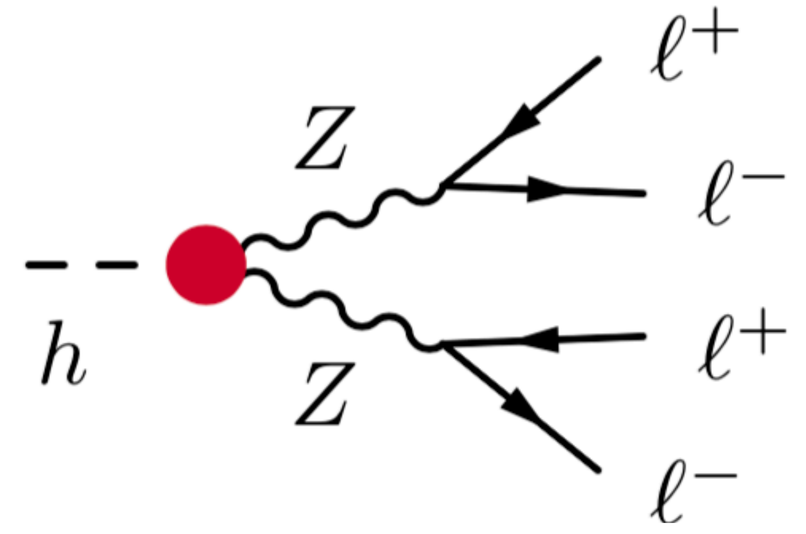
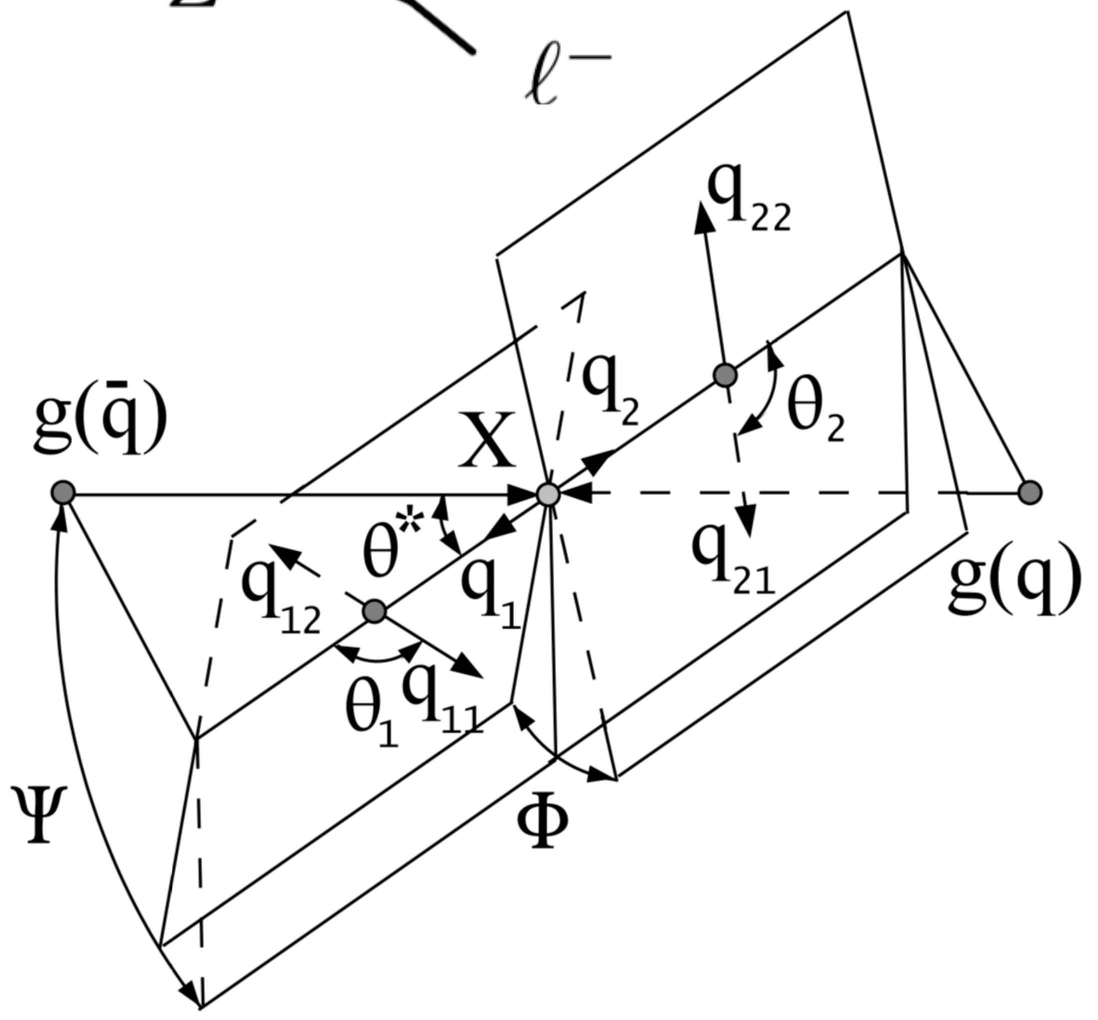
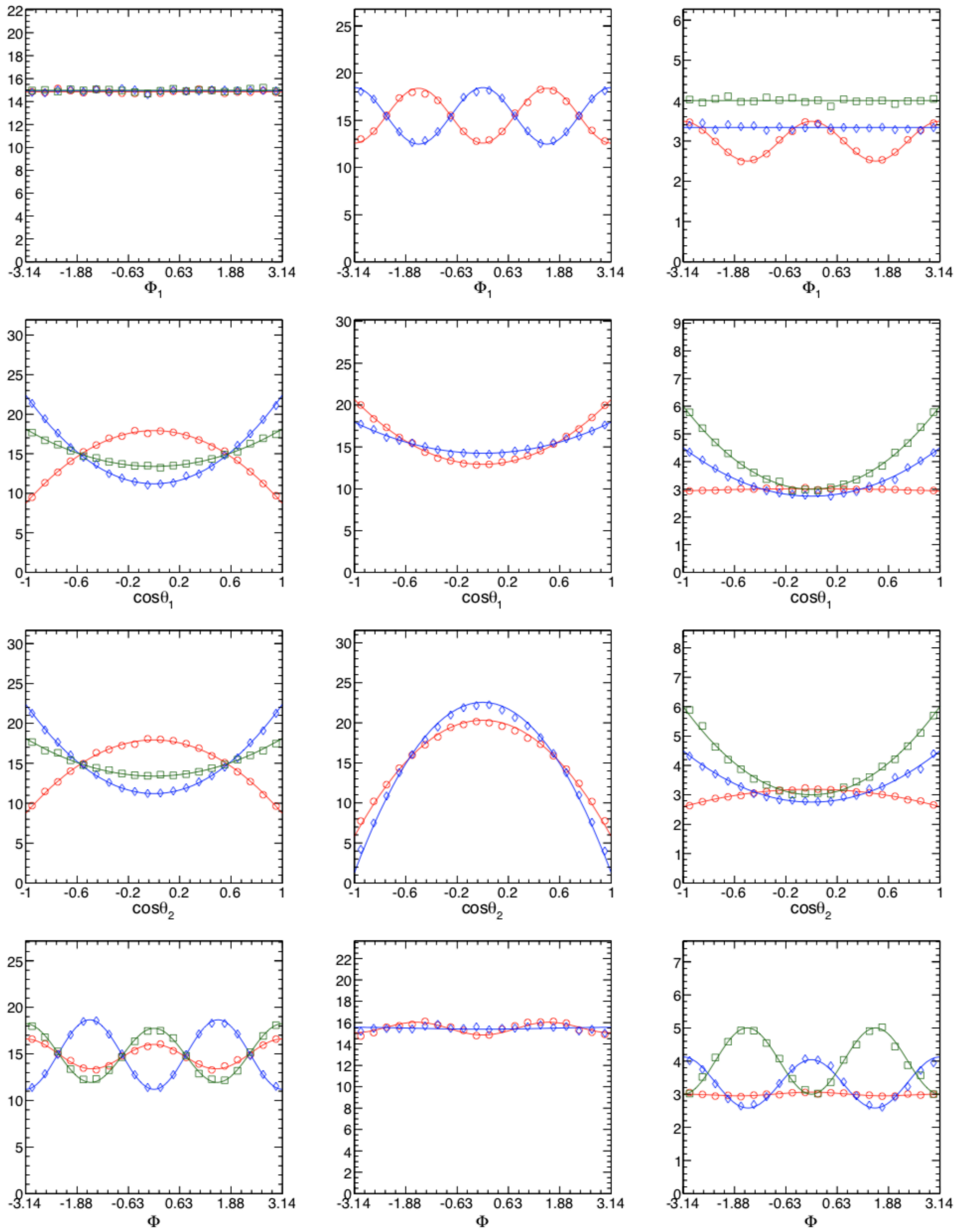




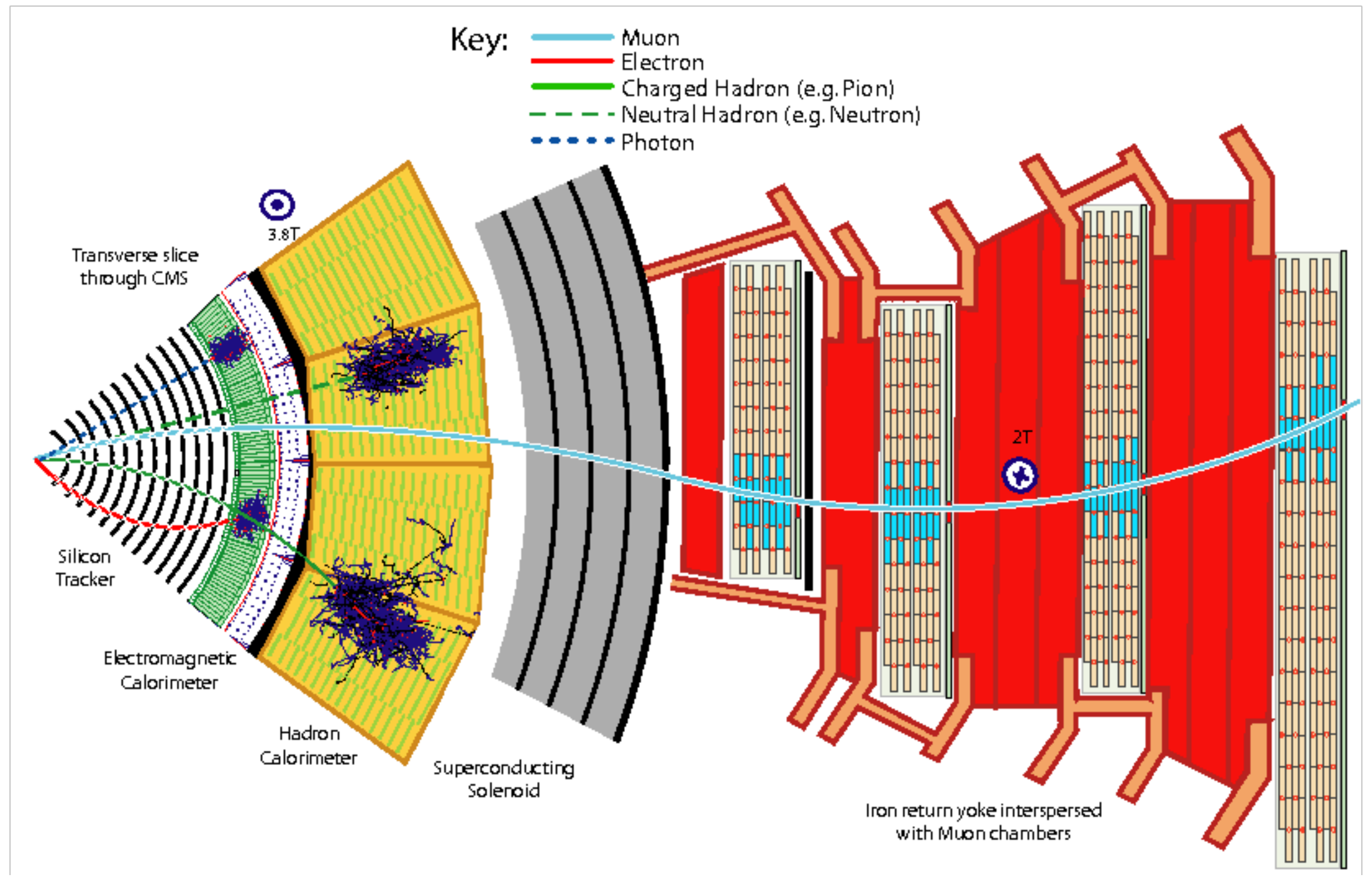


[Bolognesi et al. 1208.4018]

Solve it by approximating the integral

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

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



[CMS]

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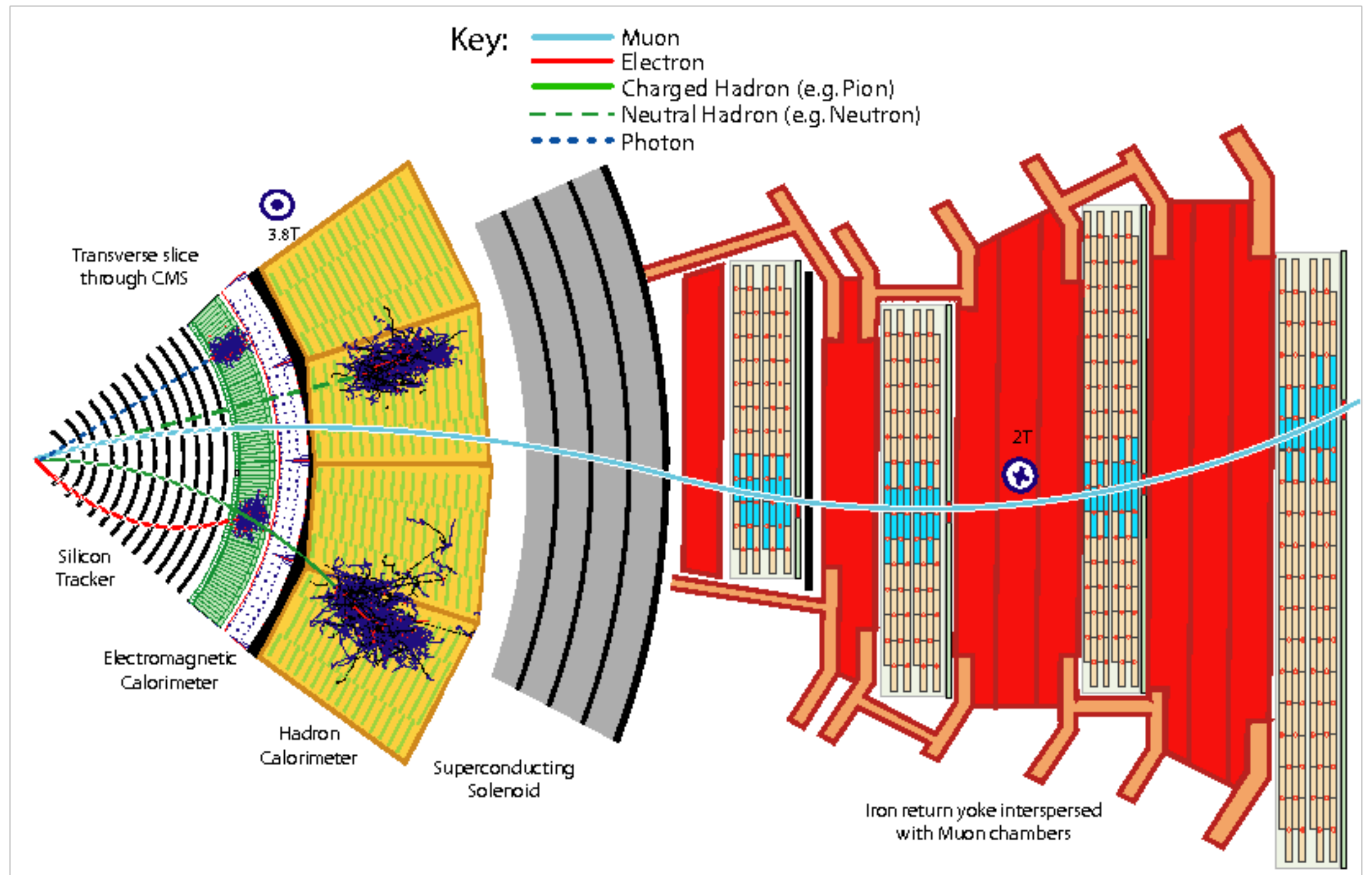
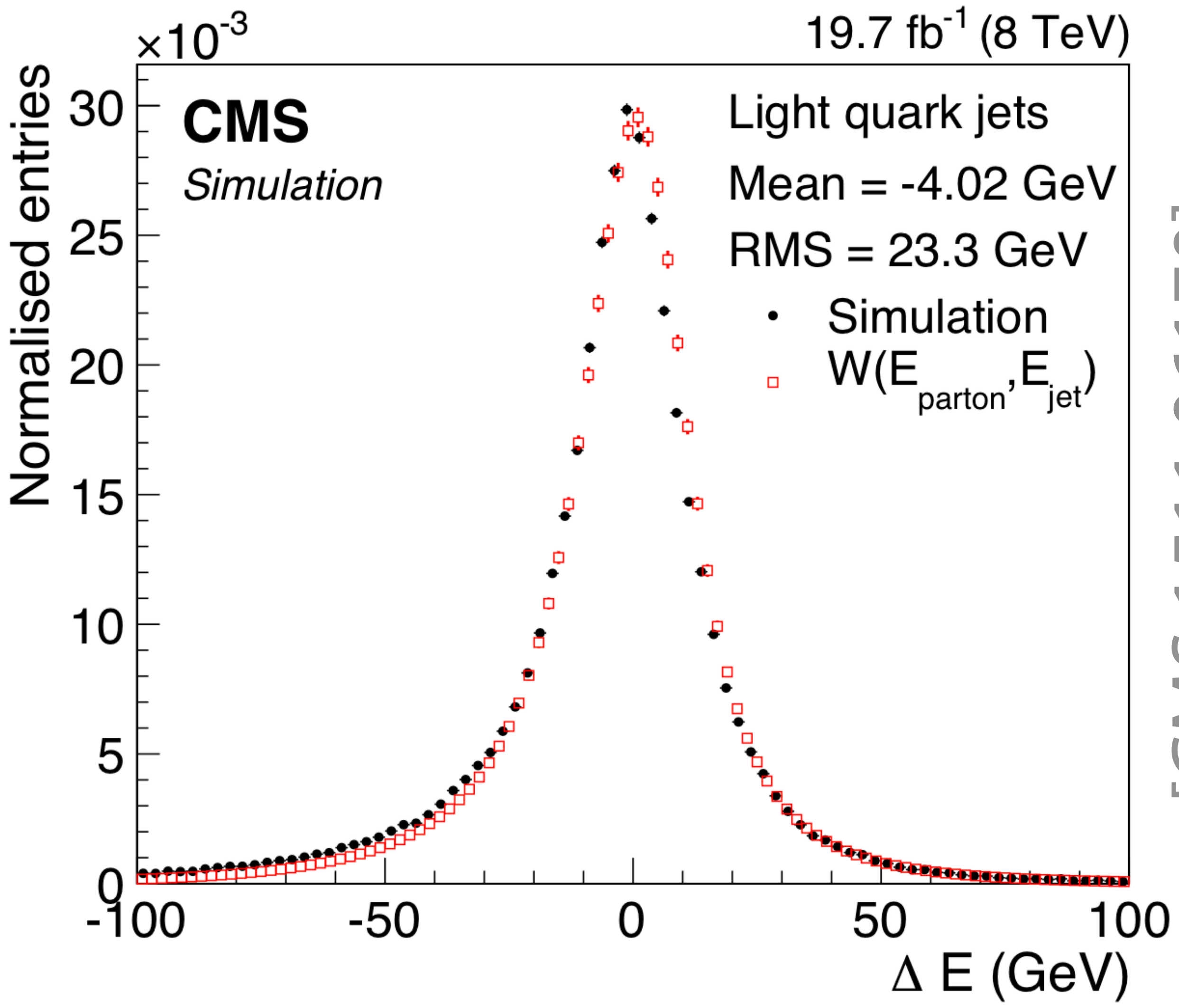
- Matrix Element Method (MEM): [K. Kondo 1988]
  - approximate shower + detector effects into transfer function $\hat{p}(x|z_p)$
  - explicitly calculate remaining integral

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



[CMS]



[CMS 1511.06170]

Solve it by approximating the integral

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

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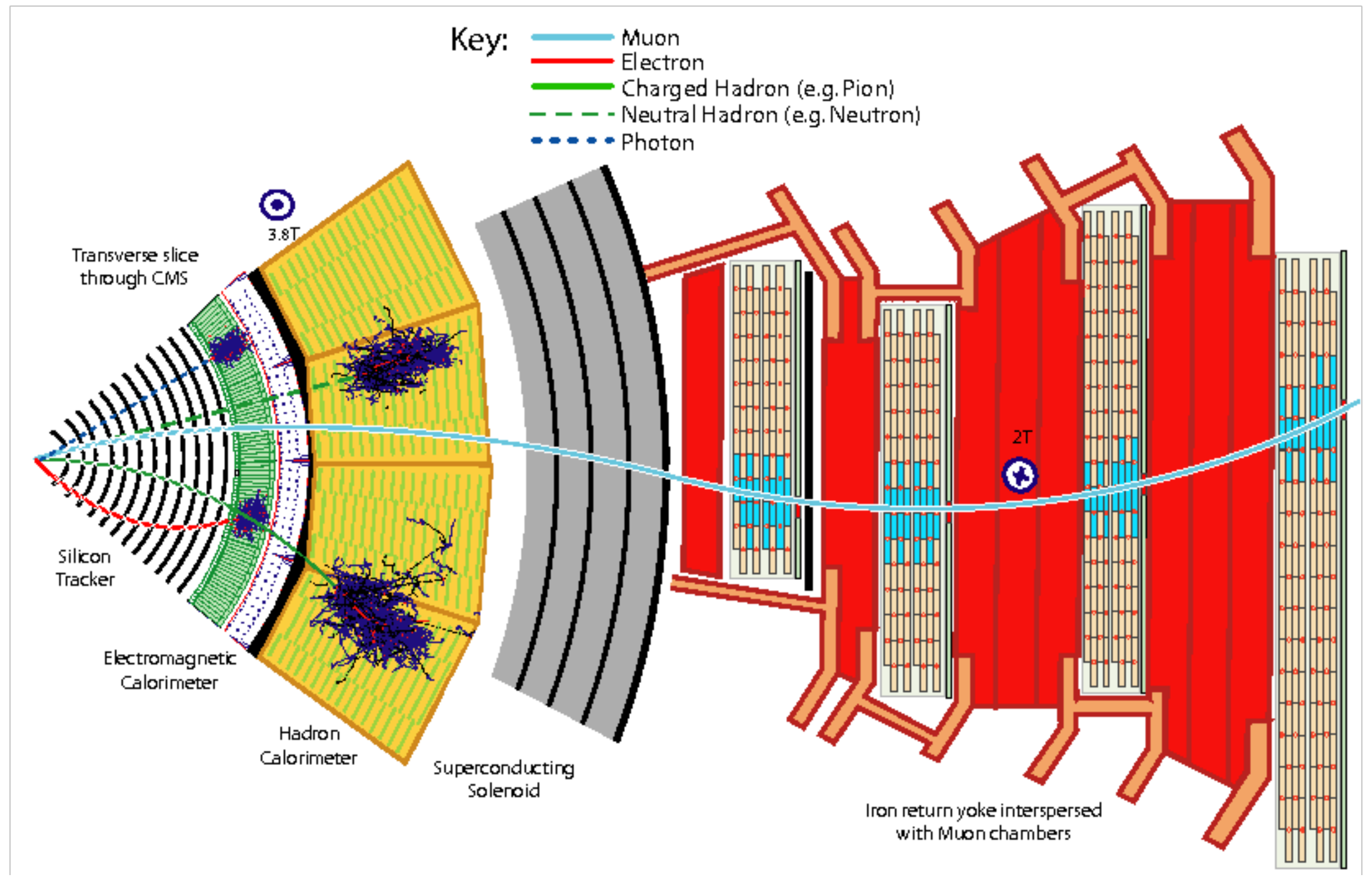

[CMS]

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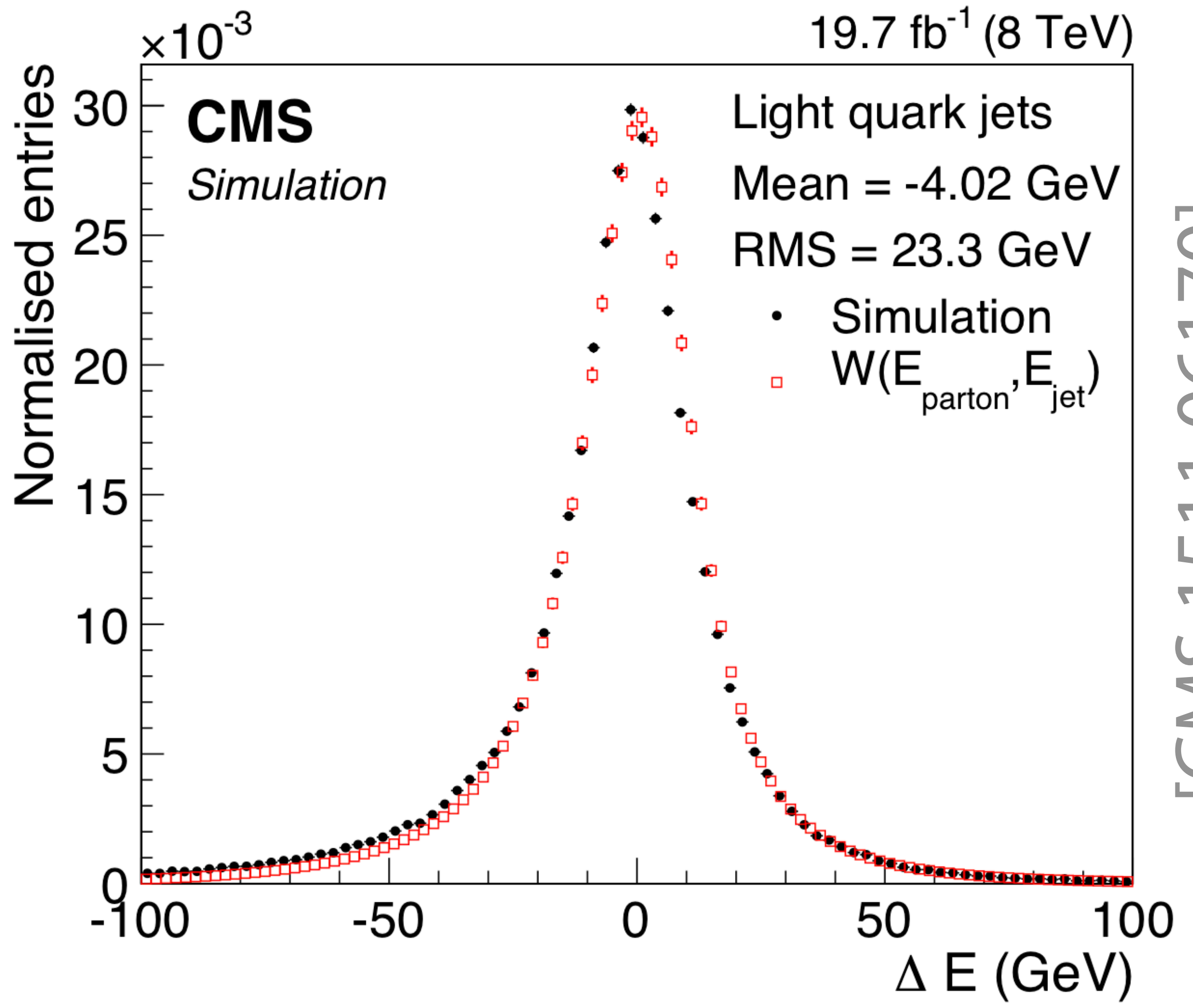


[CMS 1511.06170]

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

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

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]

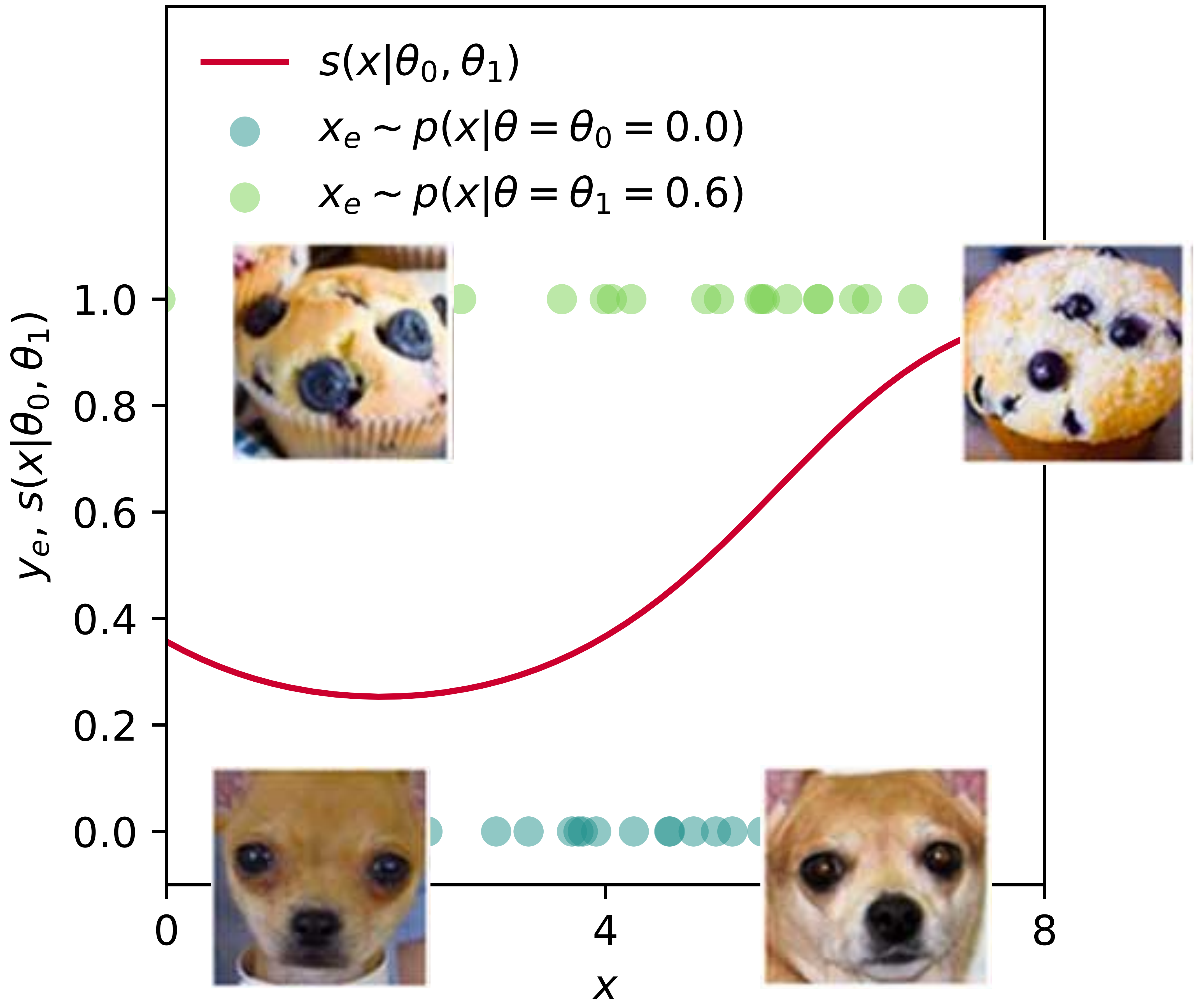
[M. Yao, idea for analogy: K. Cranmer]

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)



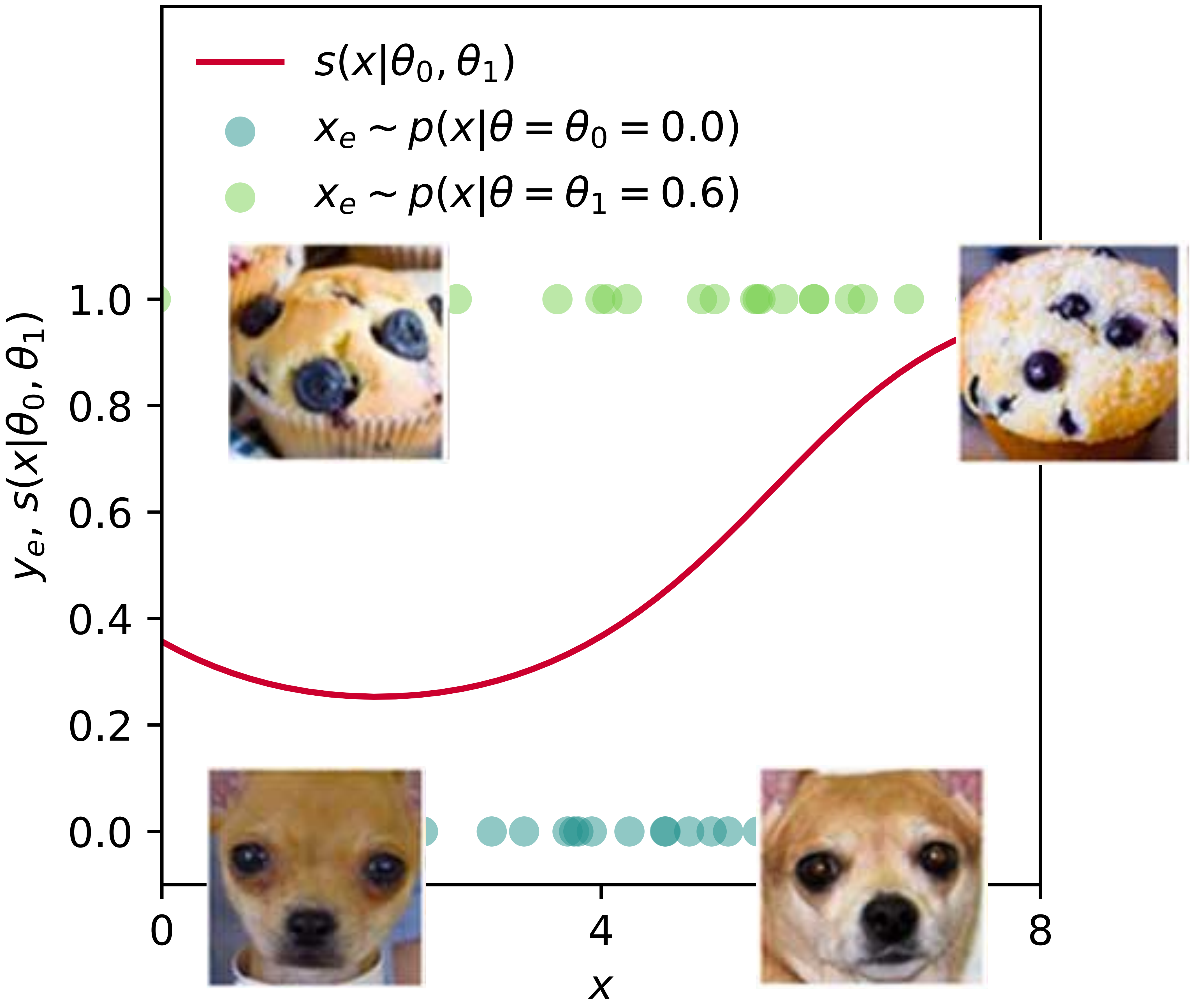
Solve it with machine learning classifiers

[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)



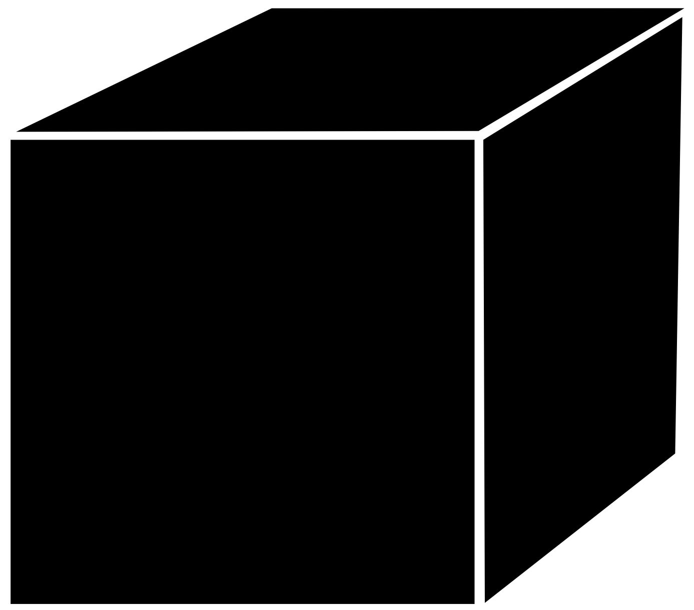
⇒ No summary statistics necessary, very fast evaluation… but may require large training samples

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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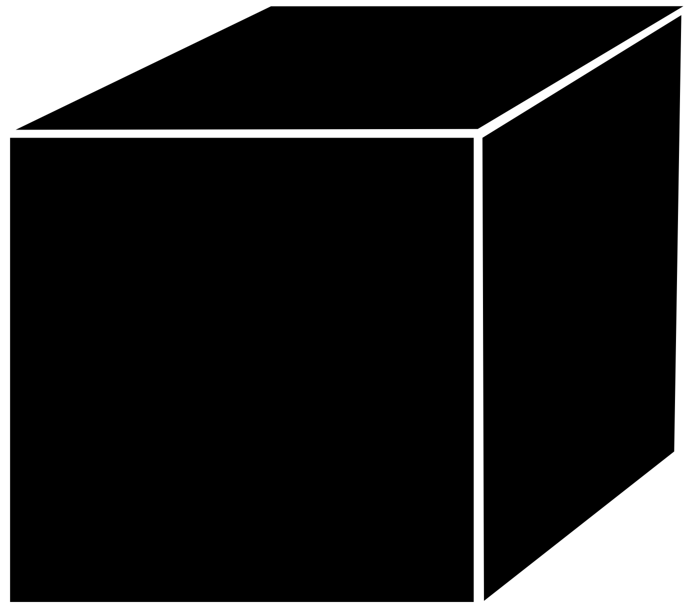

Use physics insights (matrix elements):

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

An incomplete list of likelihood-free inference methods

Treat simulator as black box:

- Histograms of observables, Approximate Bayesian Computation
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Use physics insights (matrix elements):

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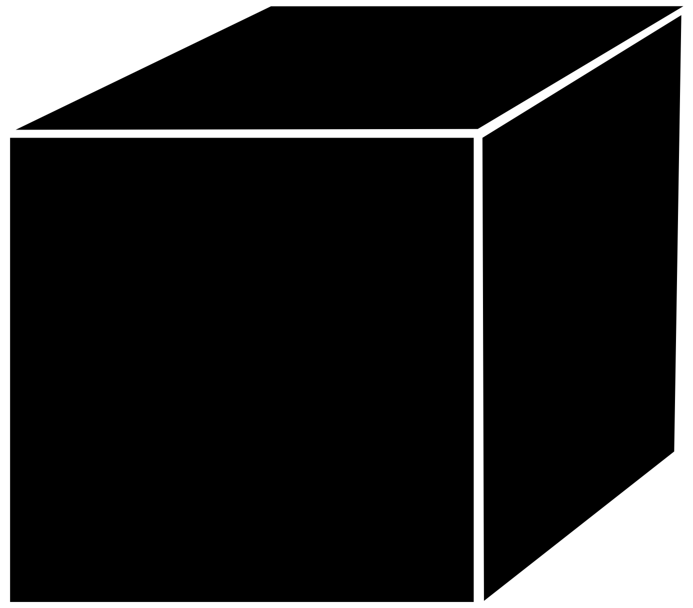
  Neglect or approximate shower + detector, explicitly calculate z integral

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

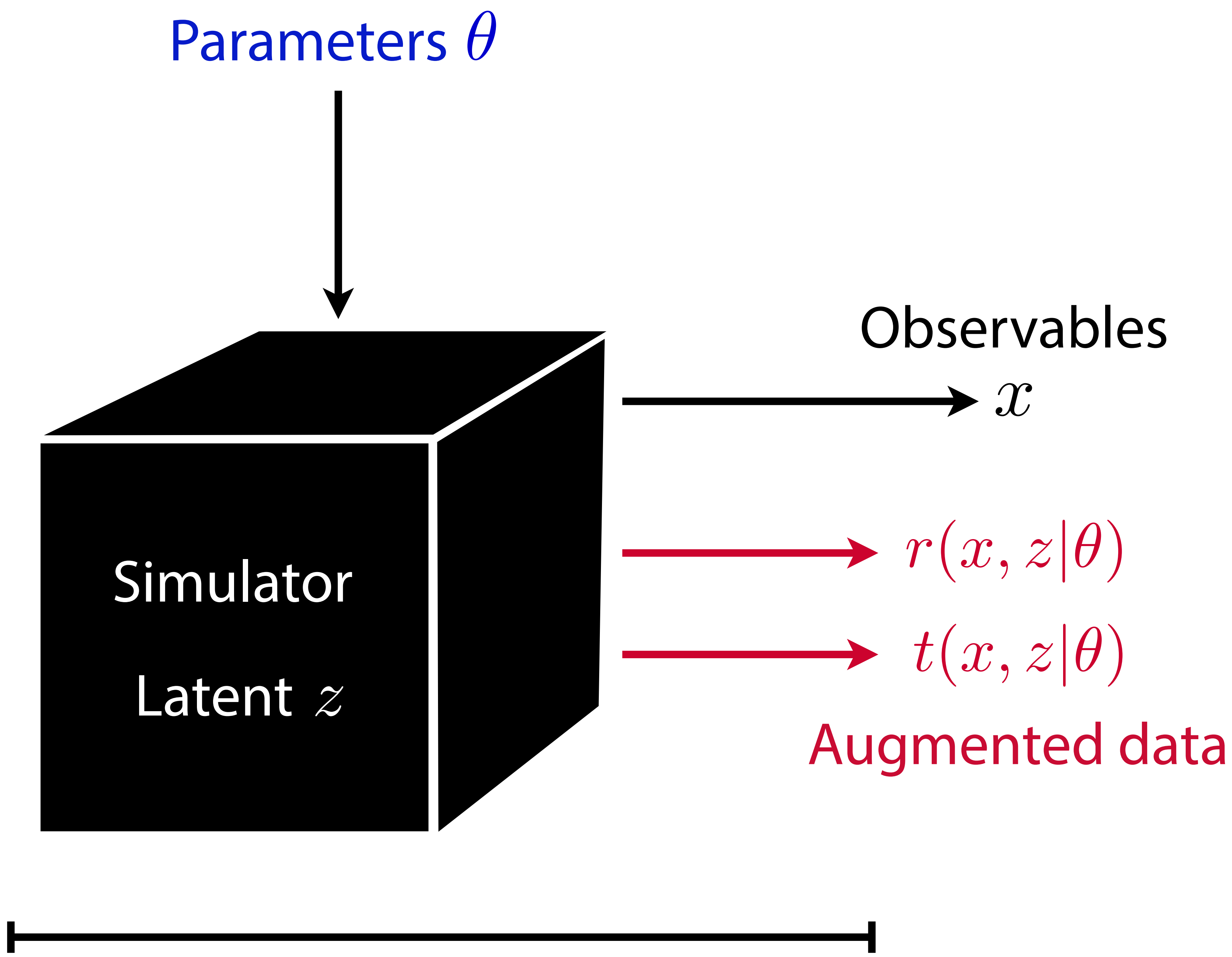
- in microseconds?

  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"

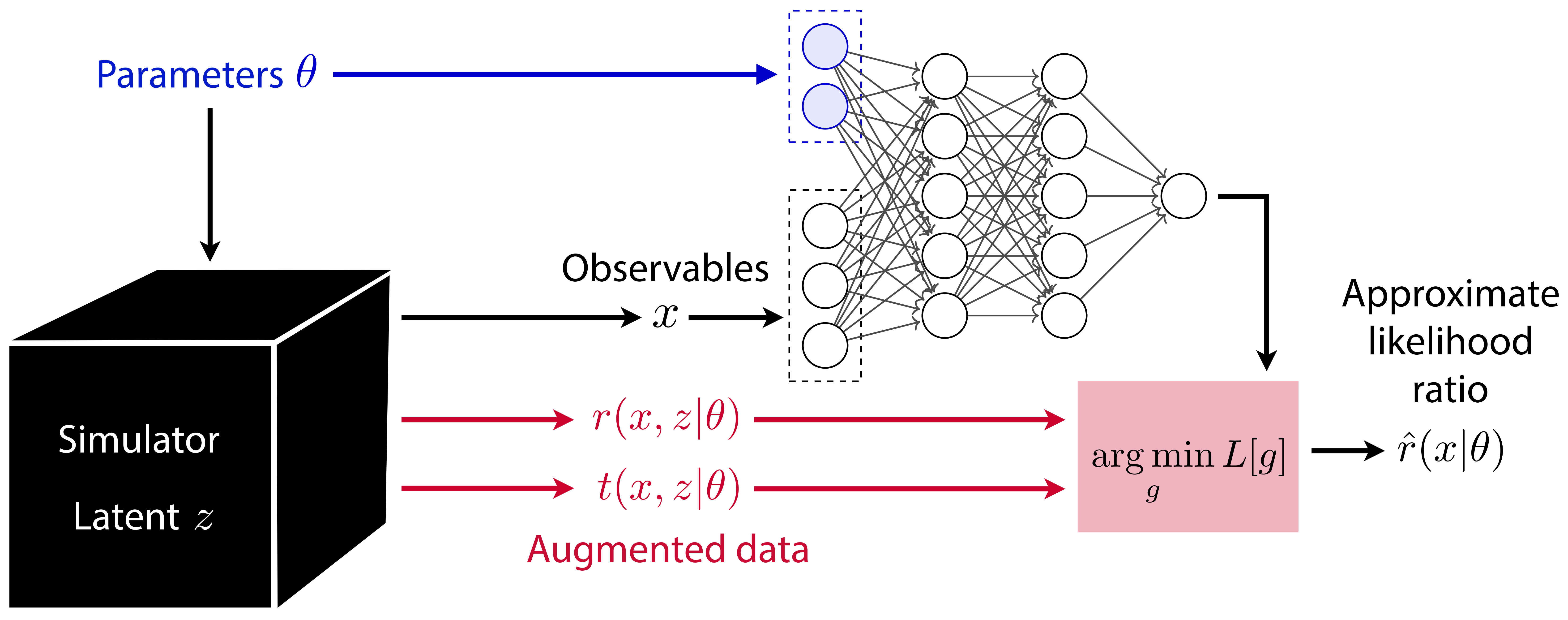
Bird’s-eye view



1. Simulation

“Mining gold”: Extract additional information from simulator

Bird's-eye view



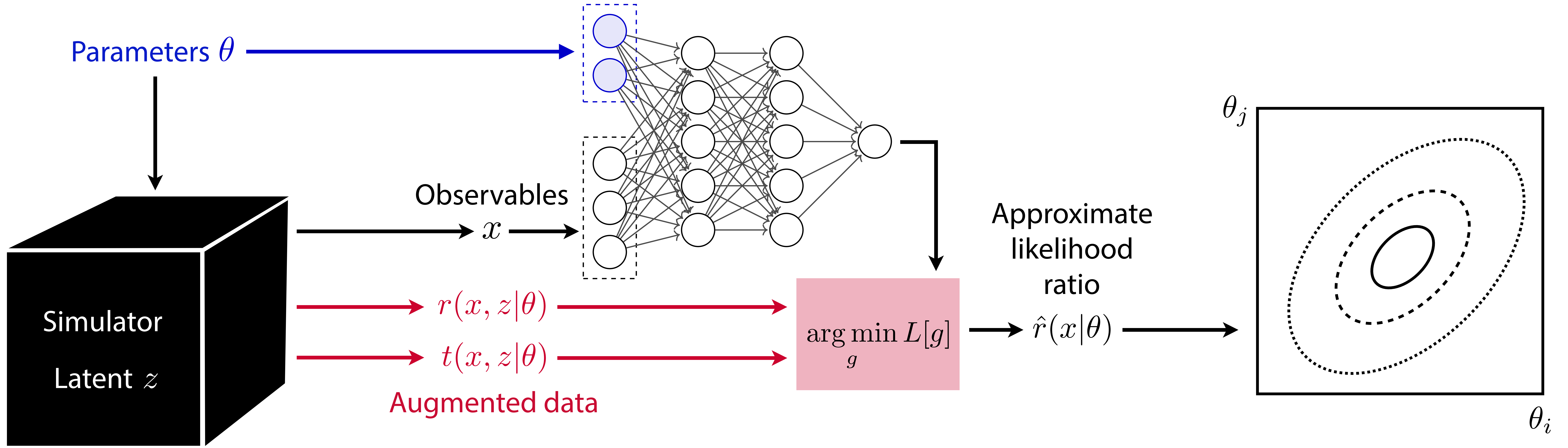
1. Simulation

"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

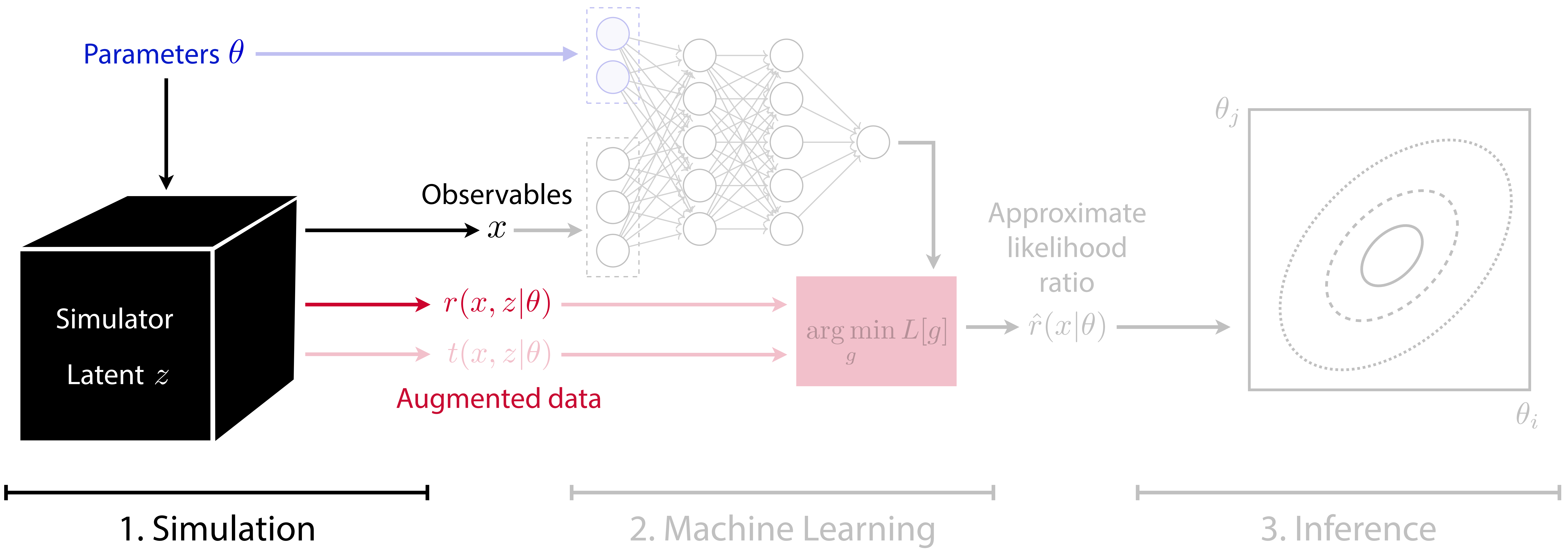
"Mining gold": Extract additional information from simulator

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
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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	$\longleftarrow$	θ

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

Intractable integrals

Mining gold from the simulator

Latent variables

Observables	Detector interactions	Shower splittings	Parton-level momenta	Theory parameters

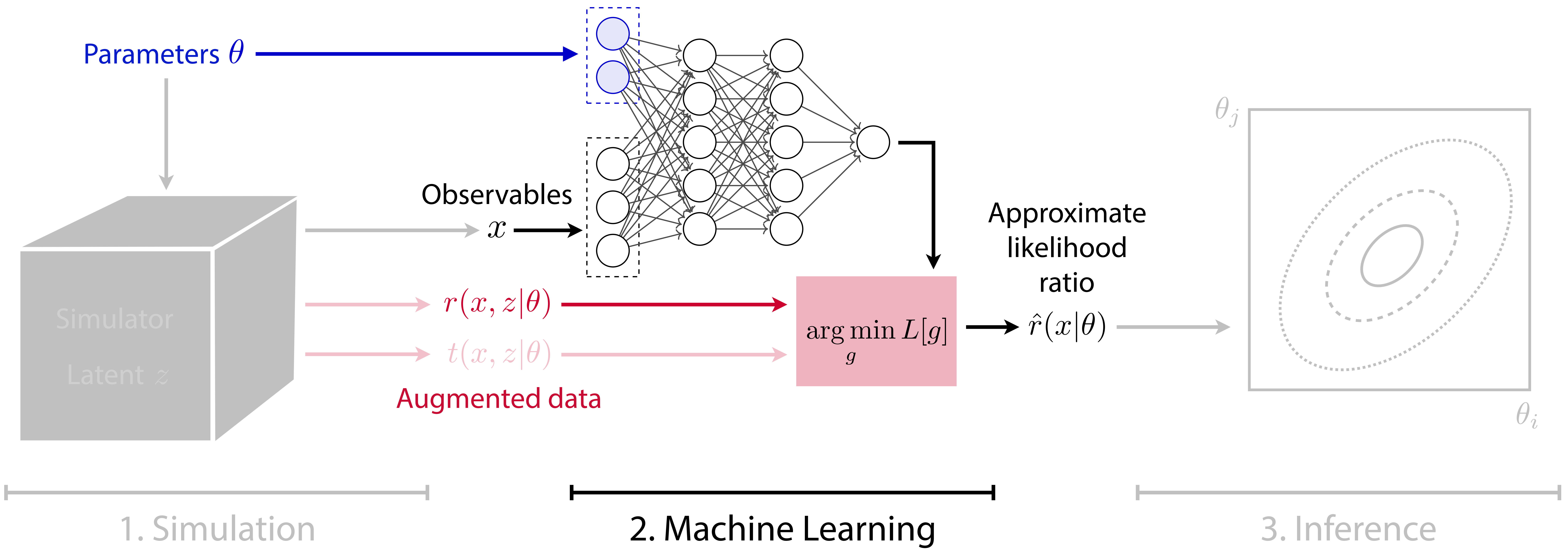
$$x \longleftarrow z_d \longleftarrow z_s \longleftarrow z_p \longleftarrow \theta$$

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

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:

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



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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

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

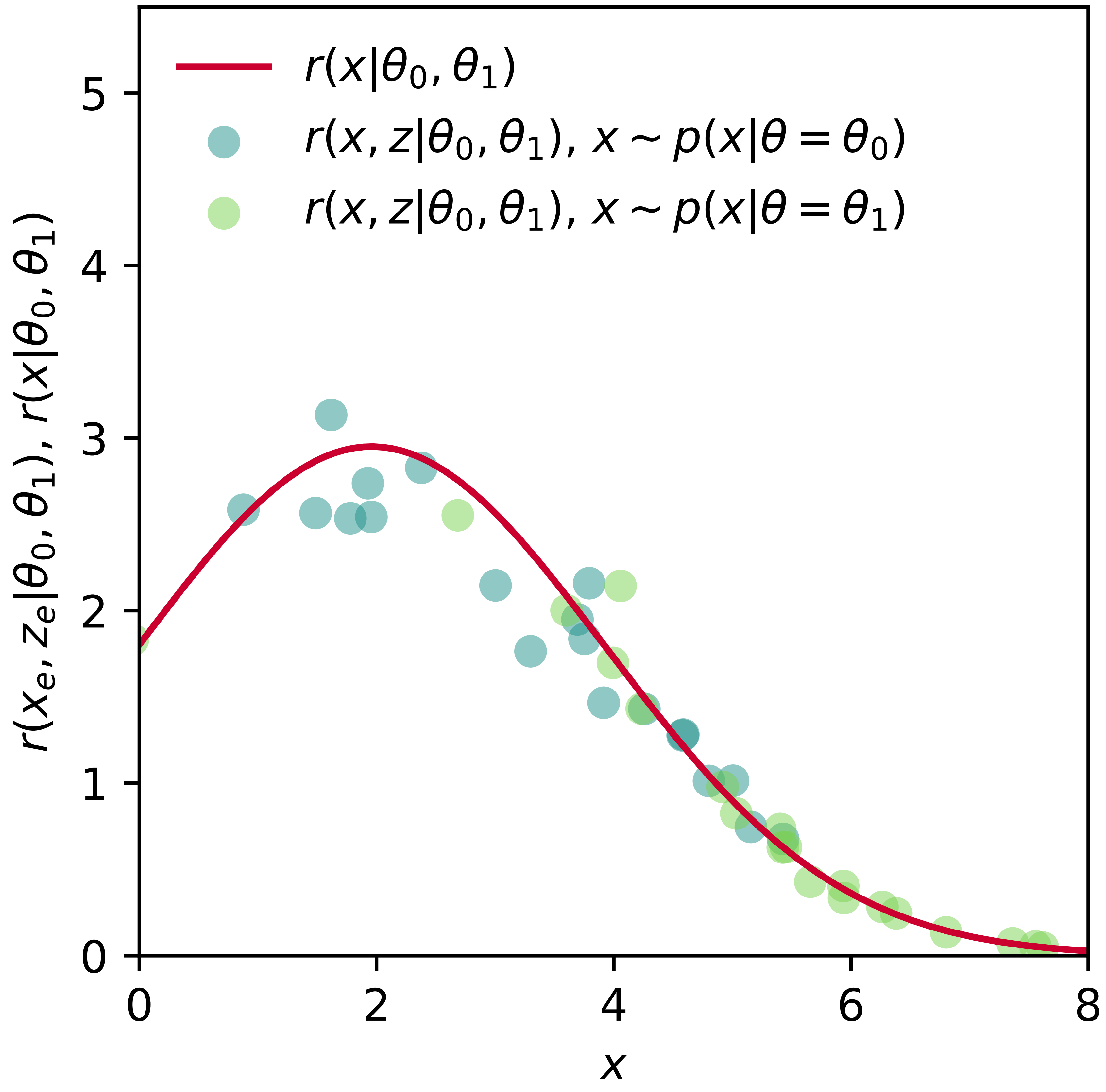
("How much more likely is the observation x for θ_0 compared to θ_1?")

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

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

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

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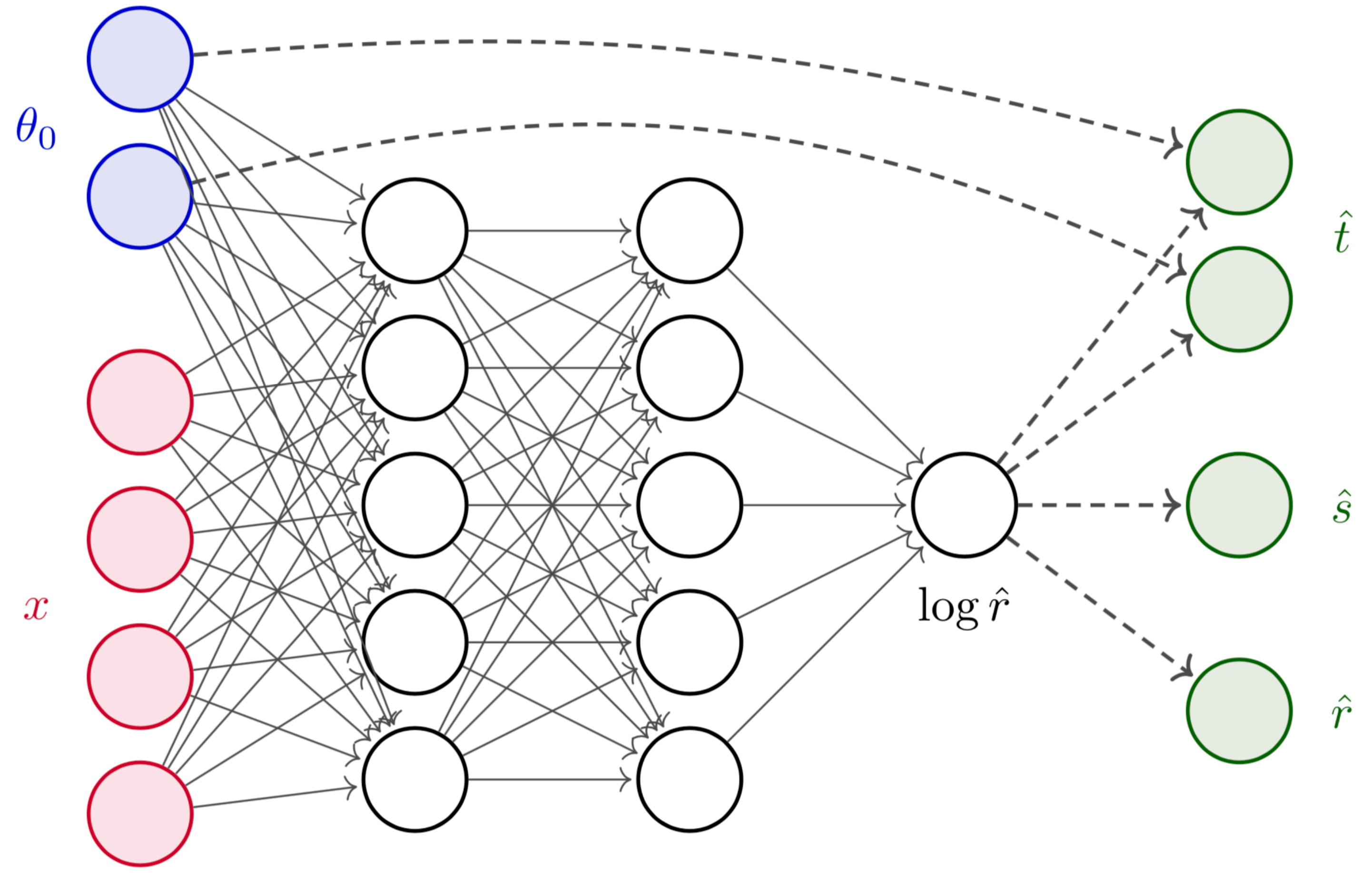
Loss function with
finite sum over samples

Stochastic gradient descent

This is where machine learning comes in!

Neural network



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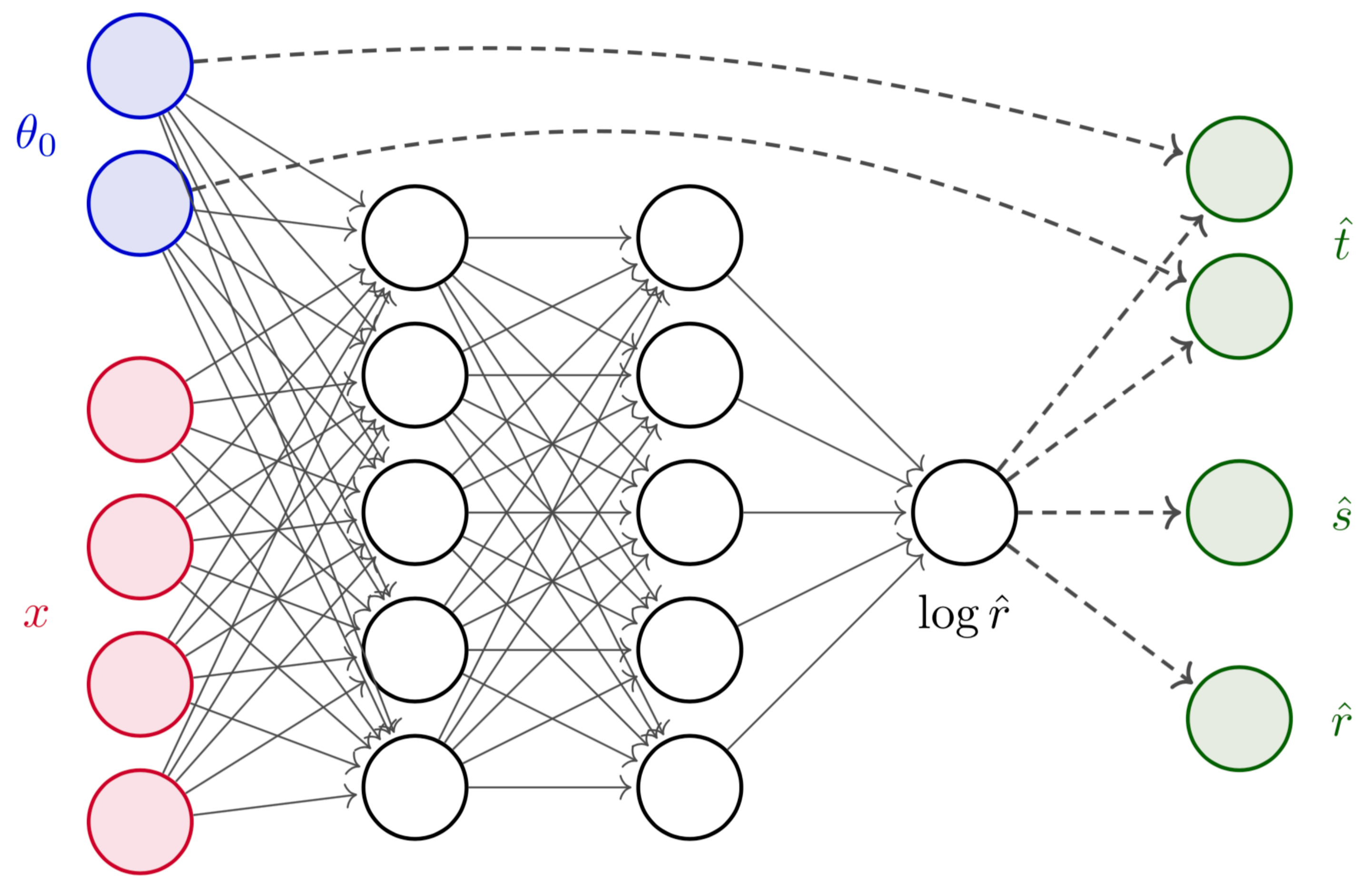
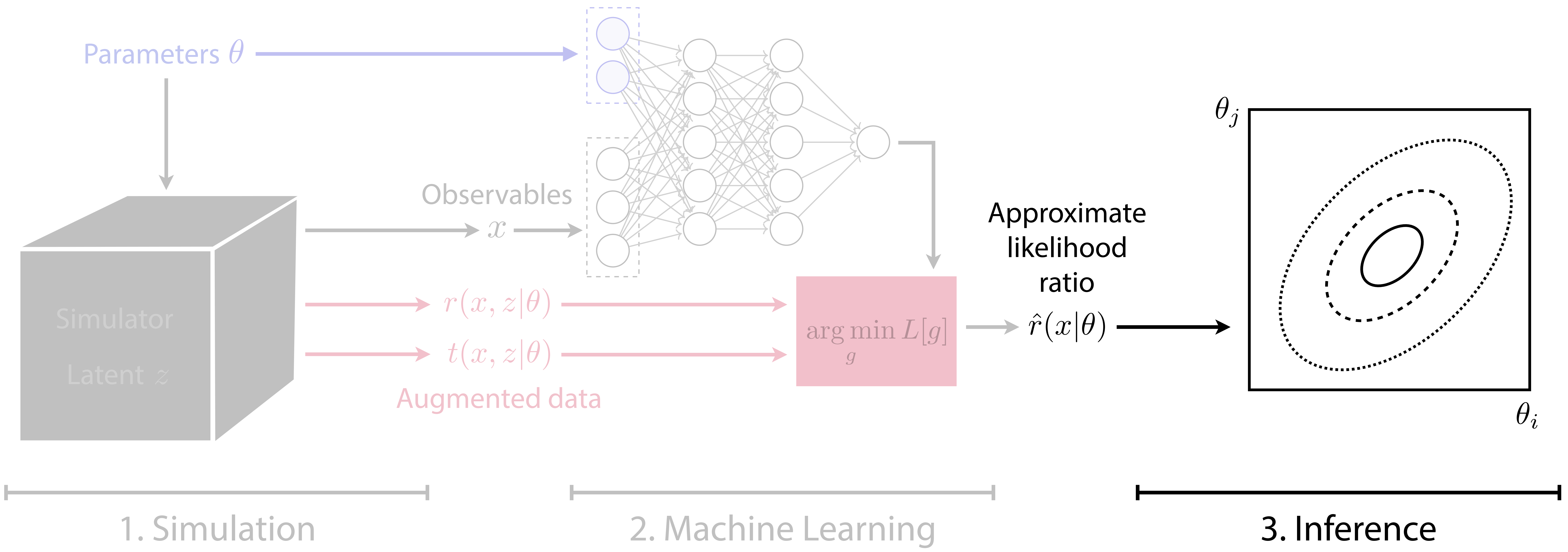


A sufficiently expressive neural network
efficiently trained in this way
with enough data will learn
the likelihood ratio function $r(x|\theta_0, \theta_1)$!



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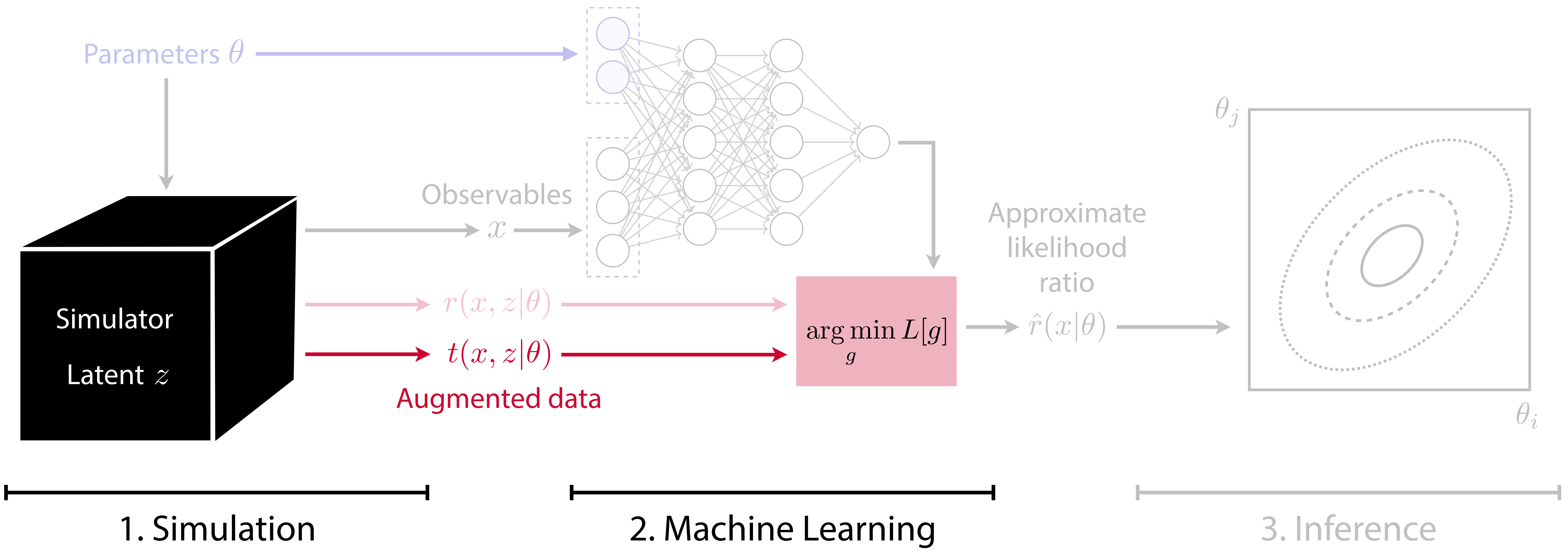

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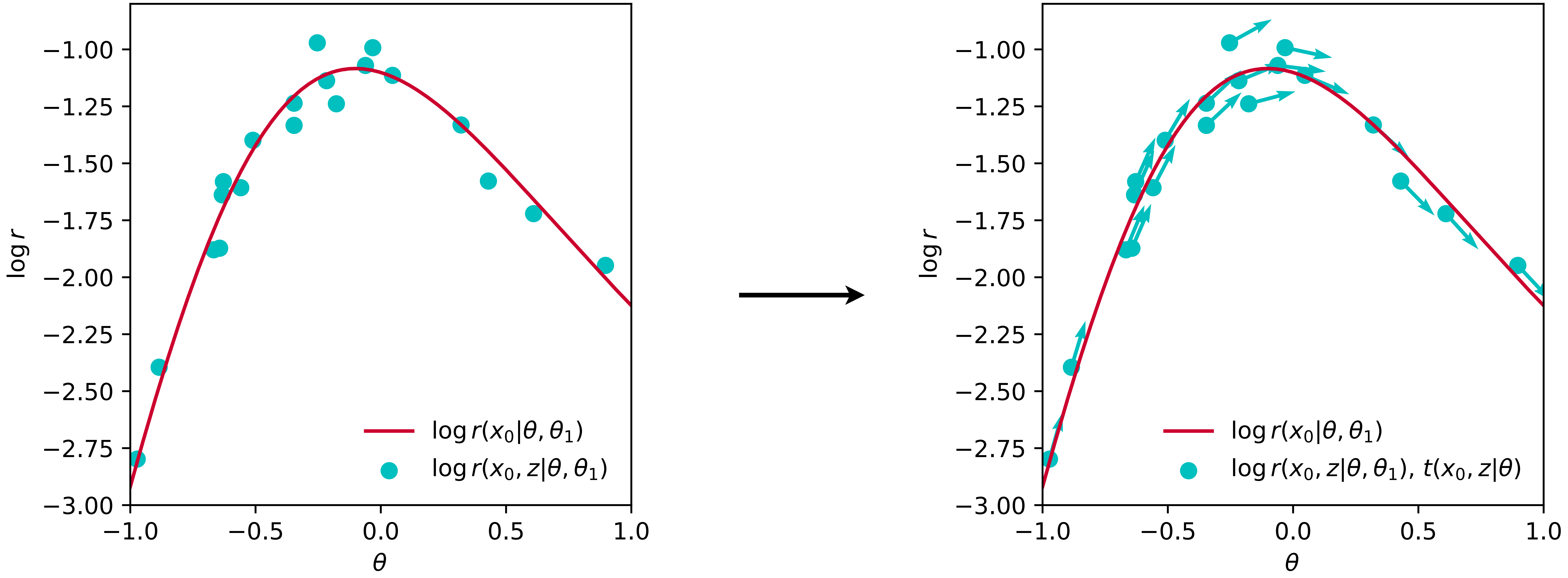
One more piece: the score

- Knowing derivative often helps fitting:



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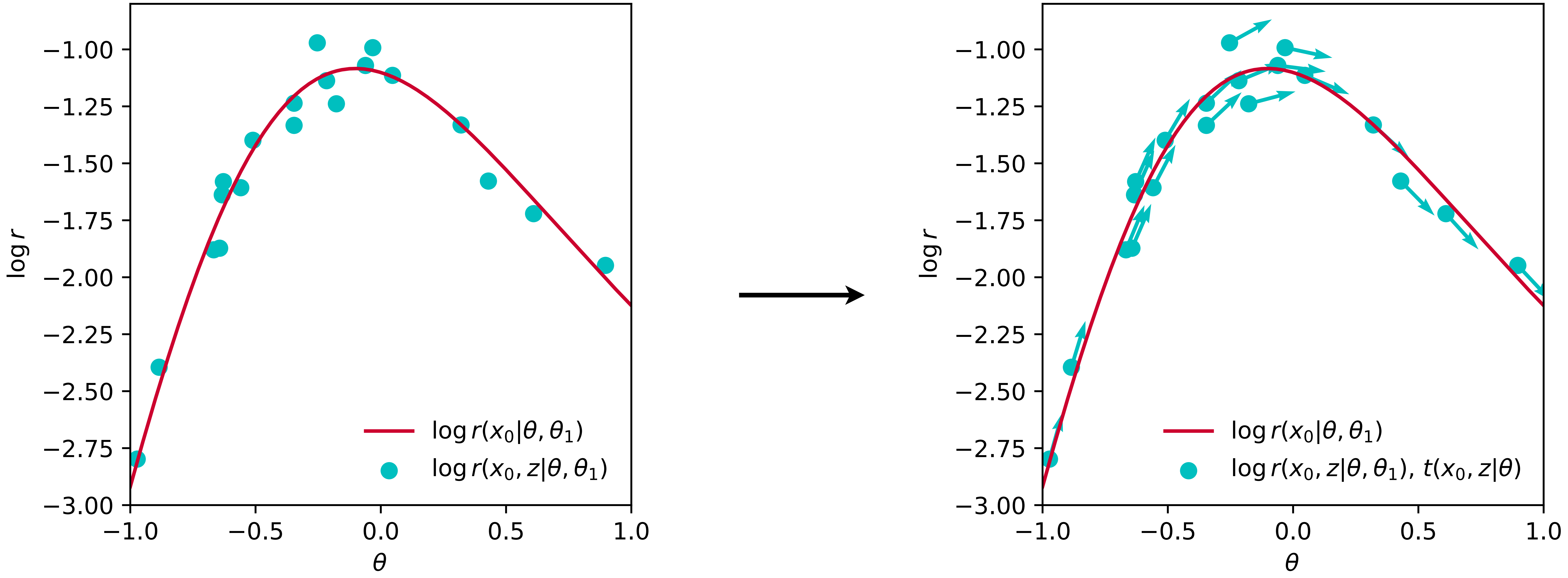

- In our case, the relevant quantity is the **score** $t(x|\theta_0) \equiv \nabla_\theta \log p(x|\theta)\Big|_{\theta_0}$.
    - The score itself is intractable. But…

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

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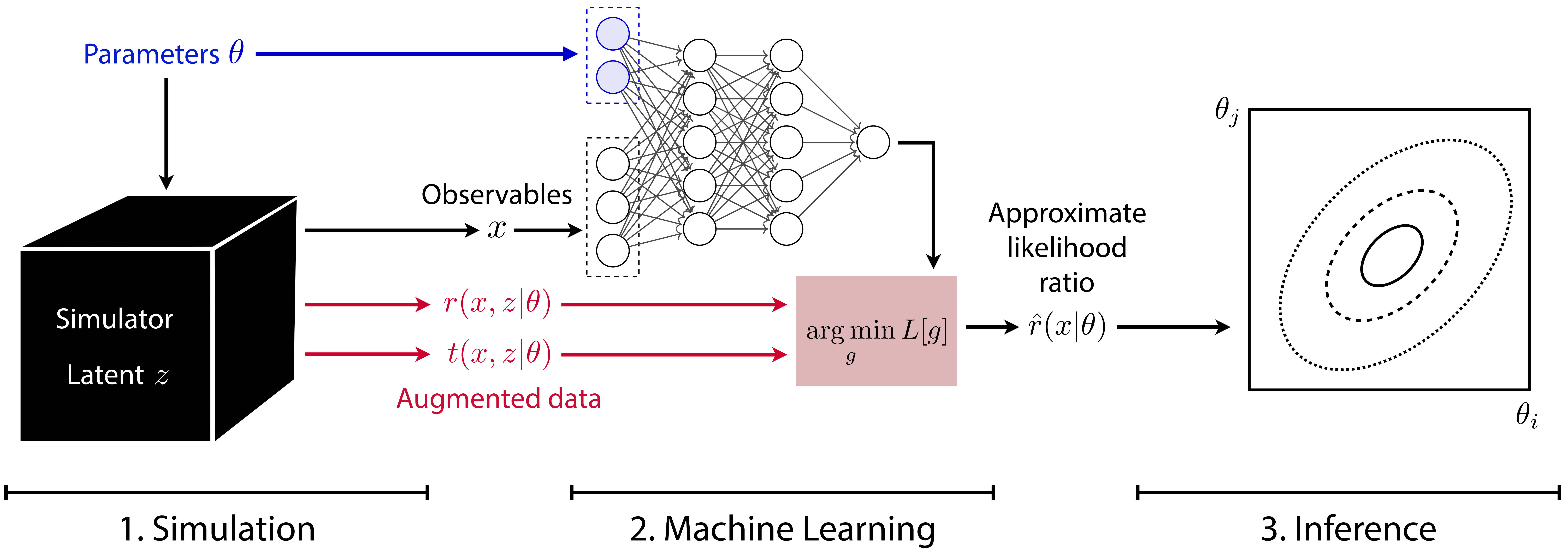
$$L_t[\hat{t}(x|\theta_0)] = \int \mathrm{d}x \int \mathrm{d}z \;\; p(x, z|\theta_0) \; \left[\left(\hat{t}(x|\theta_0) - t(x, z|\theta_0)\right)^2\right].$$

One can show it is minimized by

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

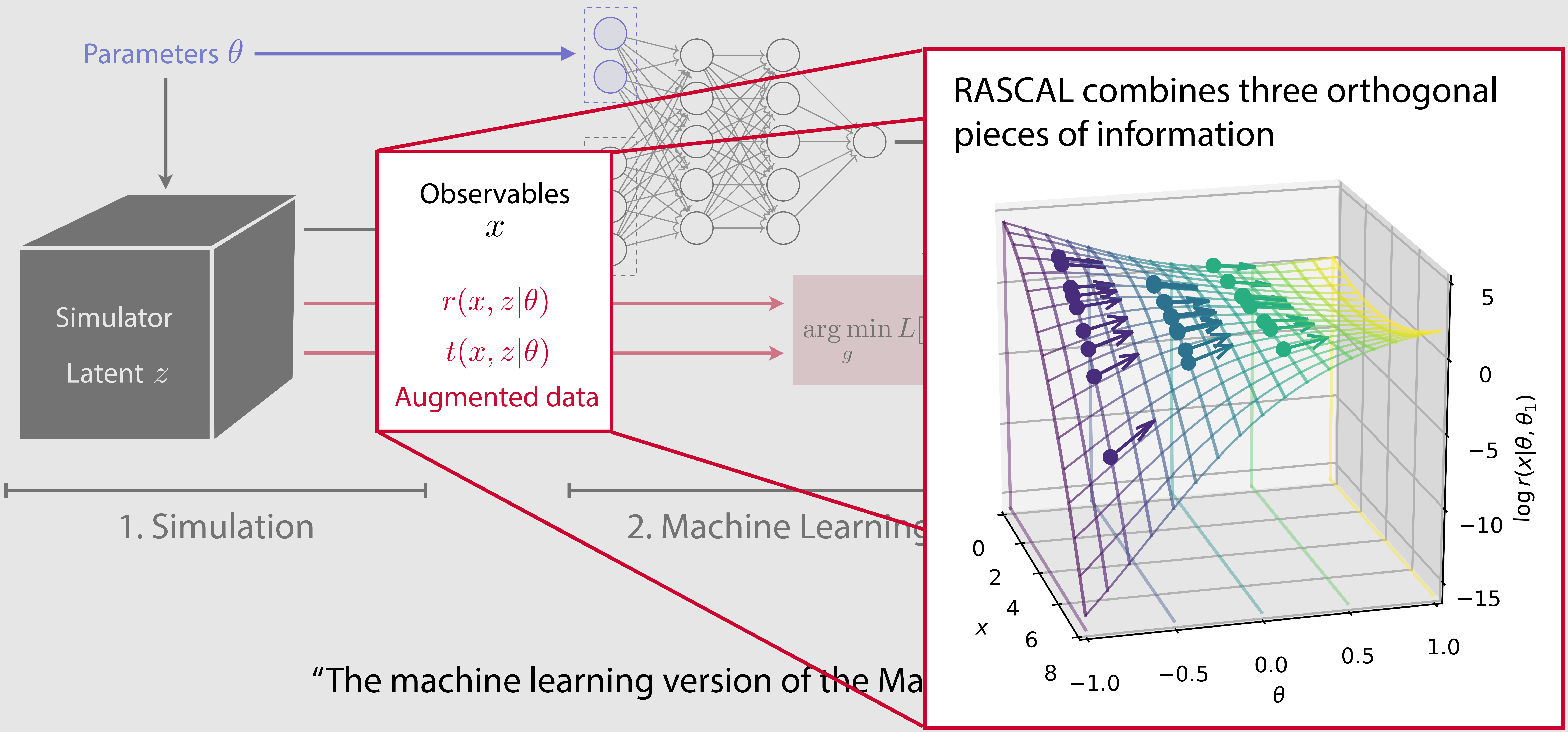
Again, we implement this minimization through machine learning.

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



"The machine learning version of the Matrix Element Method"

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



"The machine learning version of the Ma

Learning optimal observables

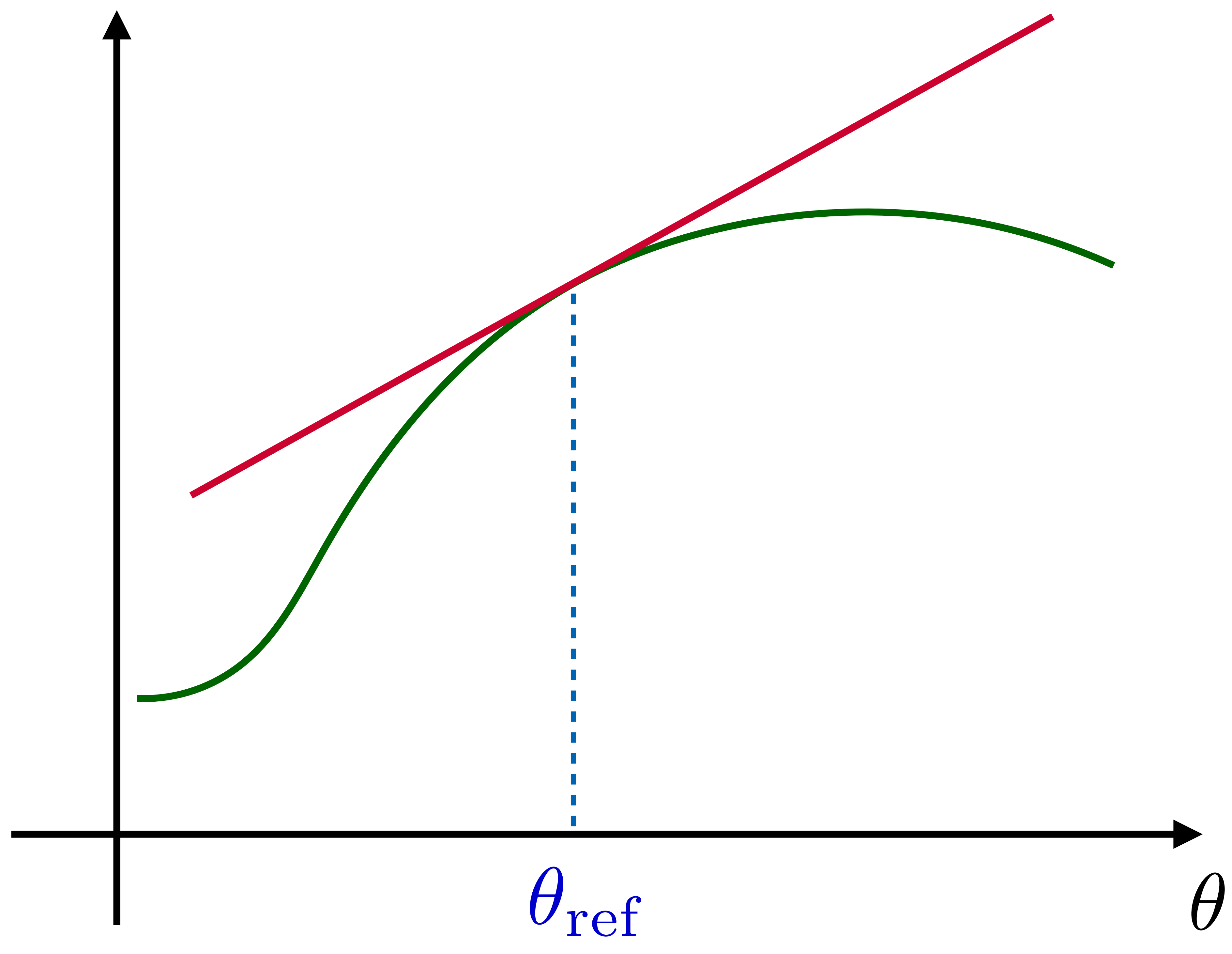
[JB, K. Cranmer, G. Louppe, J. Pavez 1805.00013, 1805.00020, 1805.12244]

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}:

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



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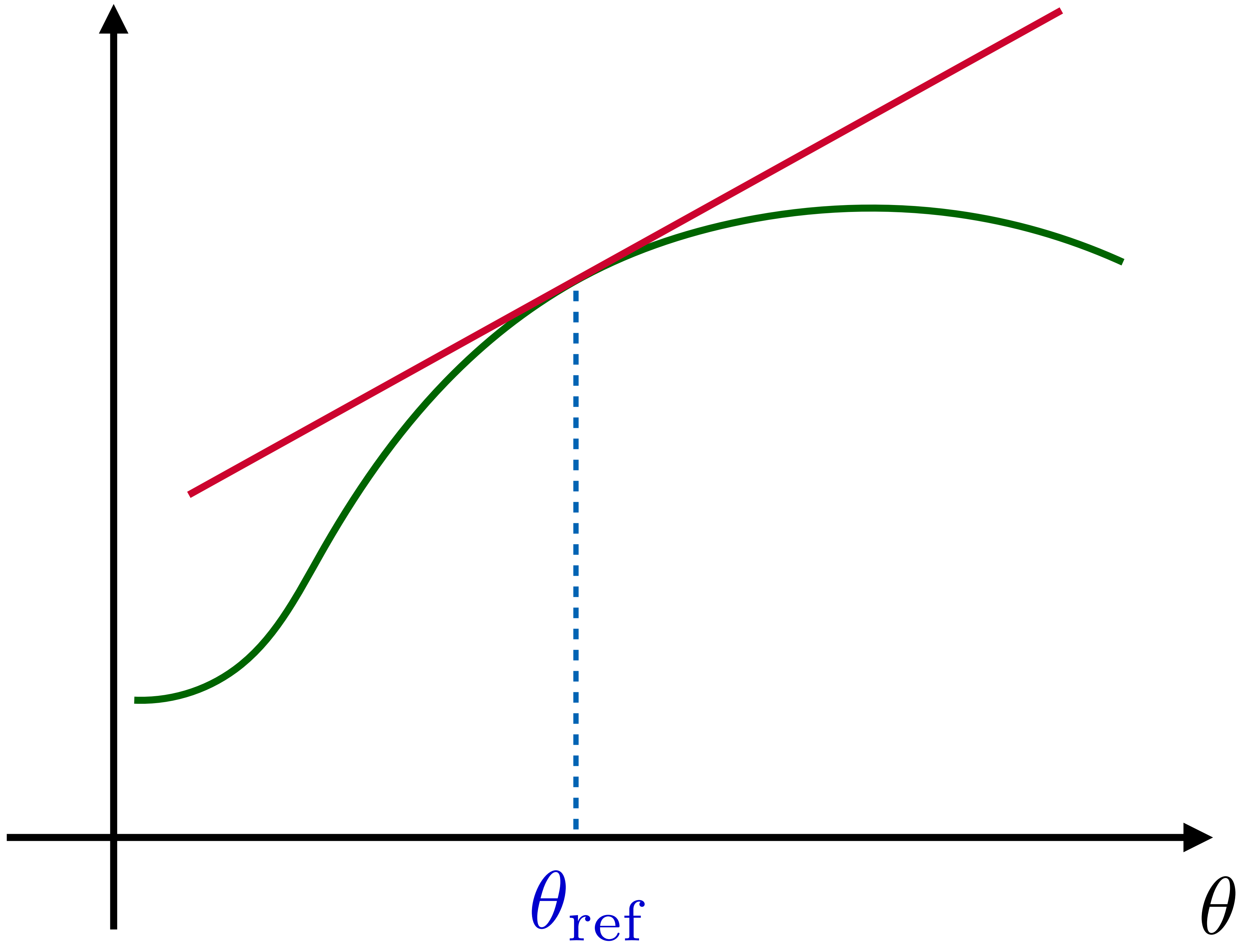
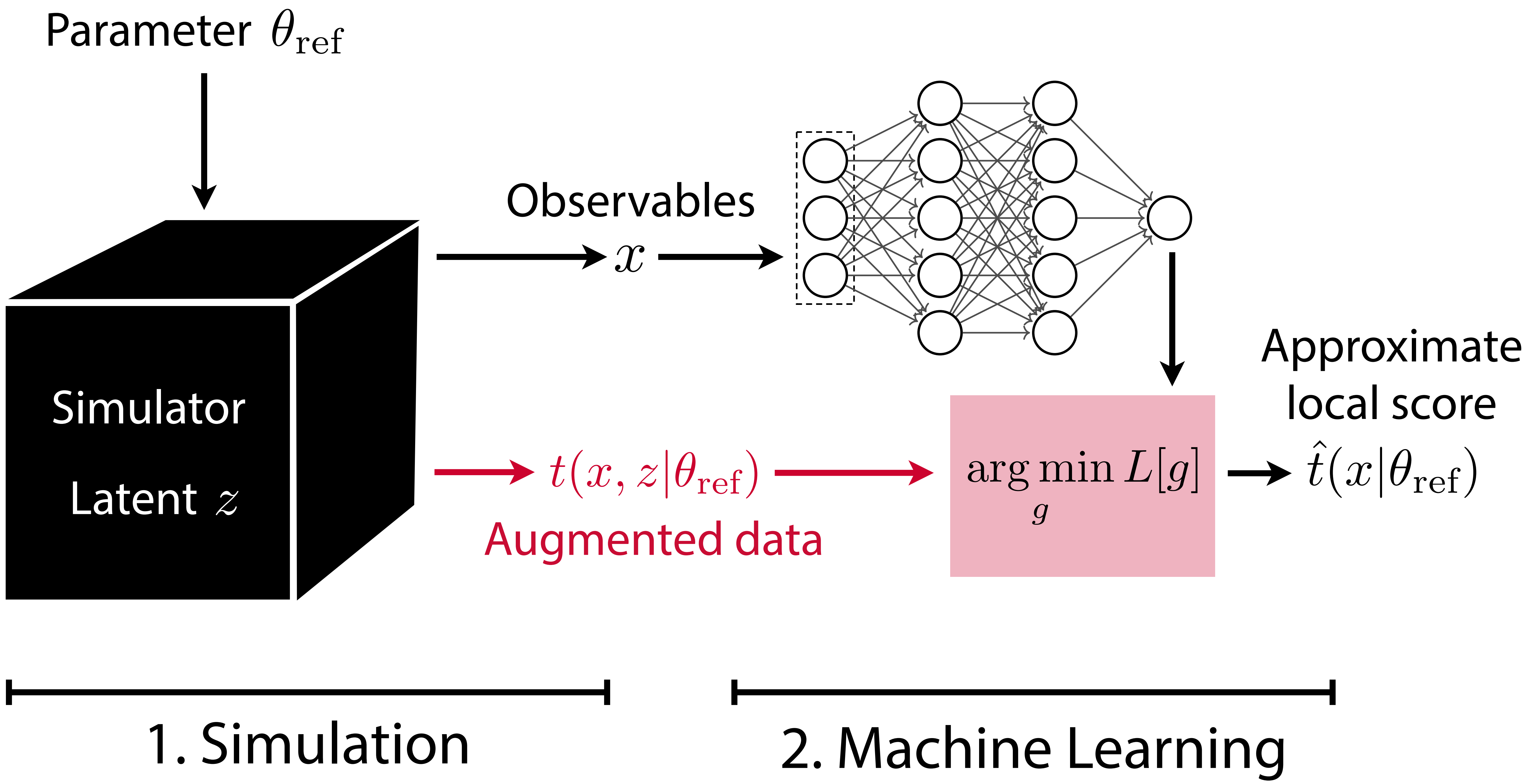


In the neighborhood of θ_{ref} (e.g. close to the SM):

- 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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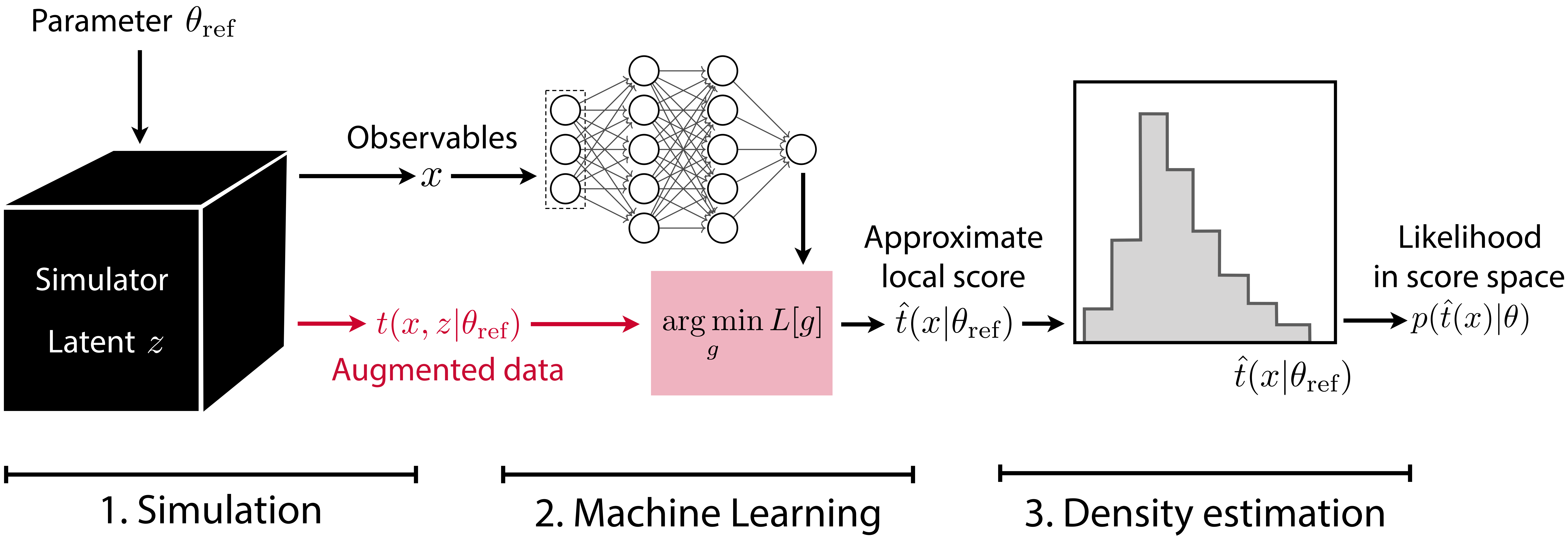

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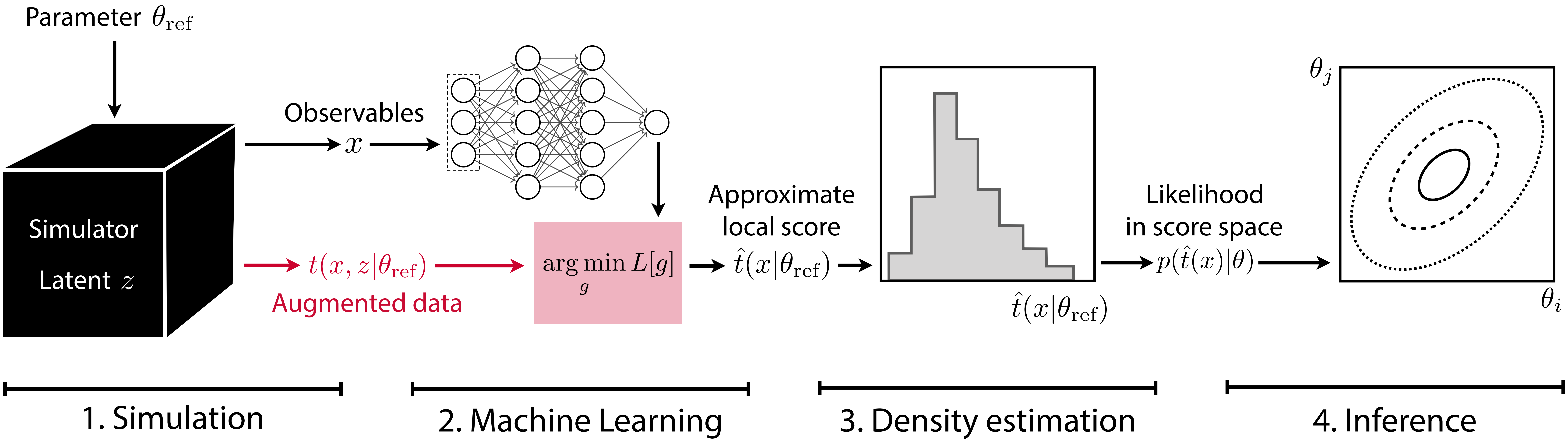

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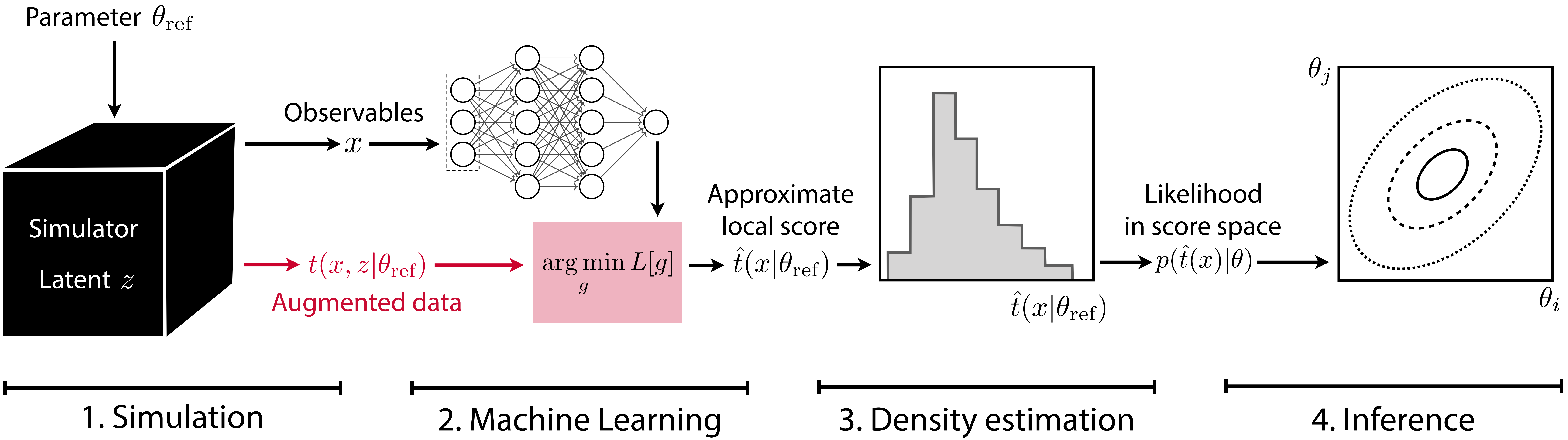

"The machine learning version of Optimal Observables":

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

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.	

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Performance gains with cross-entropy-based loss

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

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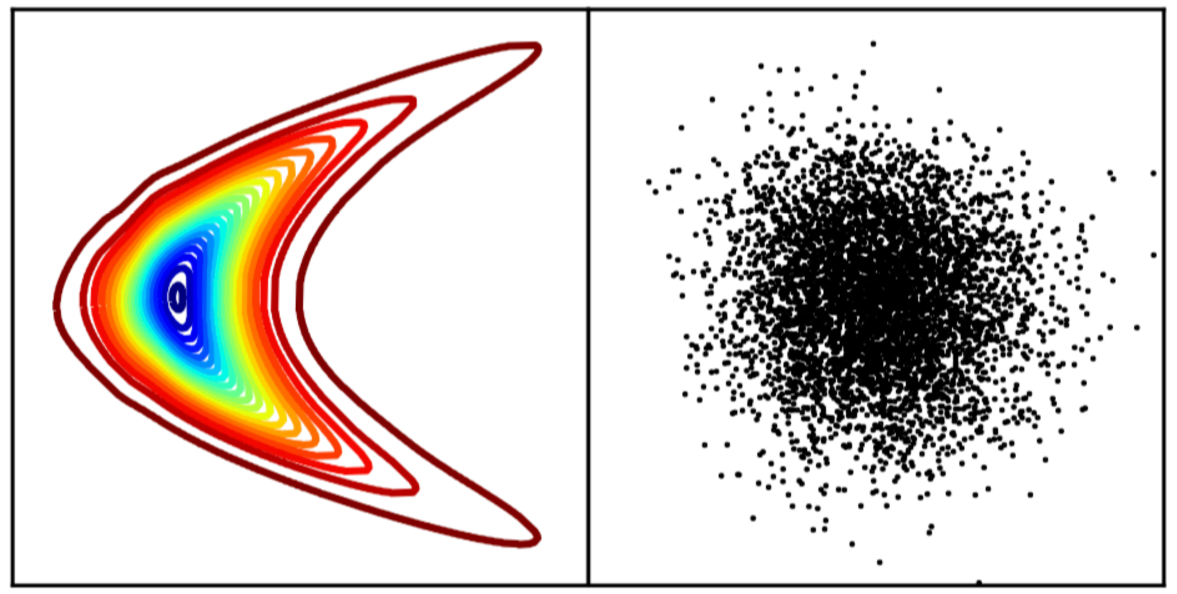
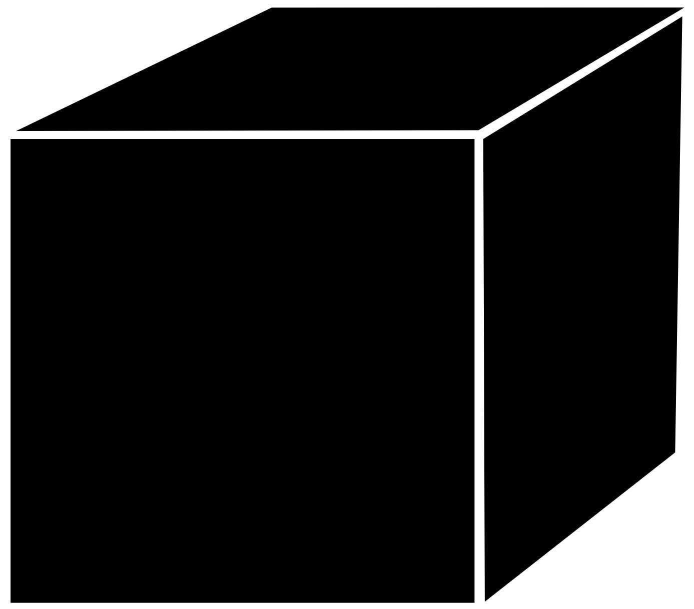


Combination with state-of-the-art conditional neural density estimators, e.g. normalizing flows

[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
  [J. Alsing, B. Wandelt 1903.01473;
  see also P. de Castro, T. Dorigo 1806.04743]
- Alternatively: Robustness to nuisance with adversarial training
  [G. Louppe, M. Kagan, K. Cranmer 1611.01046]

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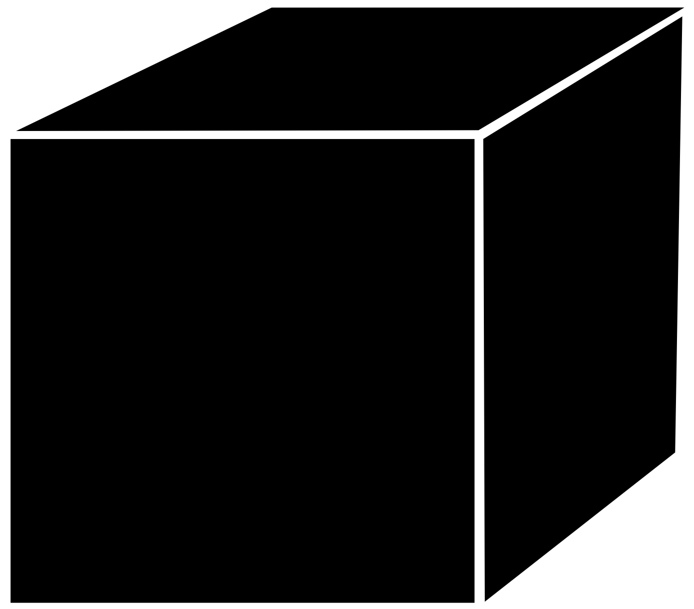

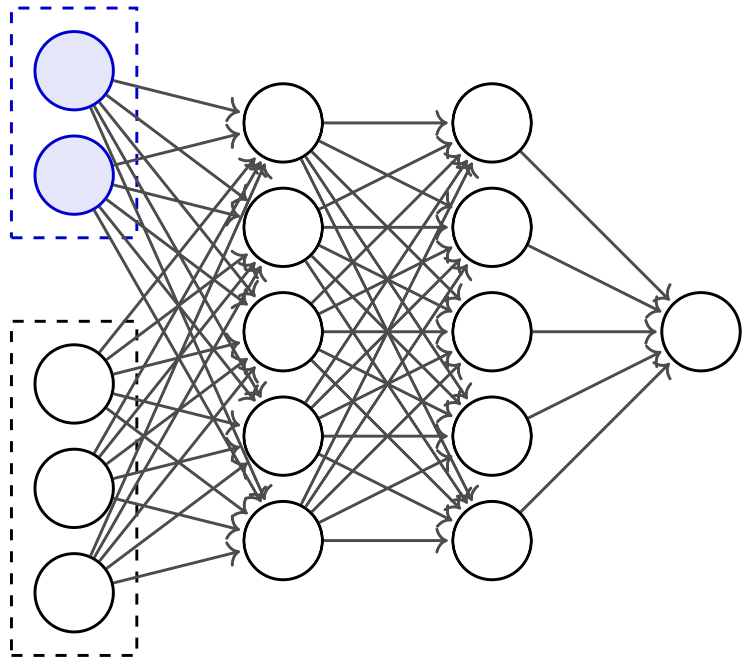

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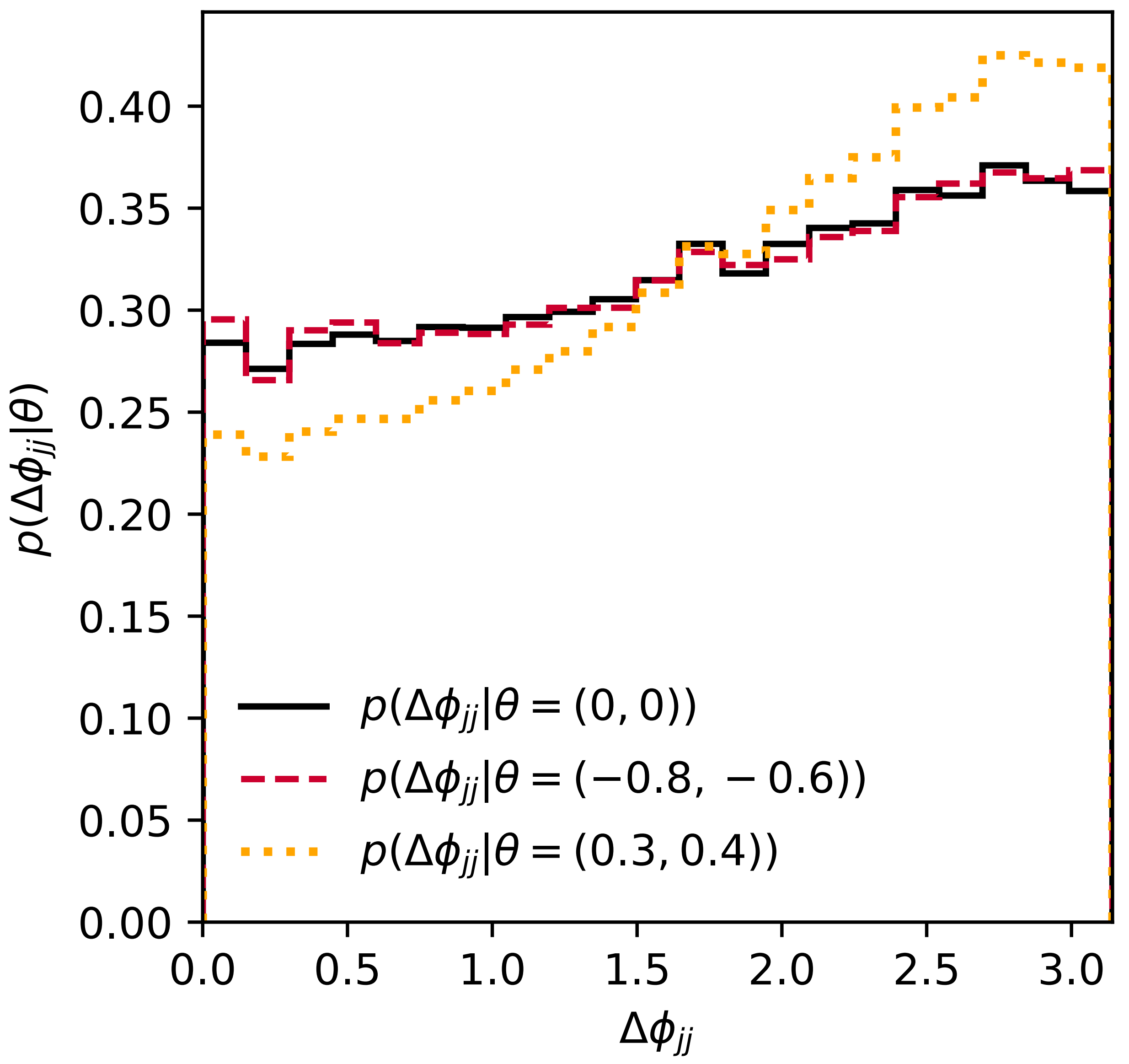
Don't blindly trust the neural network?

- 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

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)

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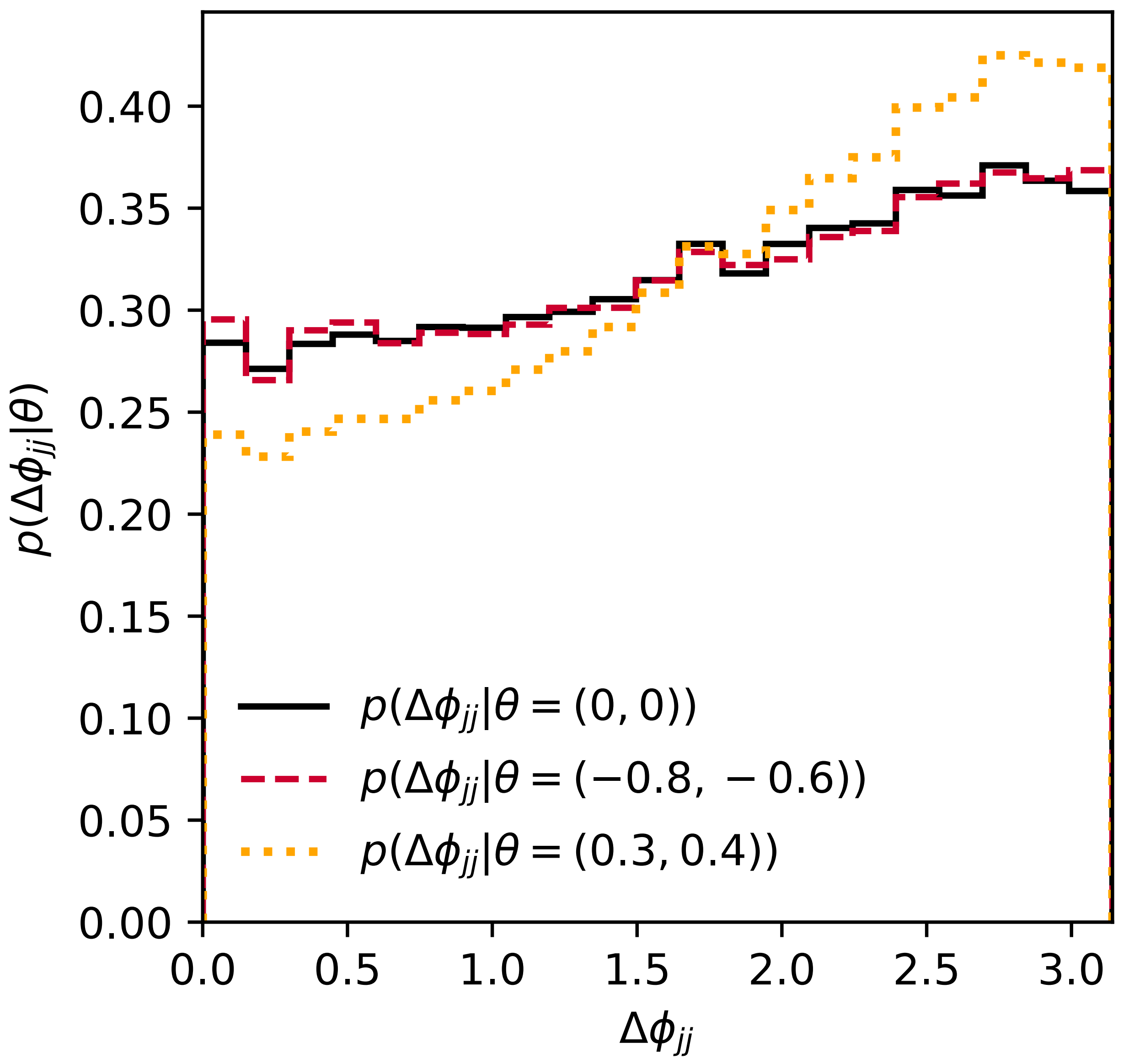

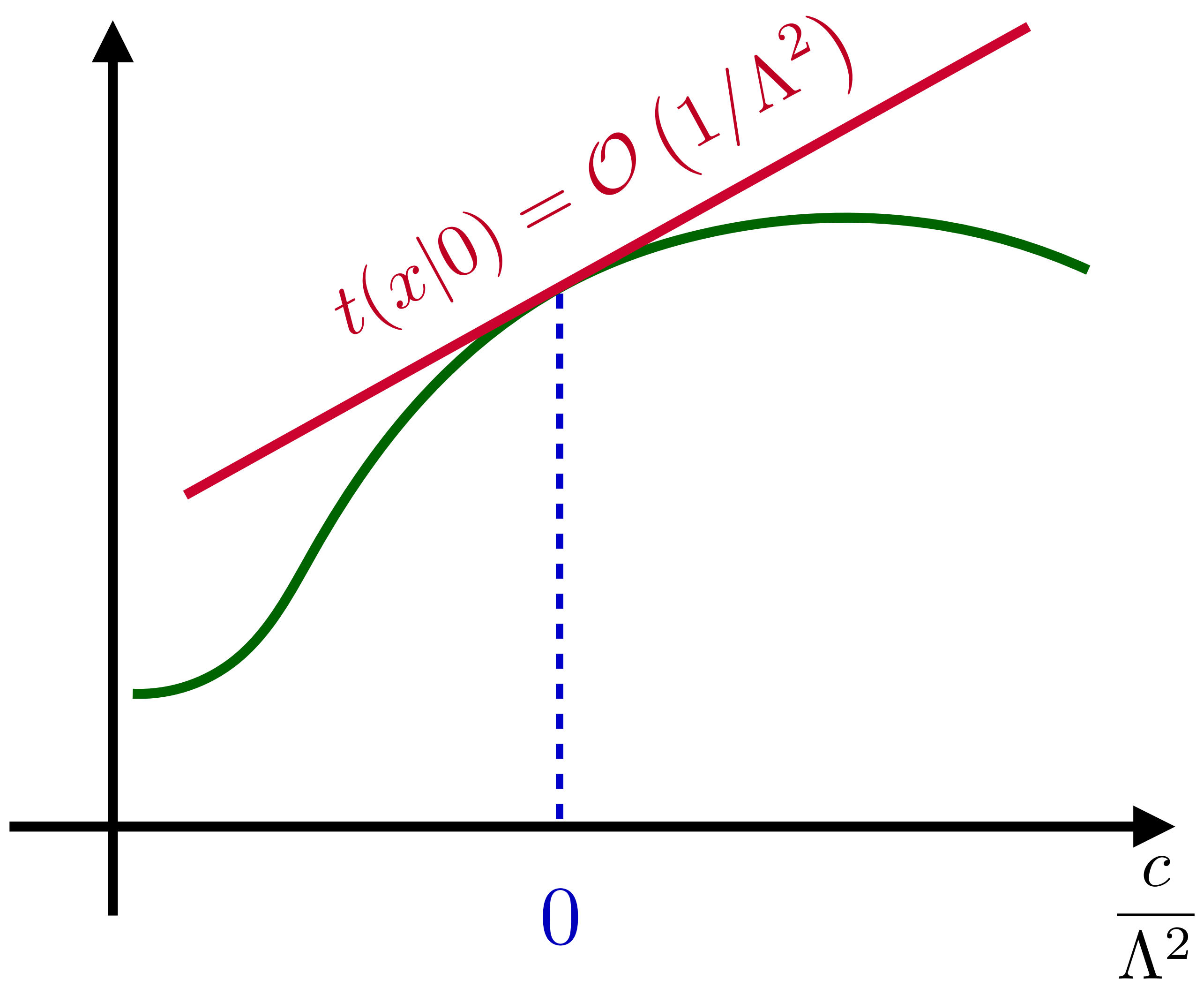

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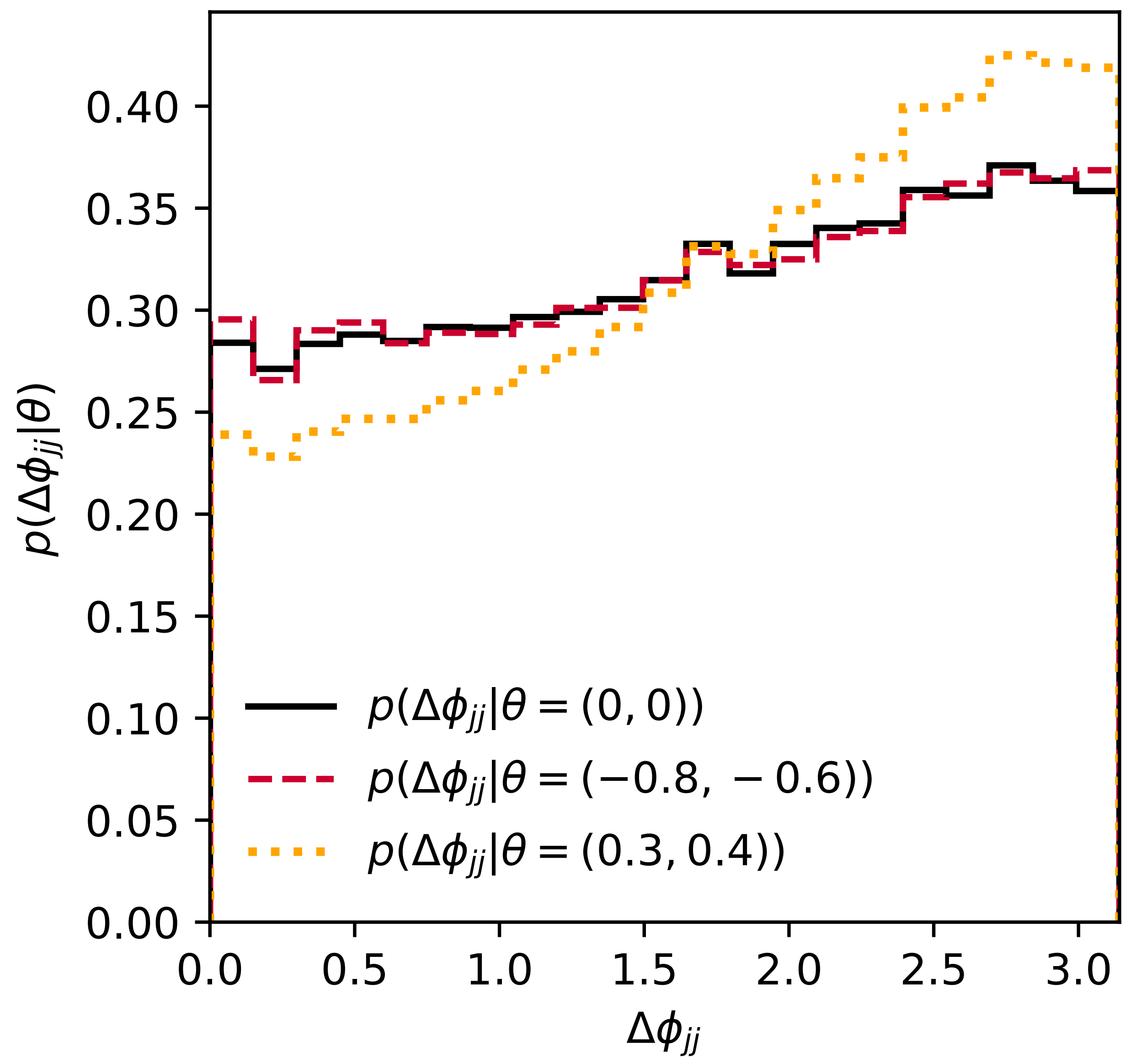

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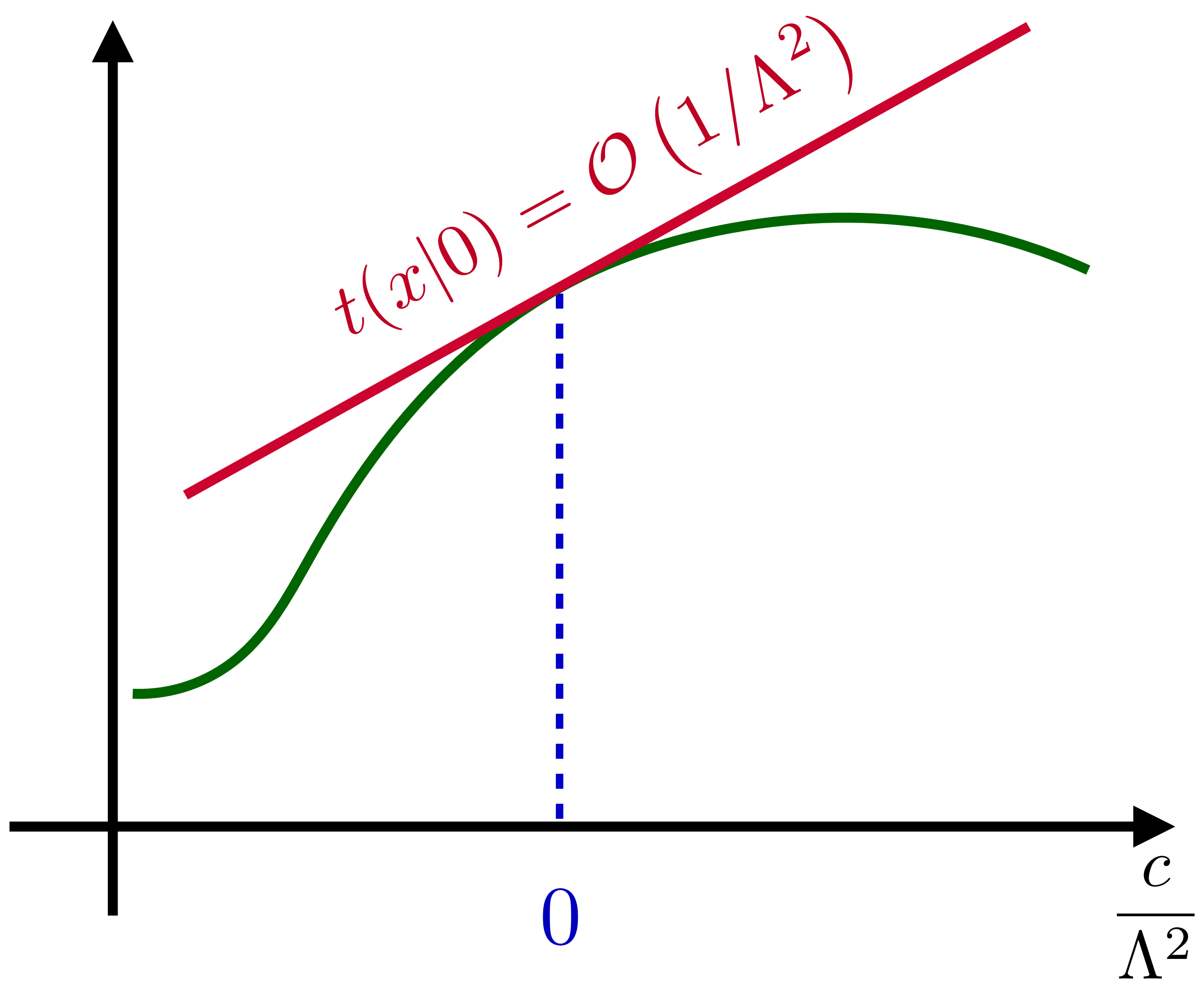
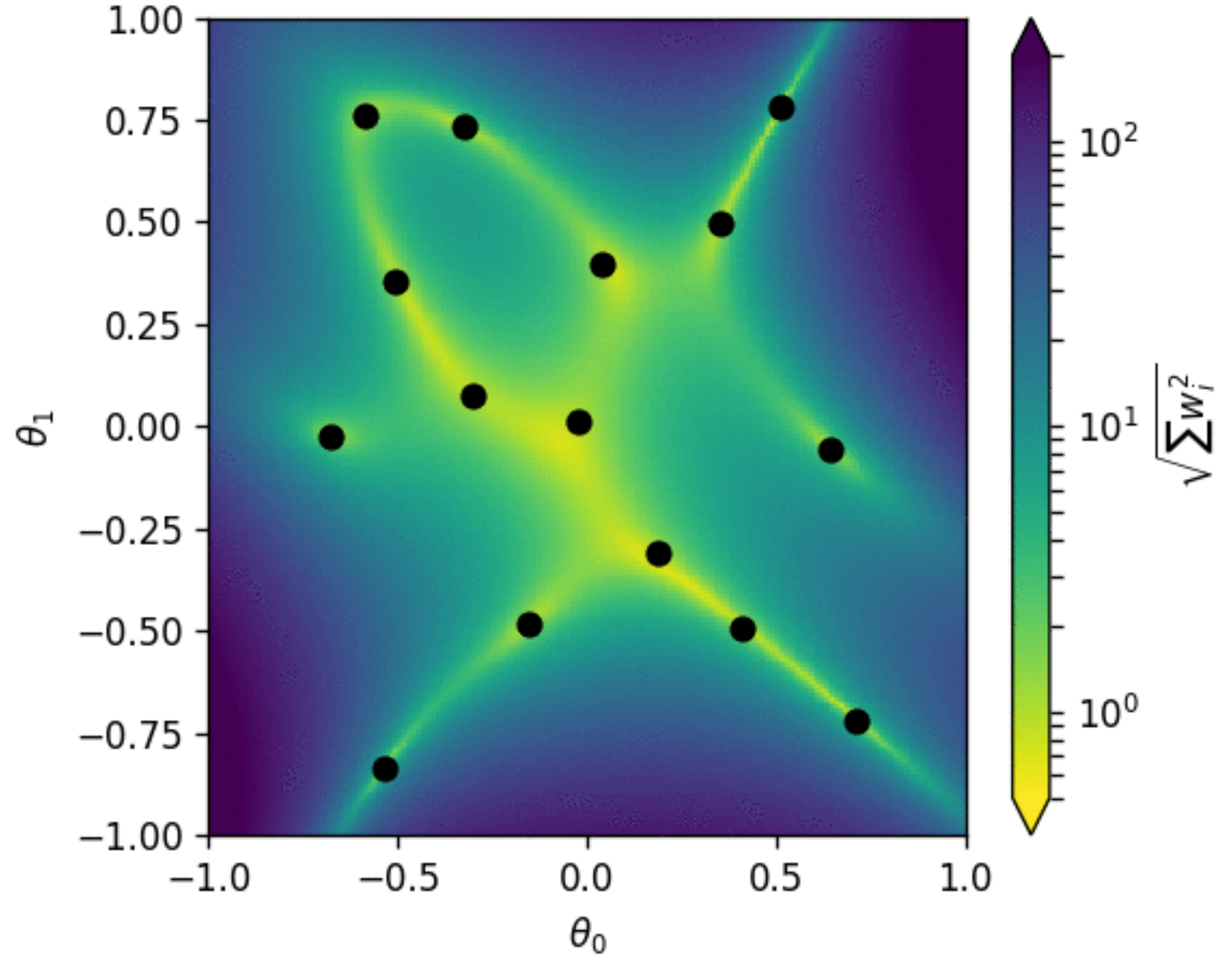


- Interference effects can be isolated using SALLY at the SM
  (SMALLY?)



- Morphing techniques allow fast reweighting to any parameter points
  [e.g. ATL-PHYS-PUB-2015-047]

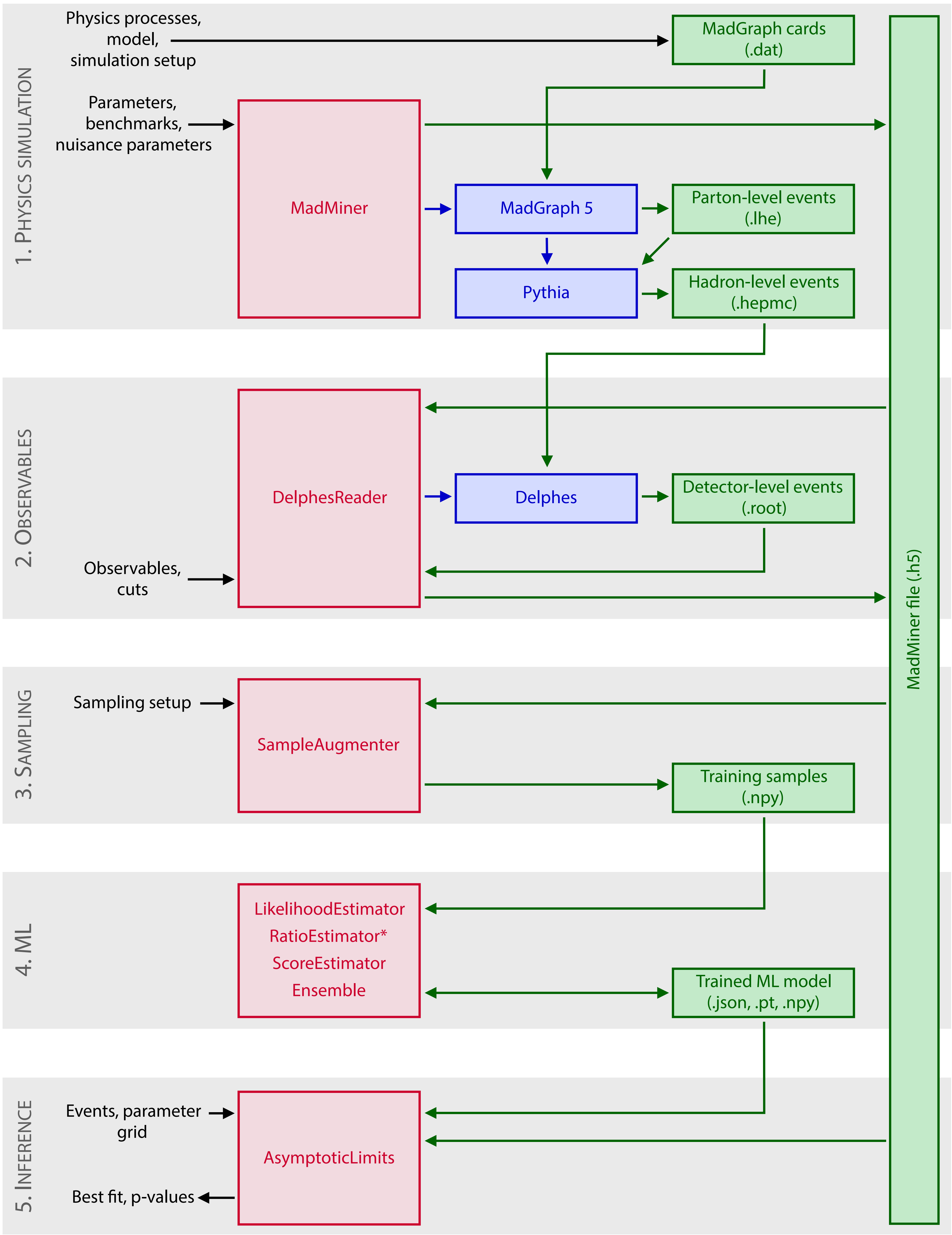
MadMiner

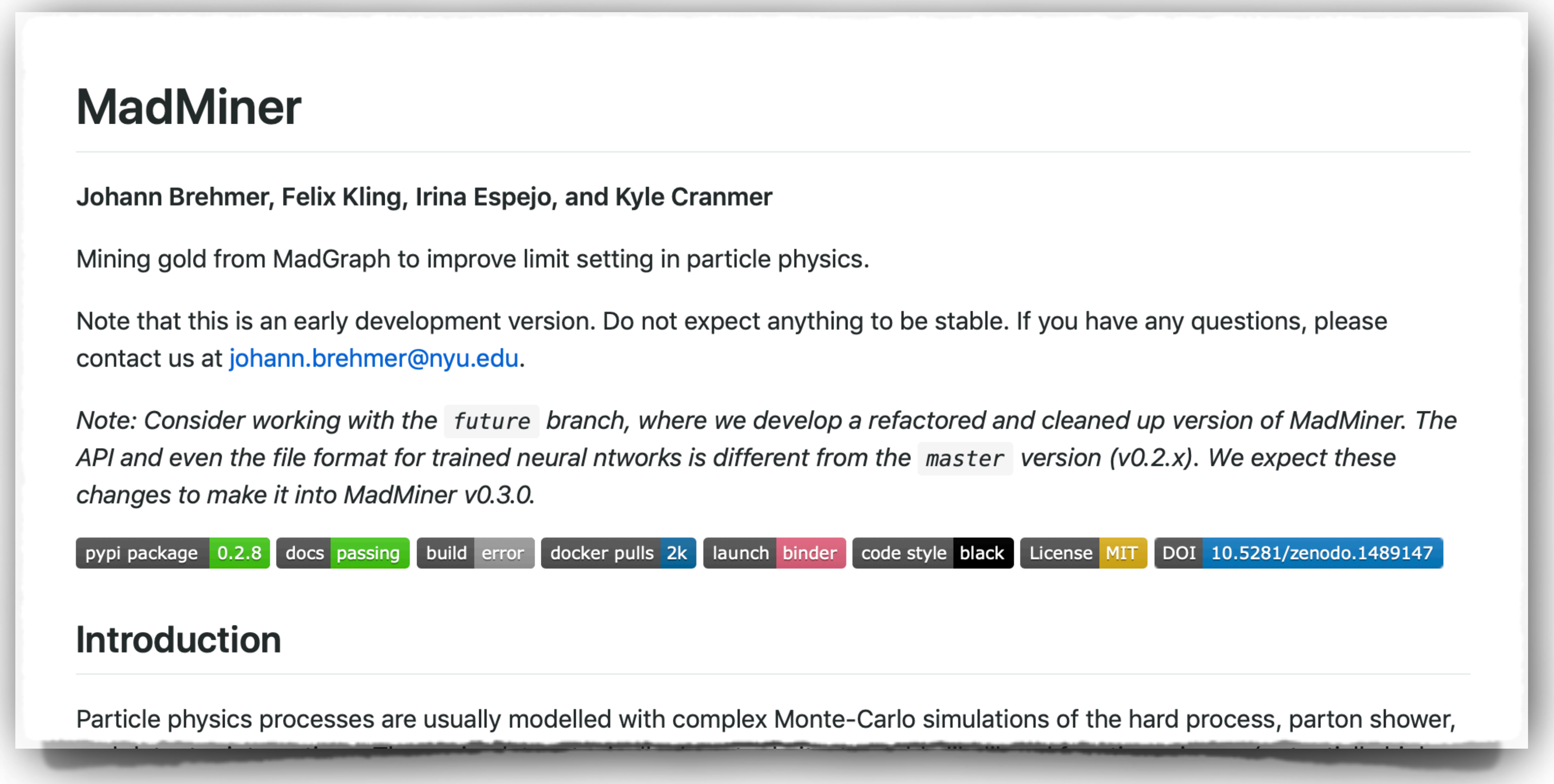
[JB, F. Kling, I. Espejo, K. Cranmer doi: 10.5281/zenodo.1489147]

Automization

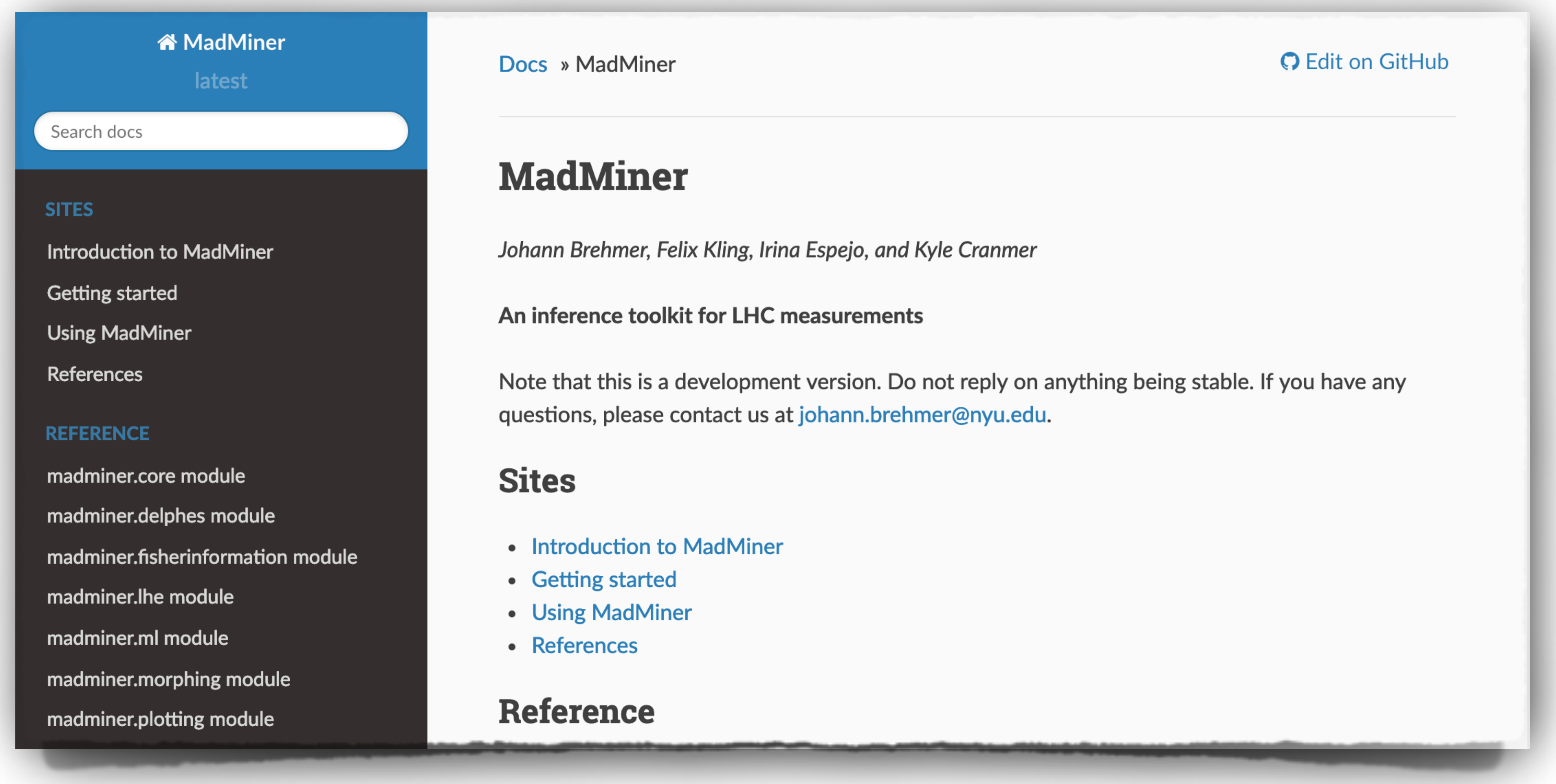
We are developing MadMiner, which makes it straightforward to apply the new techniques to LHC problems

- 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

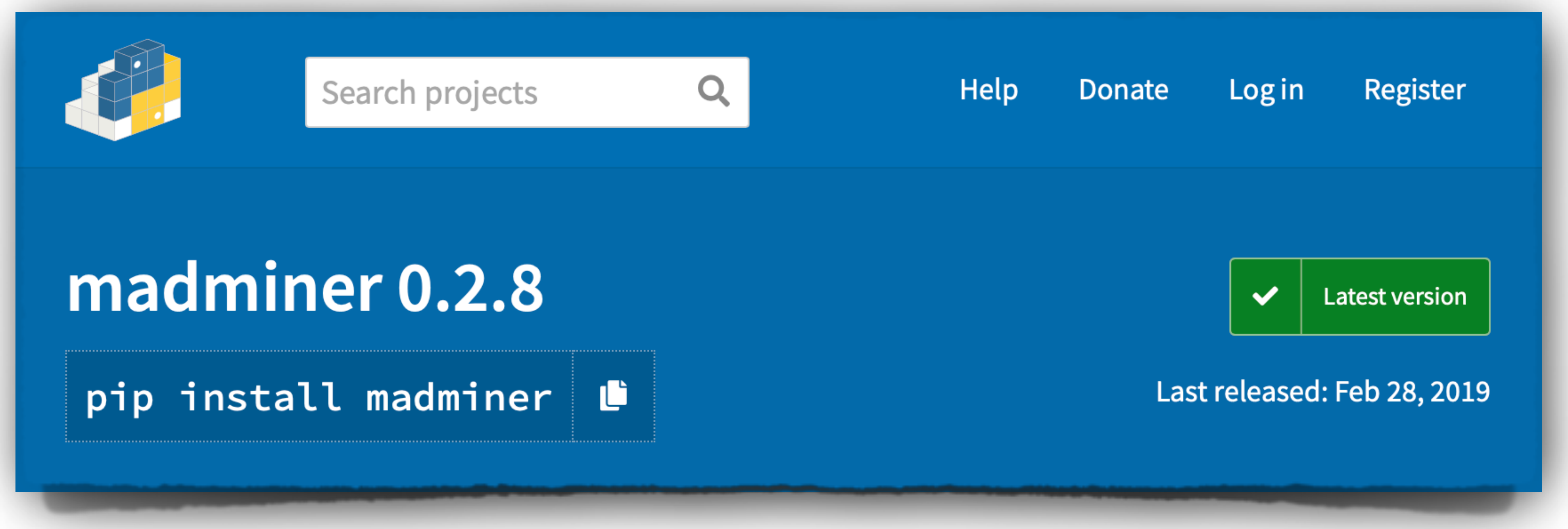




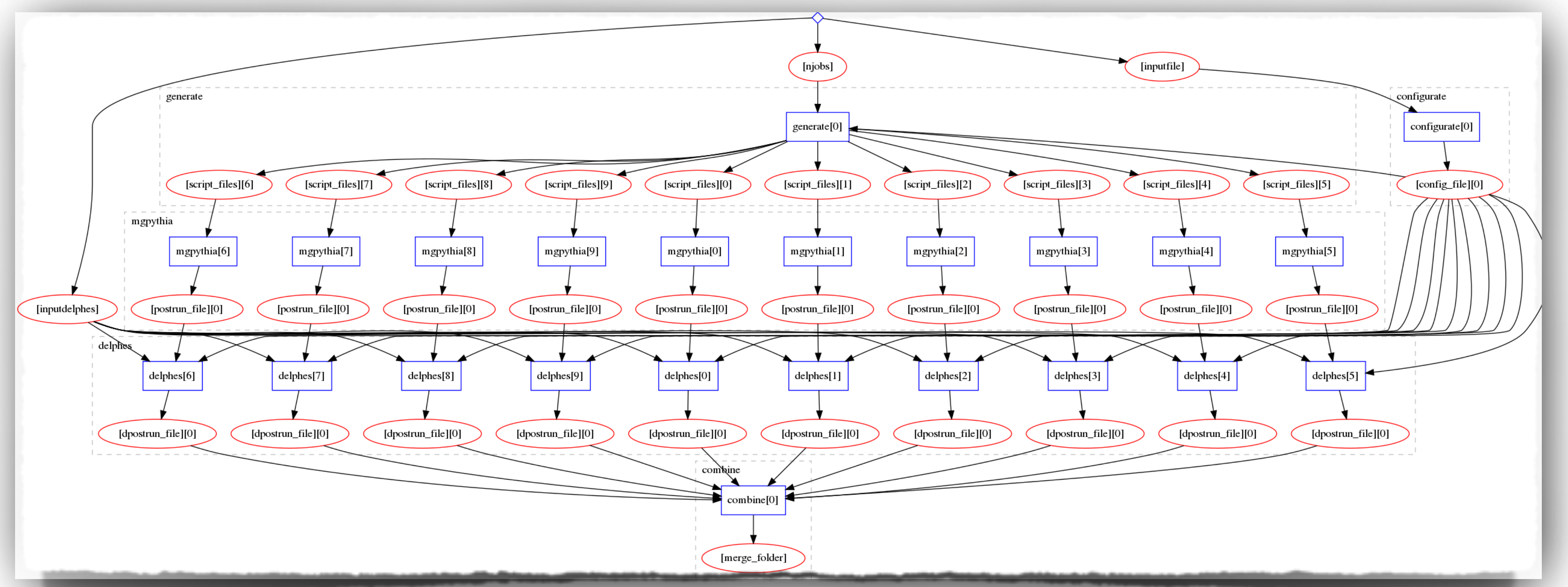
Repository and tutorials:
github.com/johannbrehmer/madminer



Documentation:
madminer.readthedocs.io



Installation:
`pip install madminer`



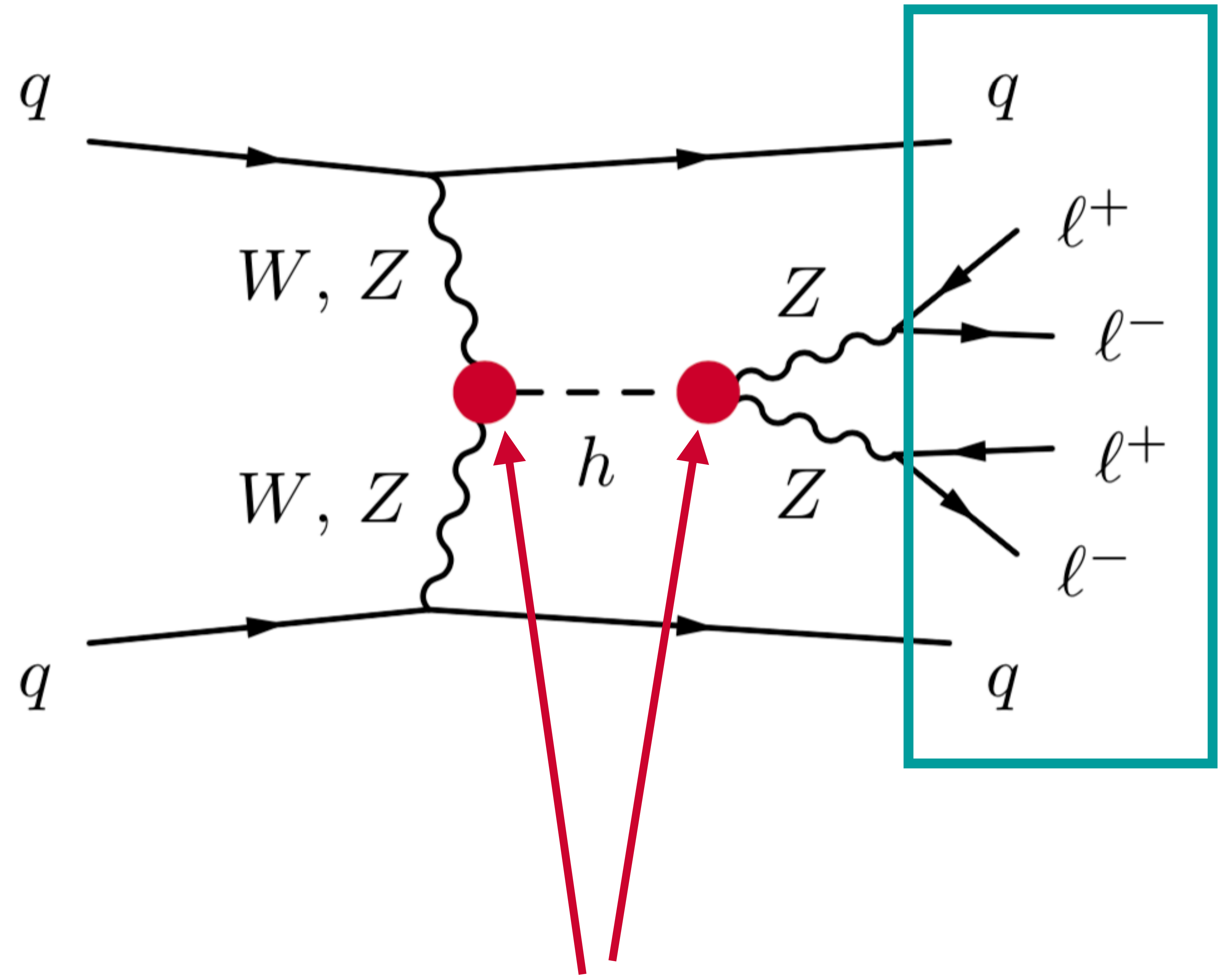
Deployment with Docker, yadage, REANA:
github.com/irinaespejo/workflow-madminer

In the wild

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:

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

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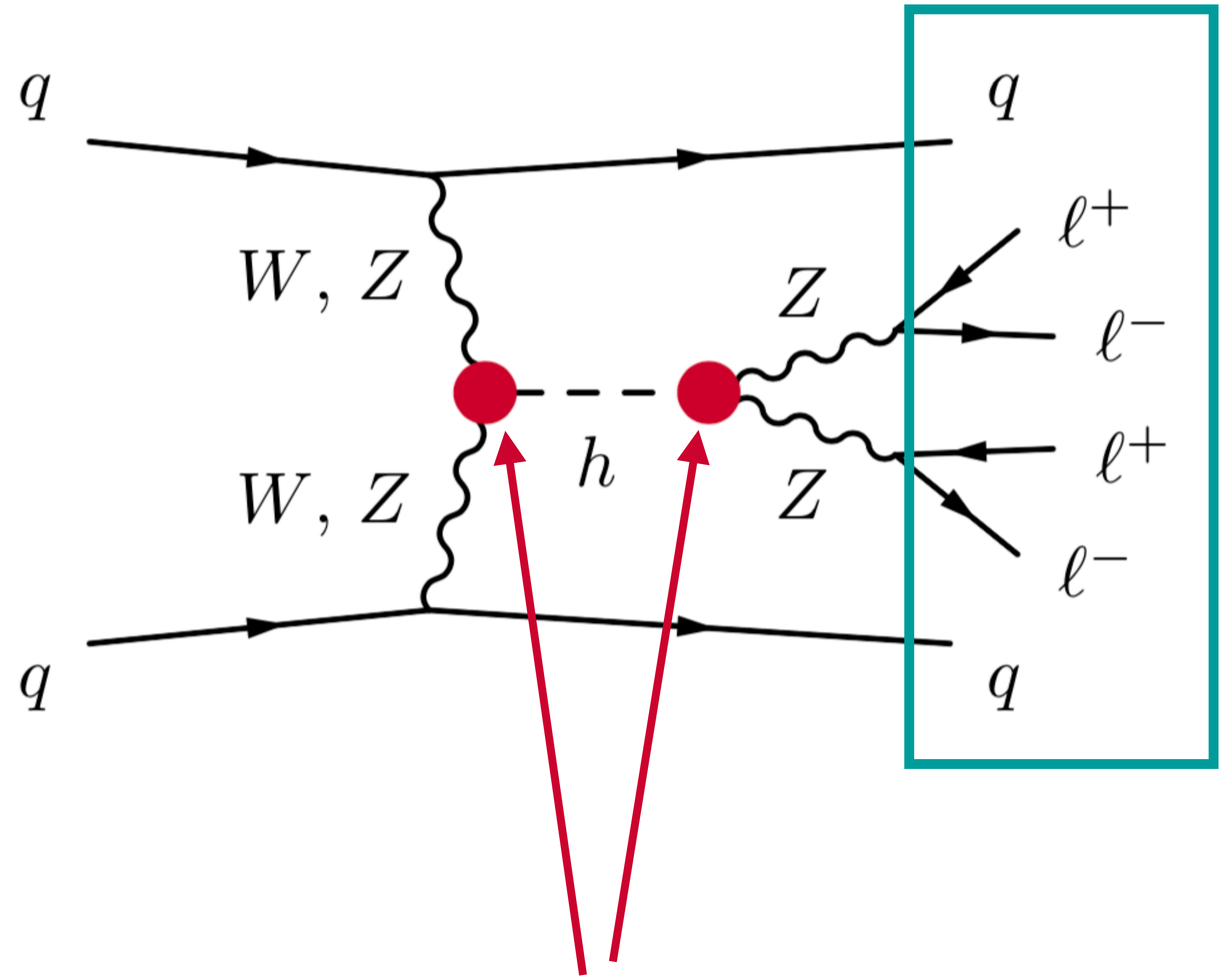

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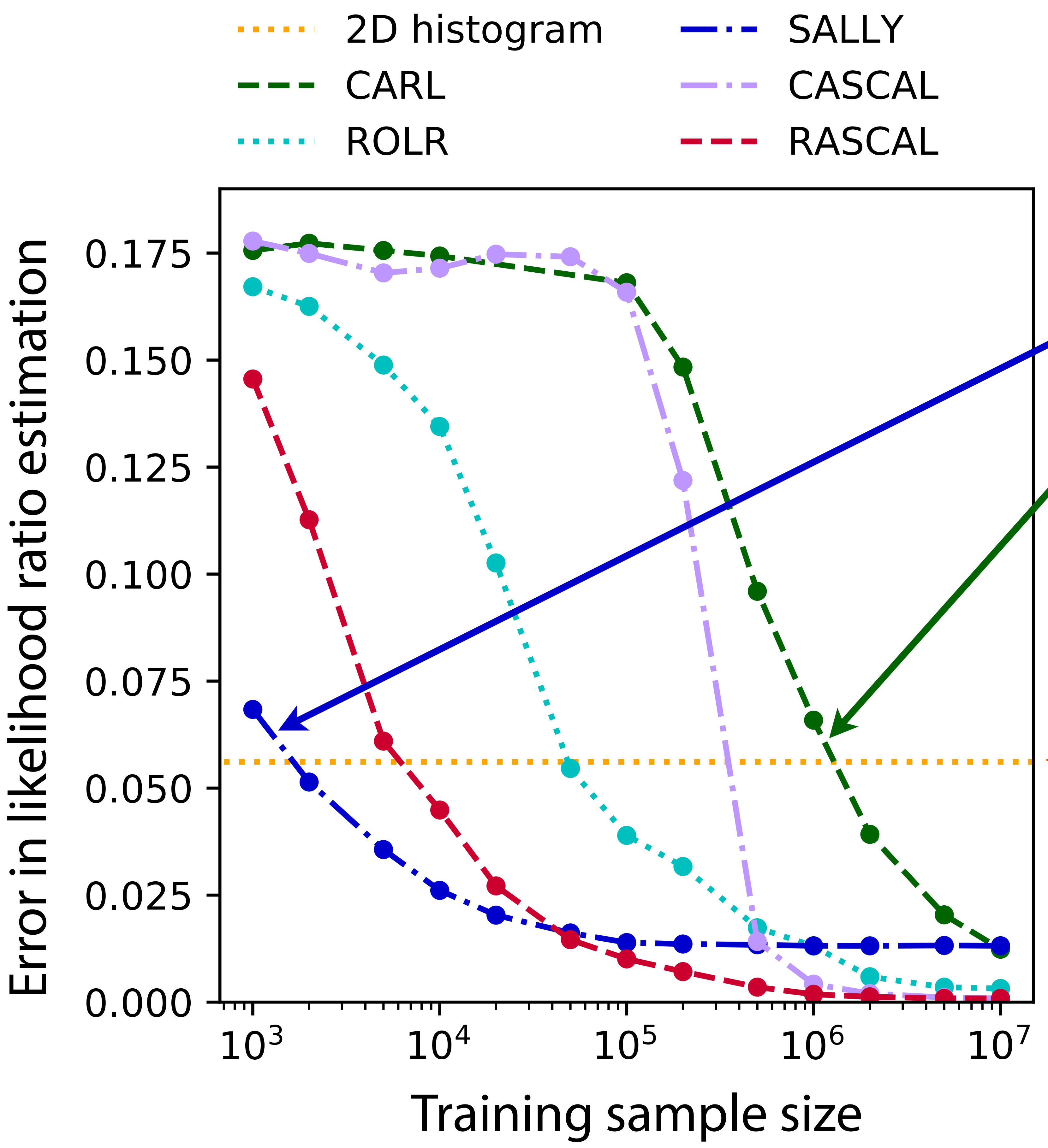
Goal: constrain the two EFT parameters

- 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

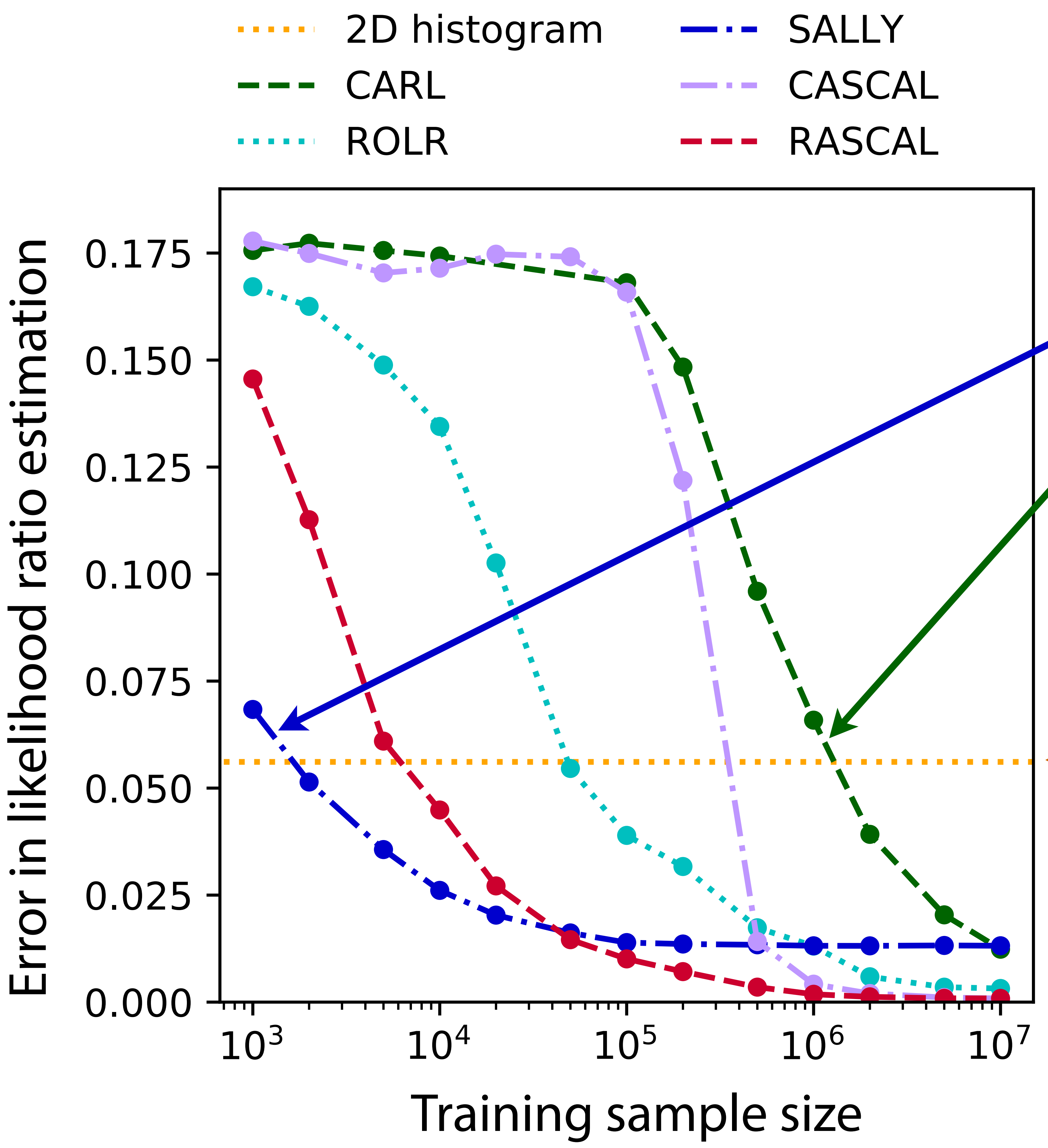
Proof of concept: Stronger constraints with less training data



SALLY and RASCAL require less data than existing ML method

Baseline: 2D histogram (based on large training sample)

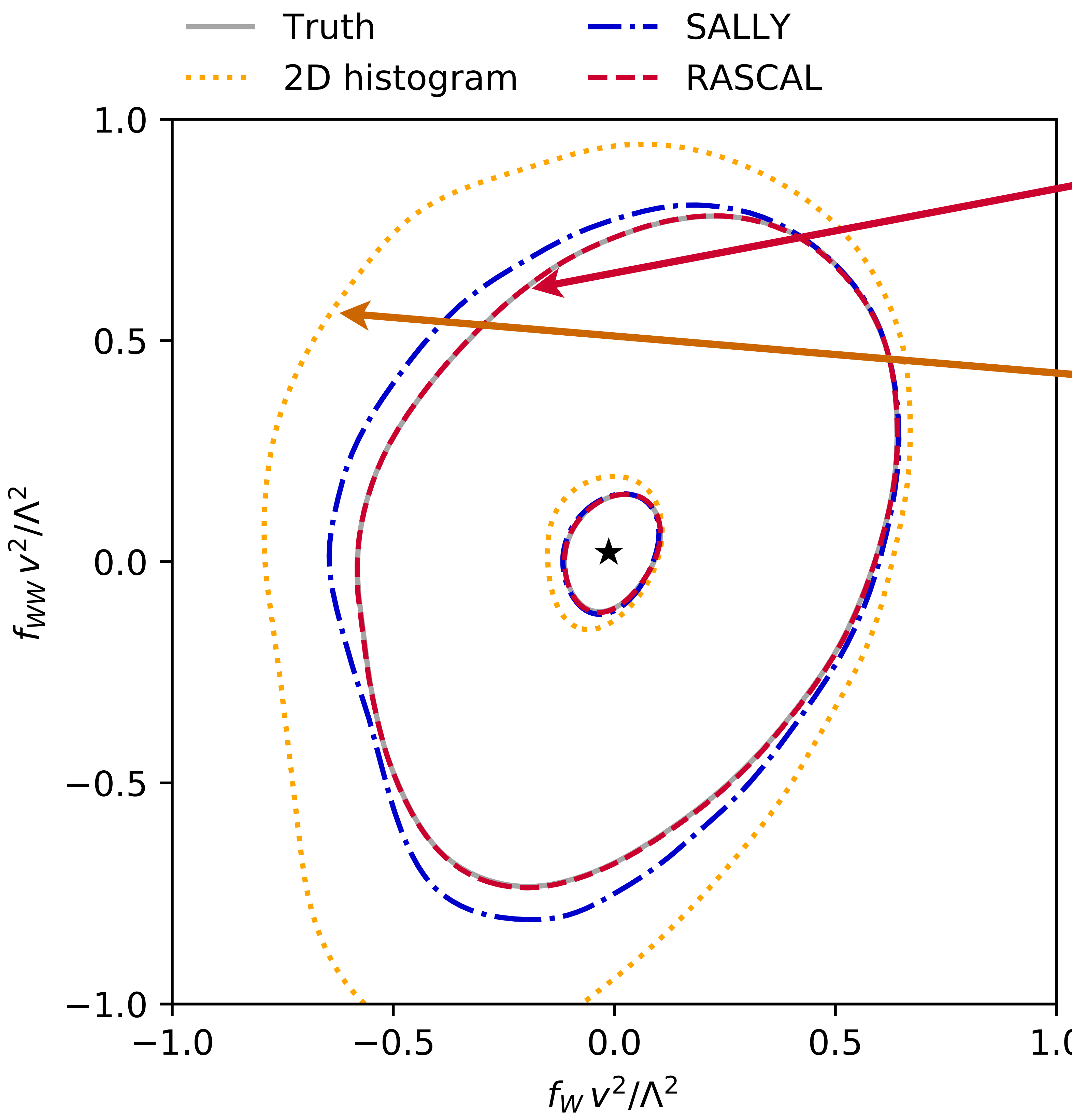
Proof of concept: Stronger constraints with less training data



SALLY and RASCAL require less data than existing ML method

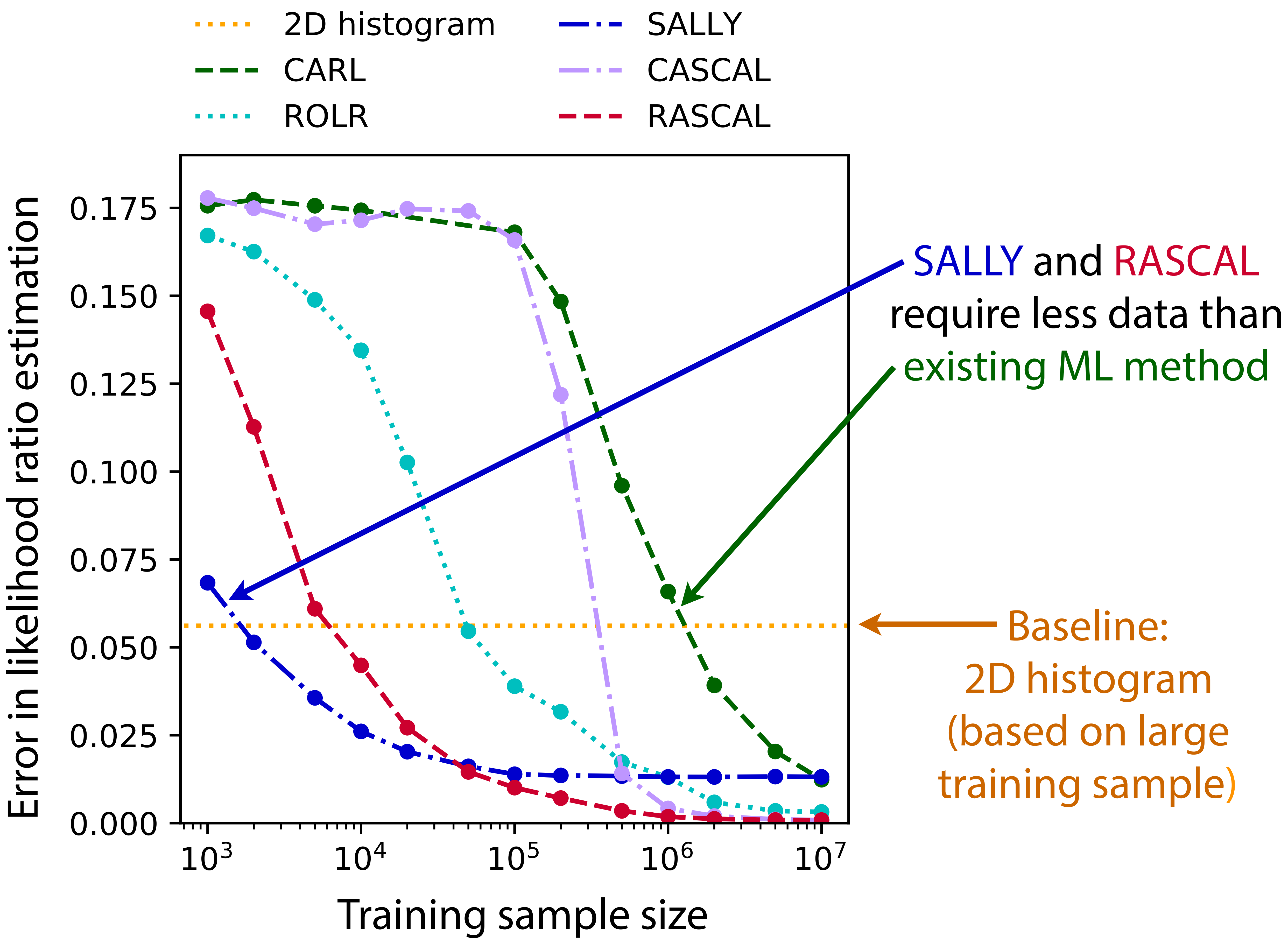
Baseline: 2D histogram (based on large training sample)

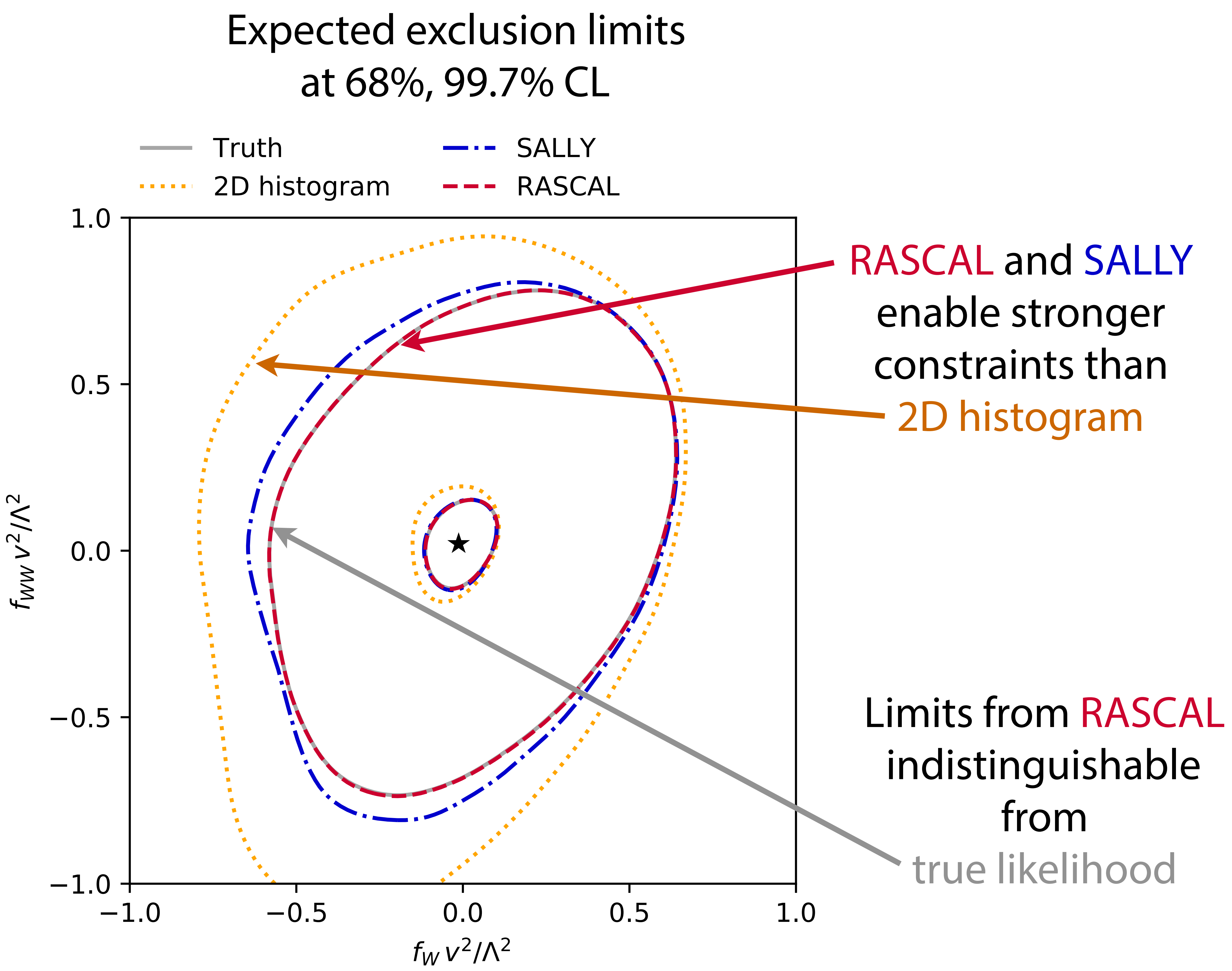
Expected exclusion limits at 68%, 99.7% CL



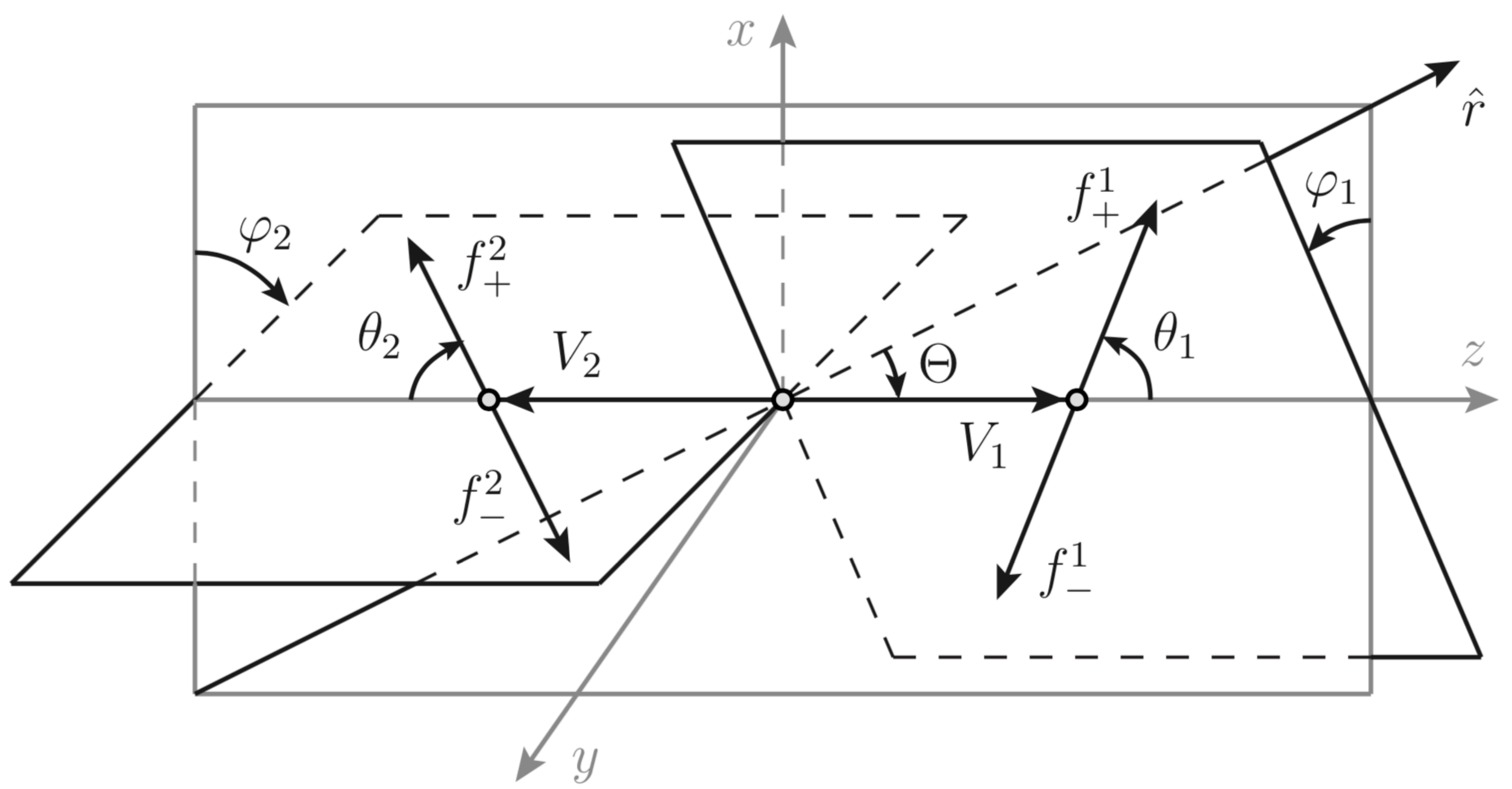
RASCAL and SALLY enable stronger constraints than 2D histogram

Proof of concept: Stronger constraints with less training data





Diboson production



- In inclusive observables, the interference between SM and new physics amplitudes vanishes

  ⇒ Reduced sensitivity to new physics

- "Diboson interference resurrection":
  an angular variable φ can be constructed to be sensitive to this interference
  [G. Panico, F. Riva, A. Wulzer 1708.07823;
  A. Azatov, D. Barducci, E. Venturini 1901.04821]

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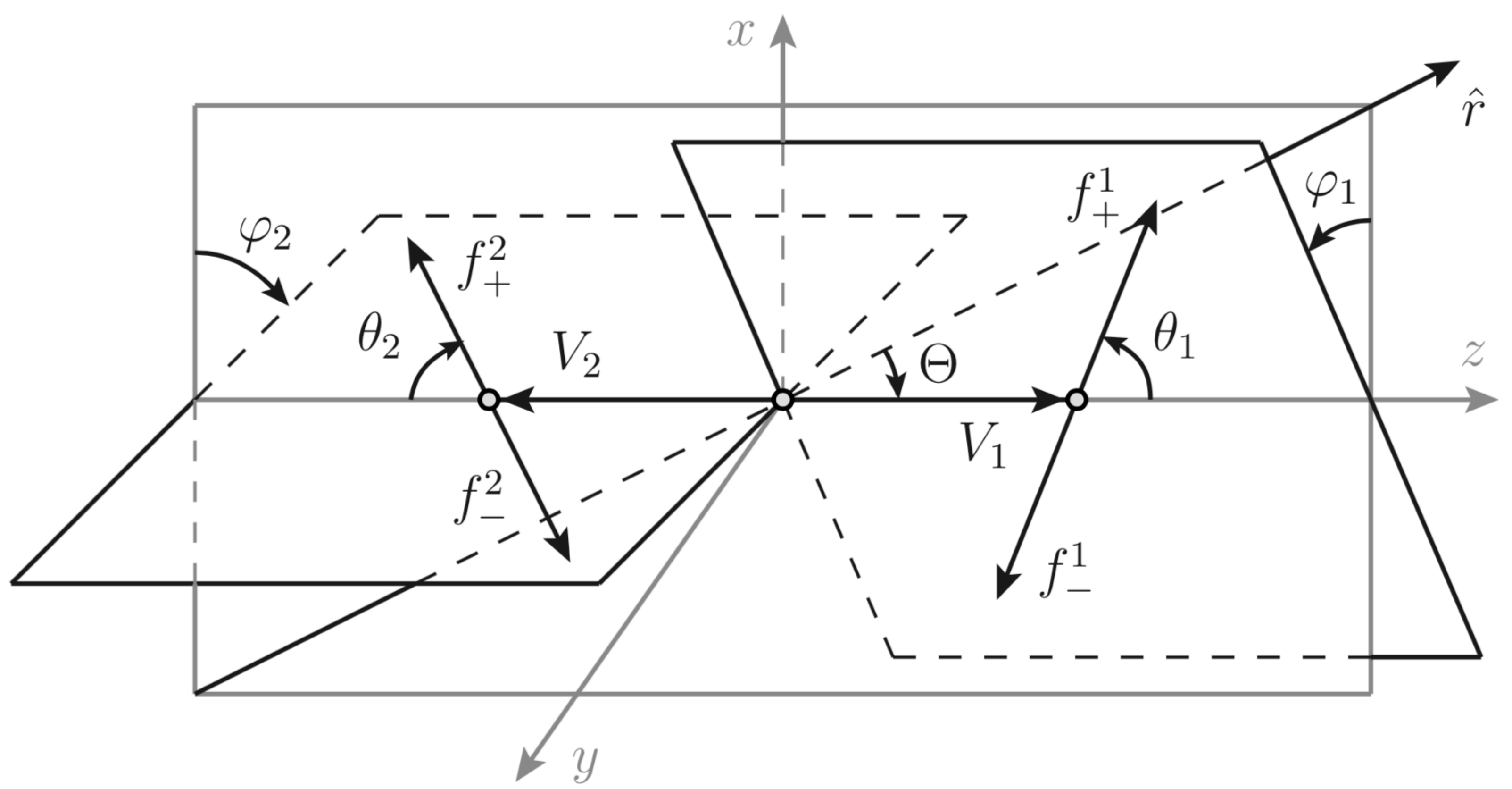
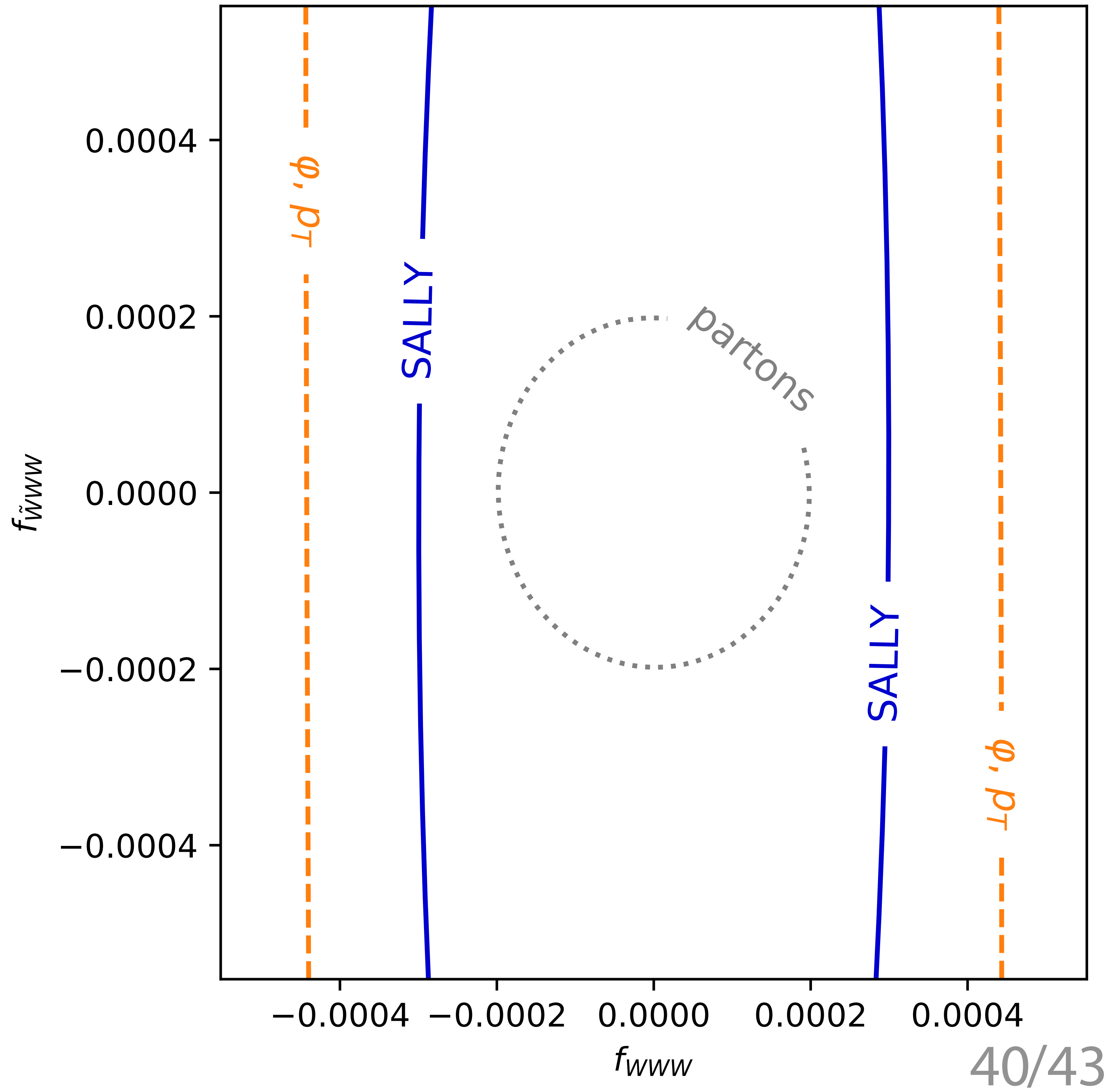
- We test the ML approach in EFT measurements in $W\gamma \to \ell\nu\ \gamma$
  [JB, K. Cranmer, M. Farina, F. Kling, D. Pappadopulo, J. Ruderman in progress]

- Preliminary results: we can extract more information when we analyze events with SALLY than with histograms of φ and standard observables



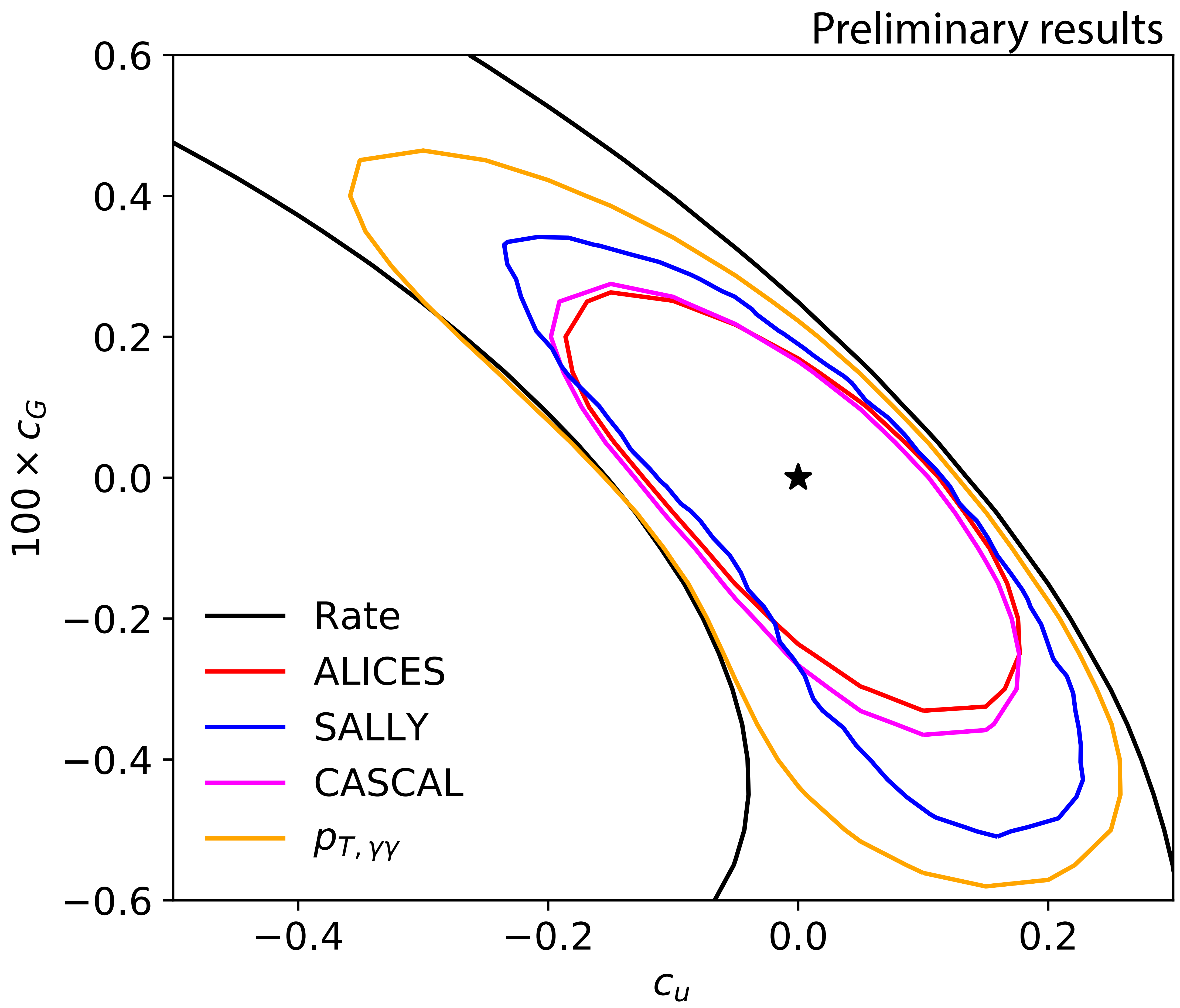
Very preliminary results



Higgs measurements

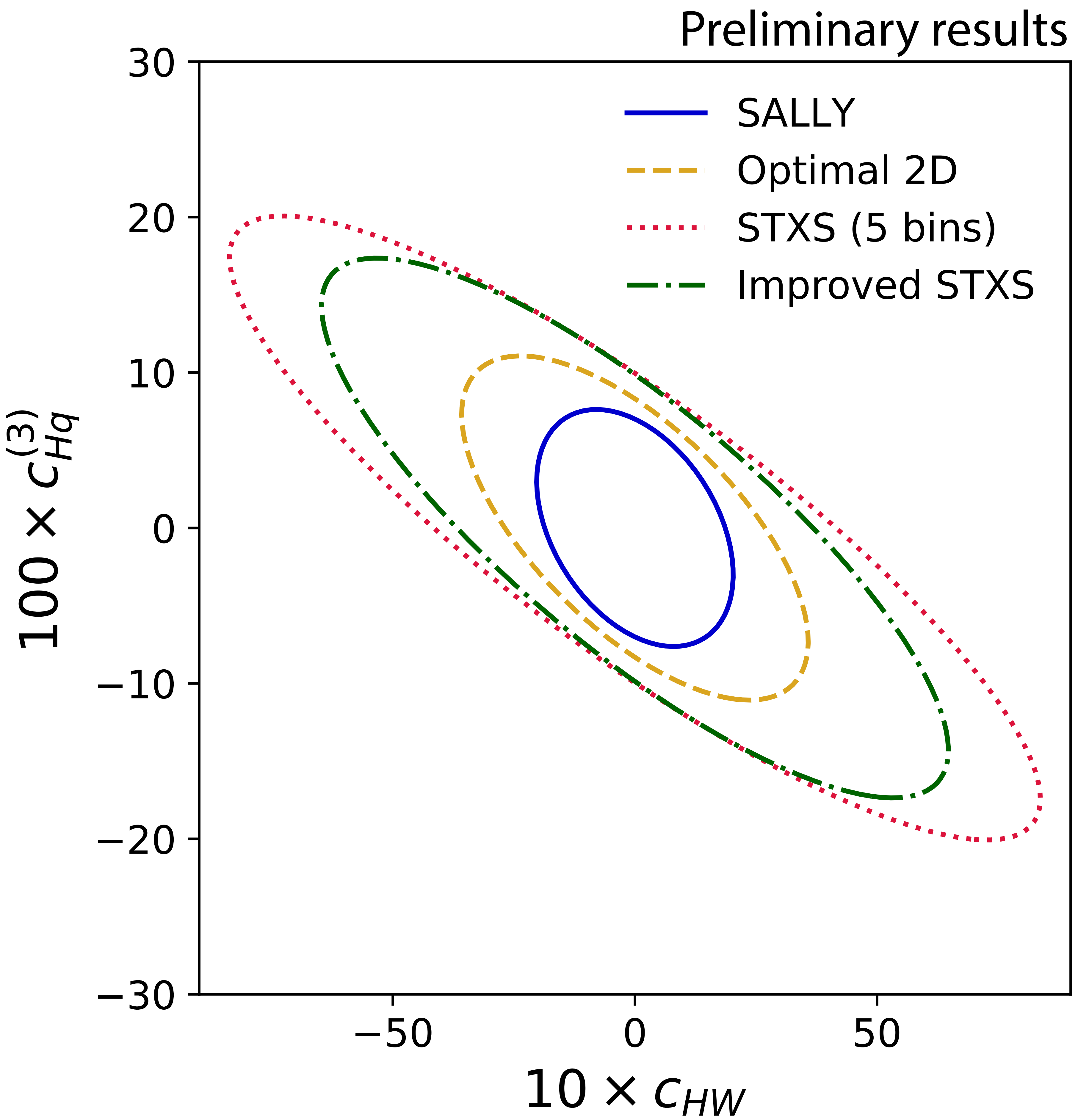
$$t\bar{t}\,h \to (b\ell^+\nu)\,(b\ell^-\bar{\nu})\,(\gamma\gamma)$$

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

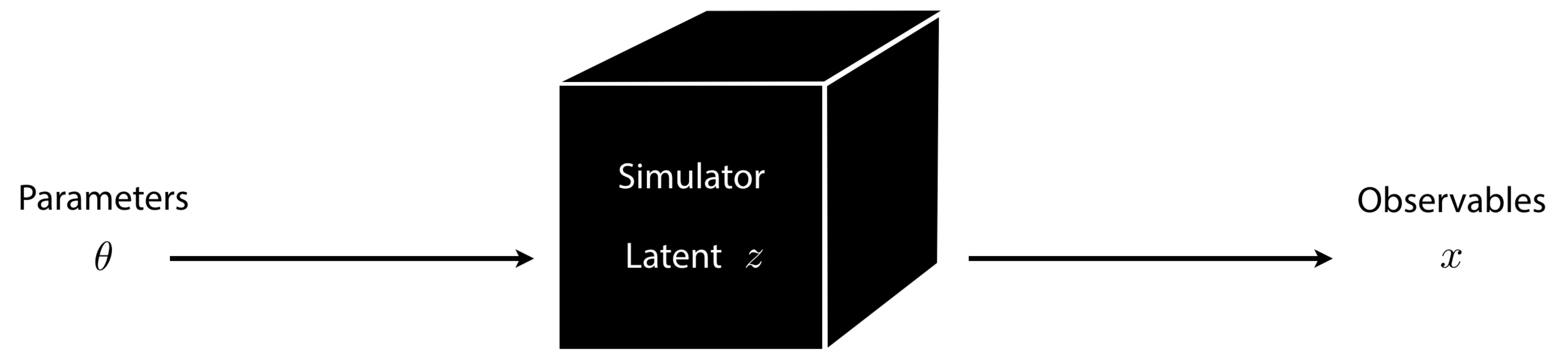


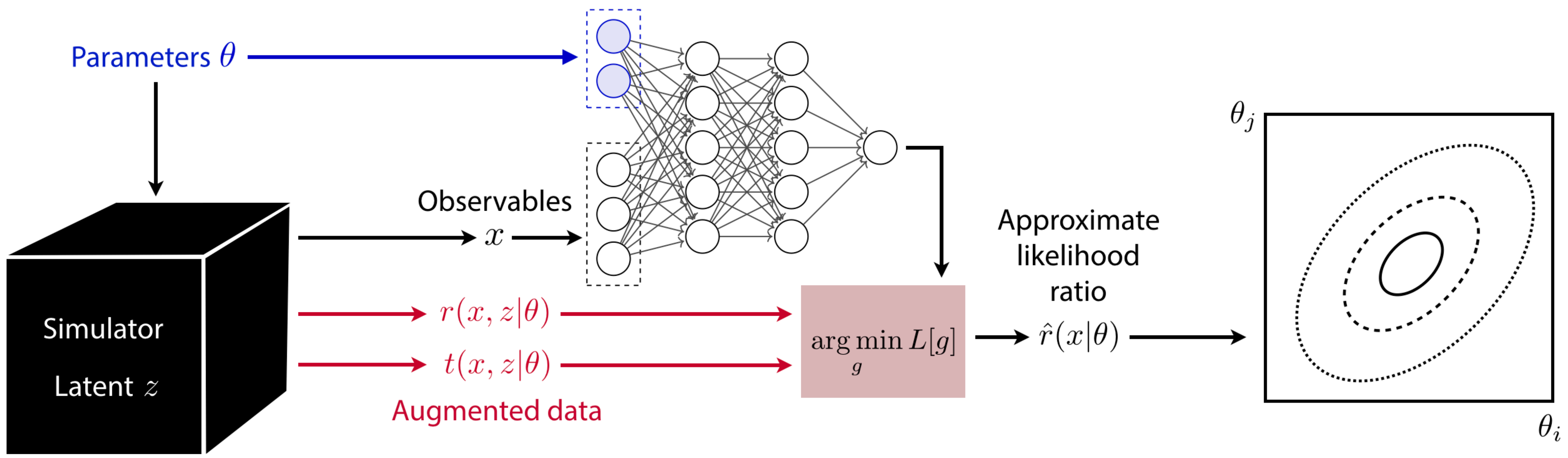
$$Wh \to (\ell\nu)(b\bar{b})$$

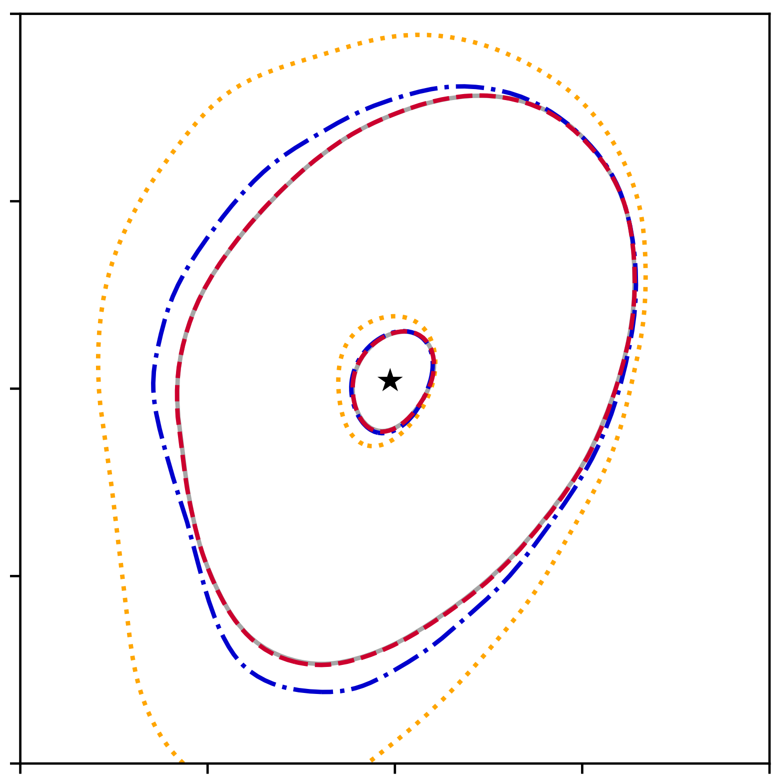
[JB, S. Dawson, S. Homiller, F. Kling, T. Plehn in progress]



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

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, KC, IE, FK, GL, JP:	Effective LHC measurements with matrix elements and machine learning	[ACAT, 1906.01578]
JB, FK, IE, KC:	MadMiner: An inference toolkit for particle physics	[doi: 10.5281/zenodo.1489147]

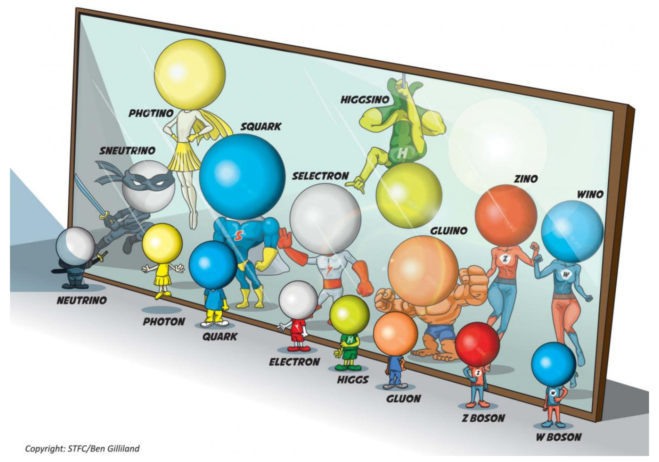
Bonus material

[STFC / Ben Gililand, Sean Carroll, Friedrich Justin Bertuch 1806, symmetry]

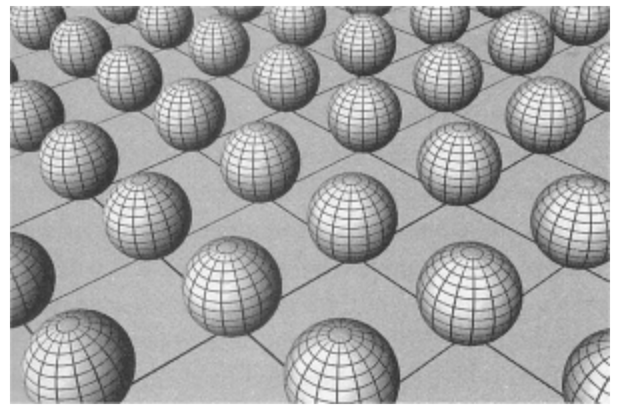
Effective field theory

Energy

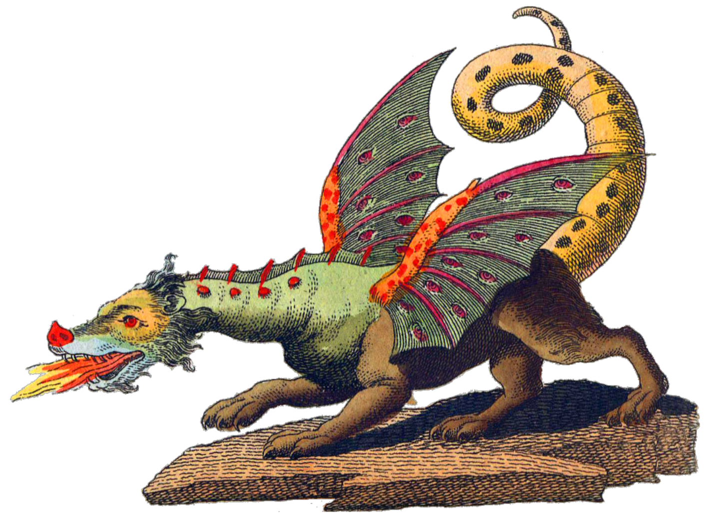
Λ



Supersymmetry?



Extra dimensions?



Dragons?

Composite Higgs?

...

Matching

$$\mathcal{L}_{\mathrm{EFT}} = \mathcal{L}_{\mathrm{SM}} + \sum_i \frac{f_i}{\Lambda^2}\,\mathcal{O}_i + \ldots$$

Effective field theory

Measurements

$E \ll \Lambda$

LHC Higgs

Other LHC measurements

LEP

Flavour

...

SMEFT (Standard Model Effective Field Theory)

[W. Buchmuller, D. Wyler 85;
B. Grzadkowski, M. Iskrzynski, M. Misiak, J. Rosiek 1008.4884; …]

$$\mathcal{L}_{\mathrm{EFT}} = \mathcal{L}_{\mathrm{SM}} + \sum_i \frac{f_i}{\Lambda^2}\,\mathcal{O}_i + \ldots$$

Operators

- all possible interactions between SM particles mediated by new physics
- fixed by SM particles + SM symmetries + expansion in $1/\Lambda$, independent of high-energy physics
- affect rates + kinematics

$$\begin{aligned}
\mathcal{O}_{\phi,1} &= (D_\mu\phi)^\dagger\phi\;\phi^\dagger D^\mu\phi &\qquad \mathcal{O}_{GG} &= (\phi^\dagger\phi)\;G^a_{\mu\nu}\,G^{\mu\nu\,a}\\
\mathcal{O}_{\phi,2} &= \frac{1}{2}\,\partial_\mu(\phi^\dagger\phi)\;\partial^\mu(\phi^\dagger\phi) & \mathcal{O}_{BB} &= -\frac{g'^2}{4}\,(\phi^\dagger\phi)\;B_{\mu\nu}\,B^{\mu\nu}\\
\mathcal{O}_{\phi,3} &= \frac{1}{3}(\phi^\dagger\phi)^3 & \mathcal{O}_{WW} &= -\frac{g^2}{4}\,(\phi^\dagger\phi)\;W^a_{\mu\nu}\,W^{\mu\nu\,a}\\
\mathcal{O}_{\phi,4} &= (\phi^\dagger\phi)\;(D_\mu\phi)^\dagger\,D^\mu\phi & \mathcal{O}_{BW} &= -\frac{g\,g'}{4}\,(\phi^\dagger\sigma^a\phi)\;B_{\mu\nu}\,W^{\mu\nu\,a}\\
& & \mathcal{O}_{B} &= \frac{\mathrm{i}g'}{2}\,(D^\mu\phi)^\dagger\,D^\nu\phi\;B_{\mu\nu}\\
& & \mathcal{O}_{W} &= \frac{\mathrm{i}g}{2}\,(D^\mu\phi)^\dagger\,\sigma^a\,D^\nu\phi\;W^a_{\mu\nu}
\end{aligned}$$

Wilson coefficients

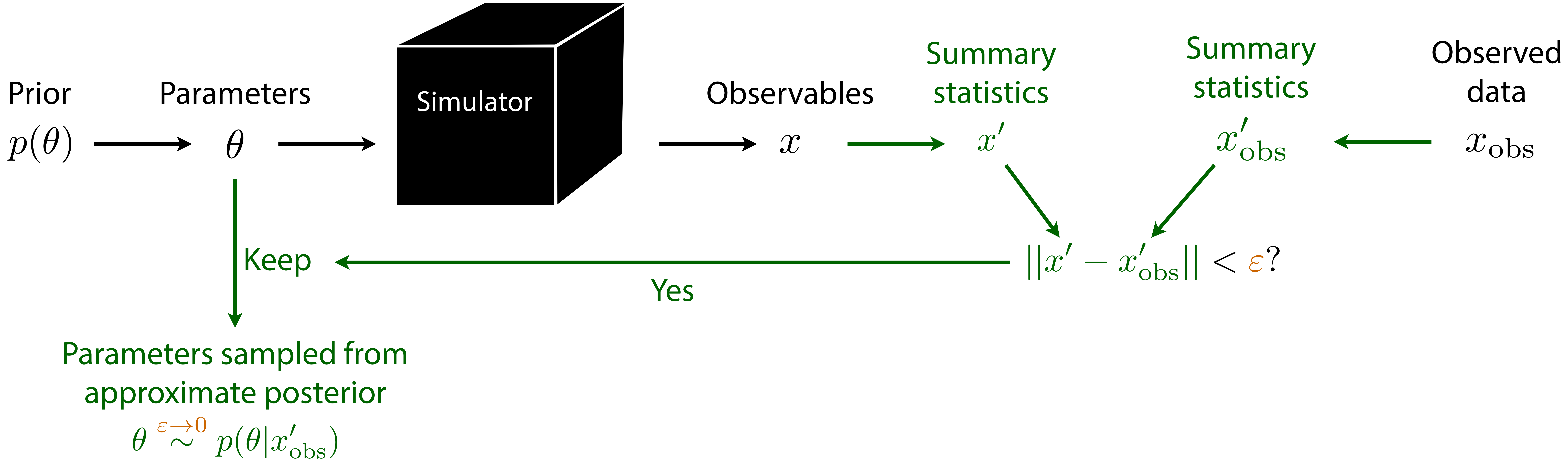
- precise measurement of these parameters is one of the most important goals of the LHC
- can be translated to high-energy physics parameters

Higher-order terms

- suppressed by additional factors of $E^2\,/\,\Lambda^2$

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

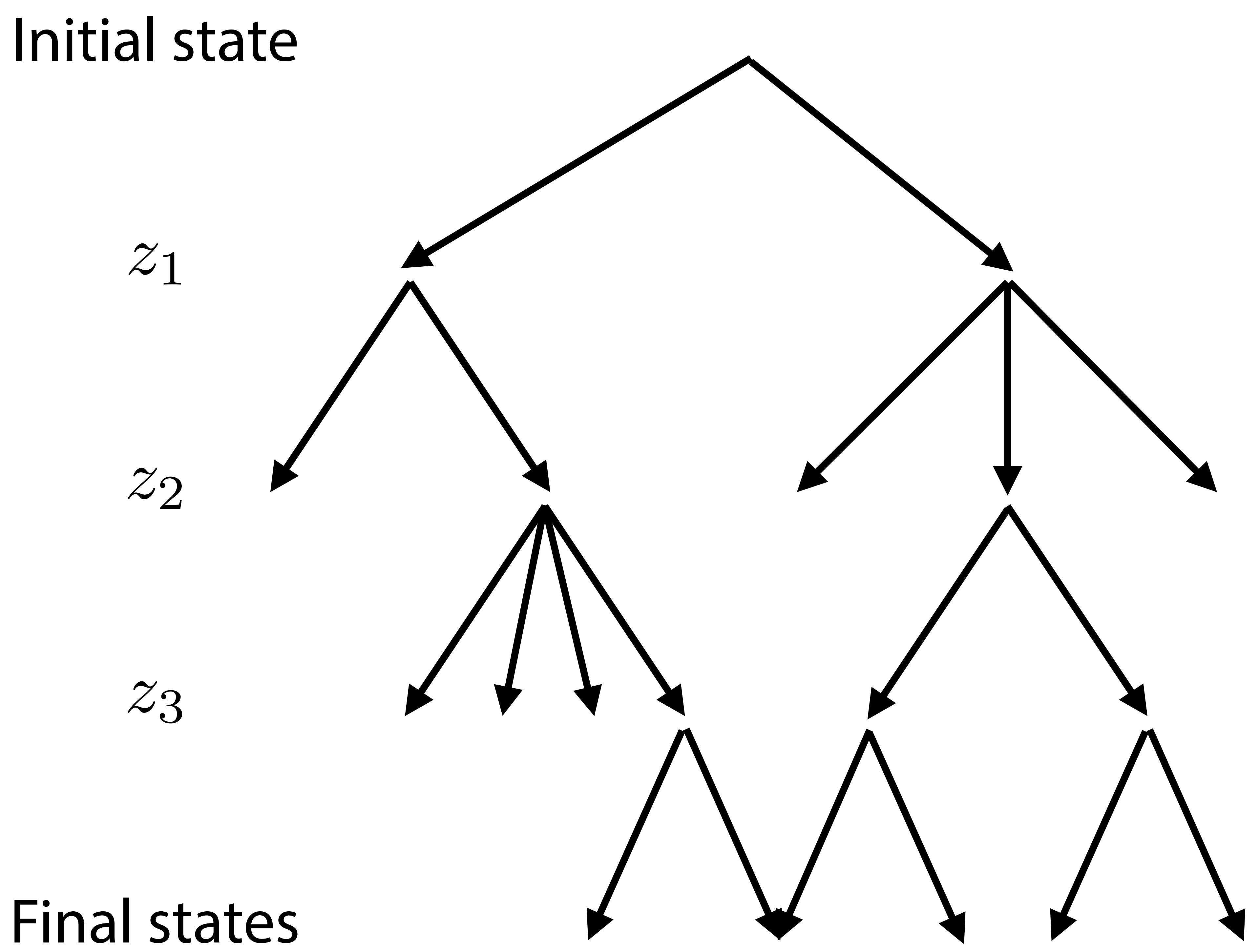
"Curse of dimensionality"

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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```
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```
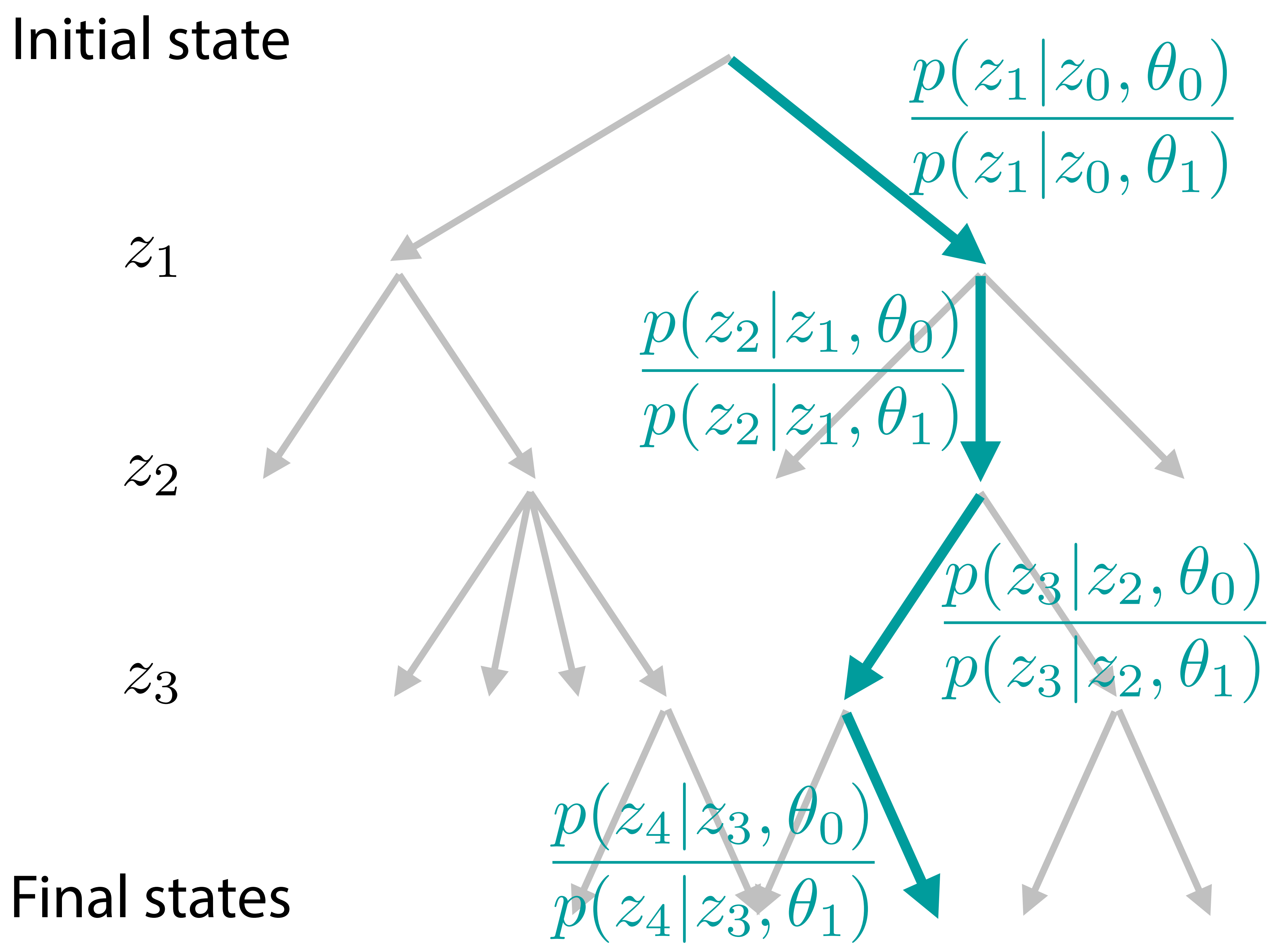

- For each run of the simulator, we can calculate the probability of the chosen path for different values of the parameters, and the "joint likelihood ratio":

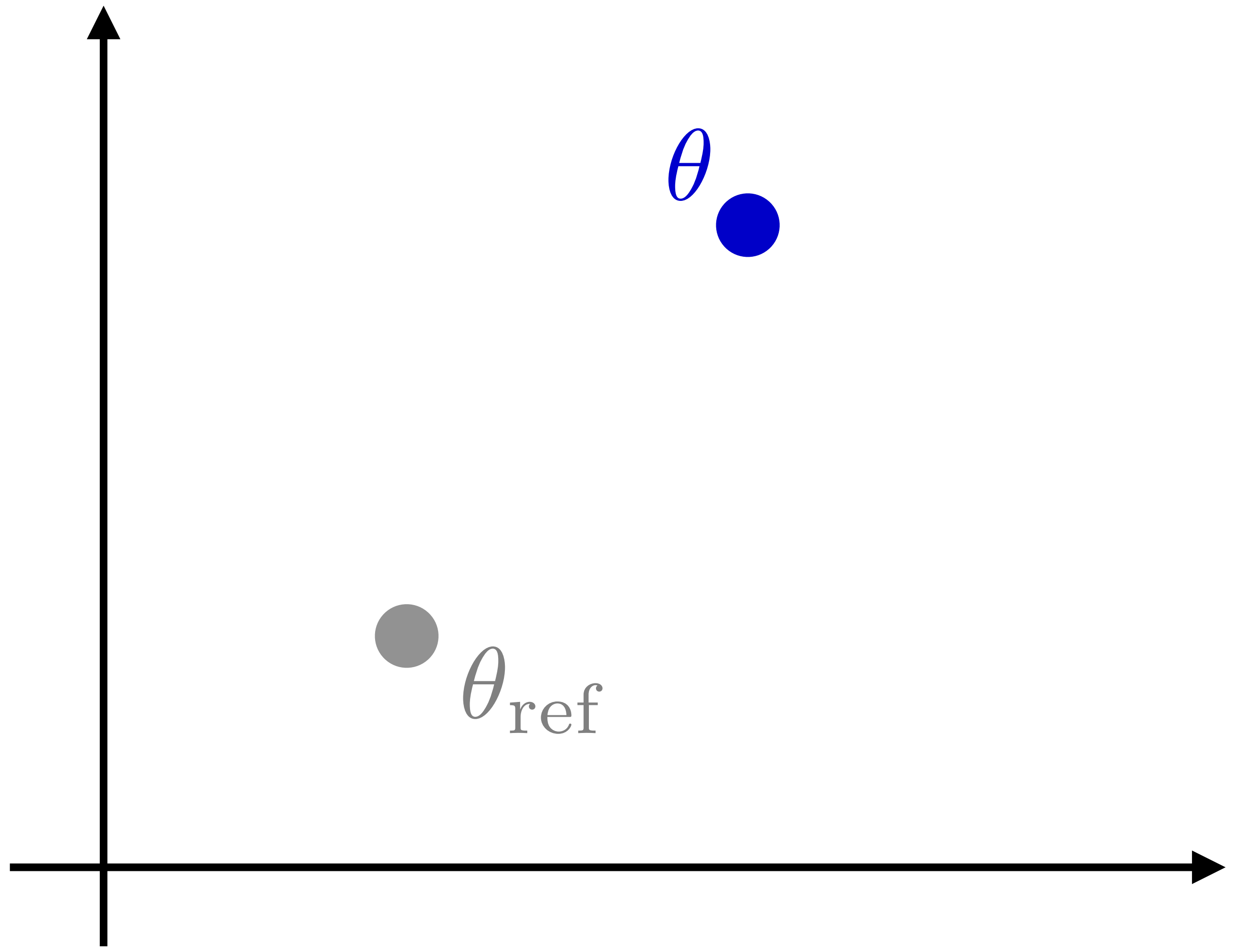
$$r(x,z|\theta_0,\theta_1) = \frac{p(x,z|\theta_0)}{p(x,z|\theta_1)} = \prod_i \frac{p(z_i|z_{i-1},\theta_0)}{p(z_i|z_{i-1},\theta_1)}$$



Limit setting (frequentist, standard ATLAS / CMS practice)

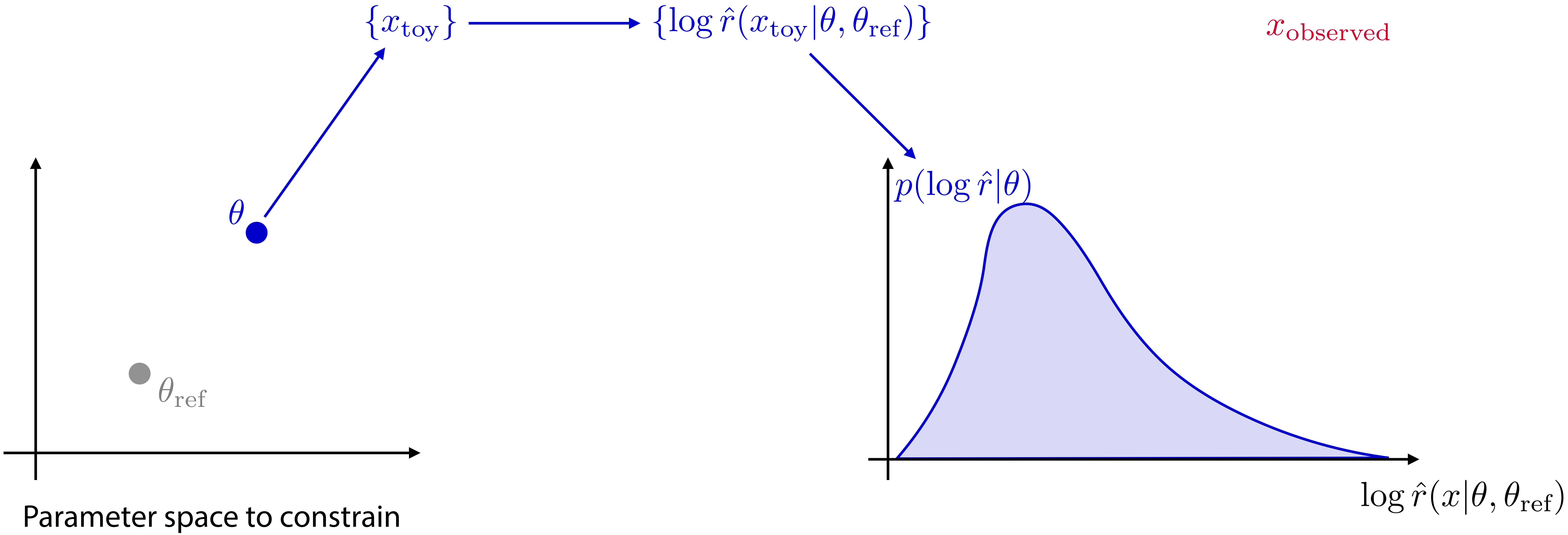
Observed data

x_{observed}



Parameter space to constrain

Limit setting (frequentist, standard ATLAS / CMS practice)



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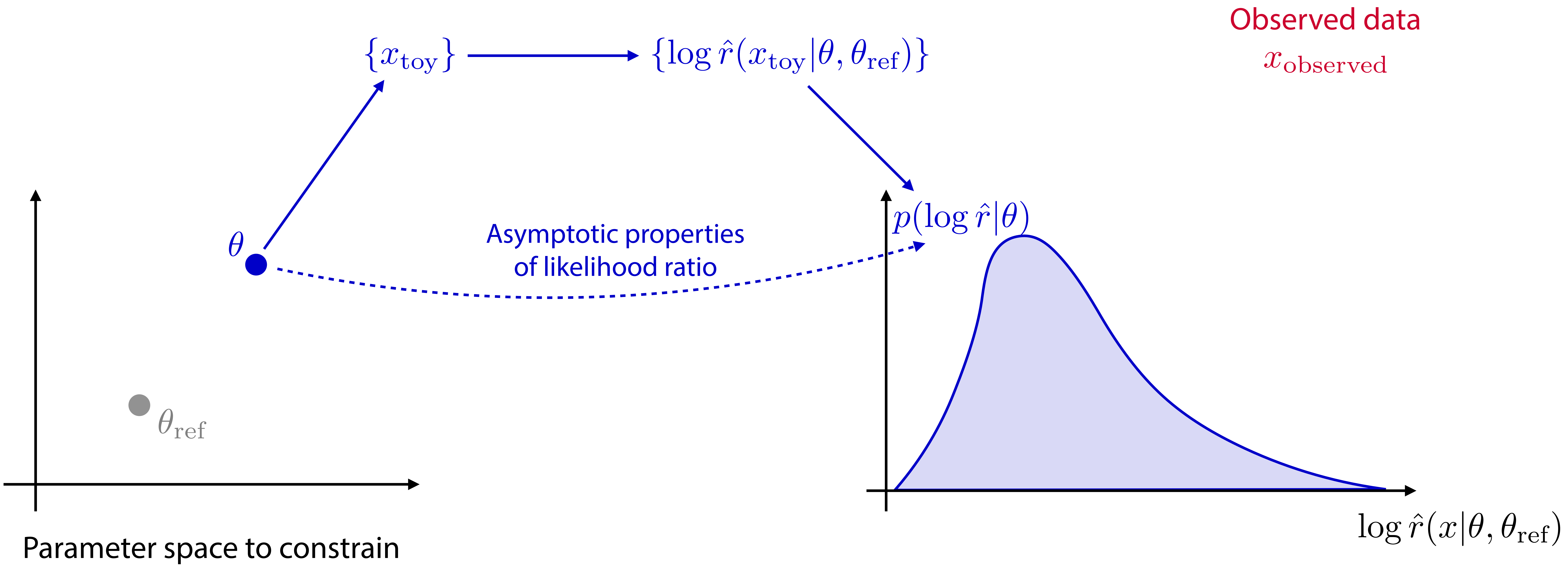

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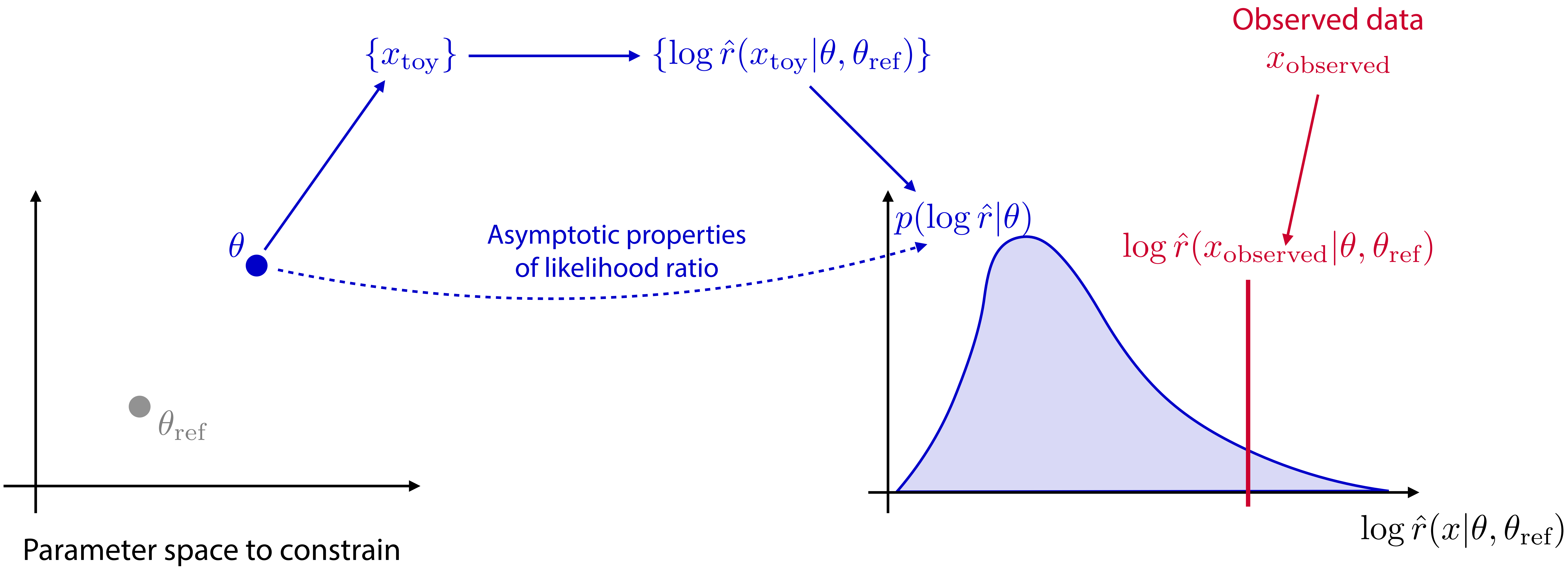

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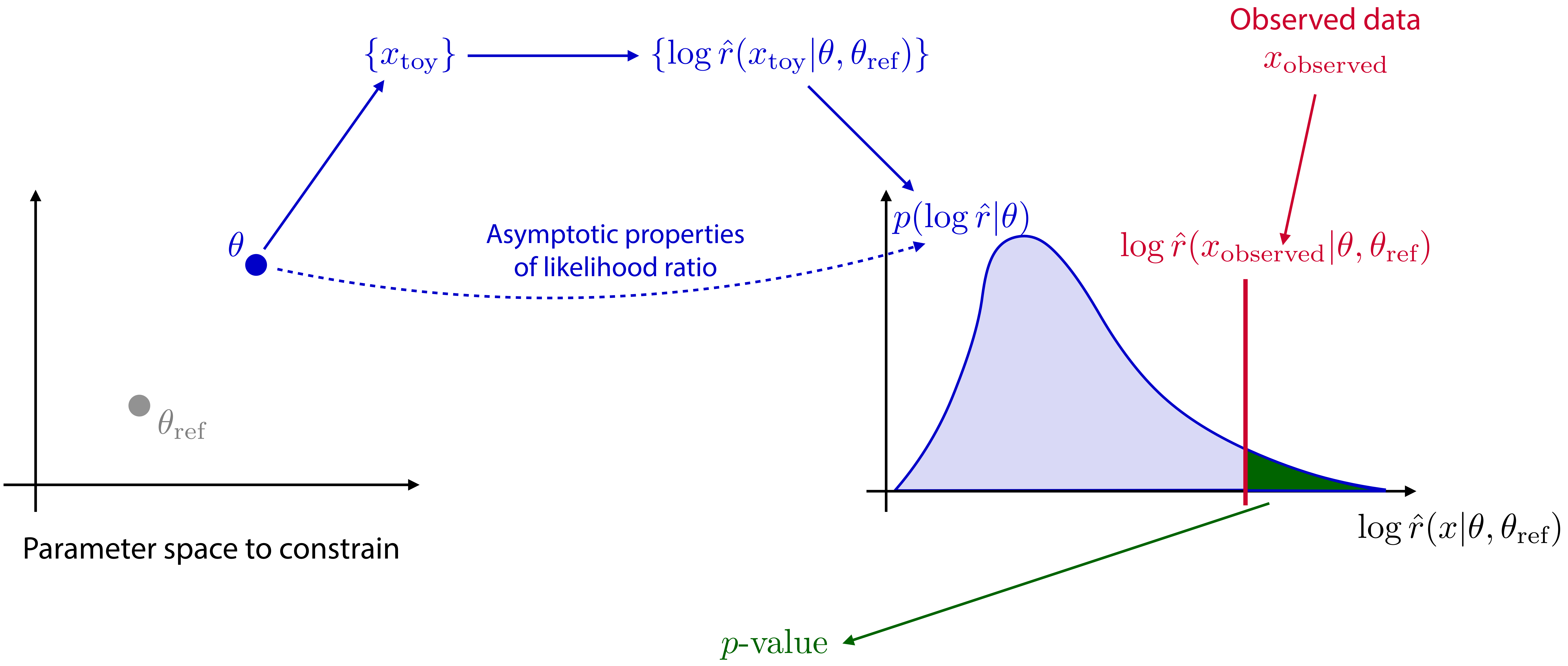

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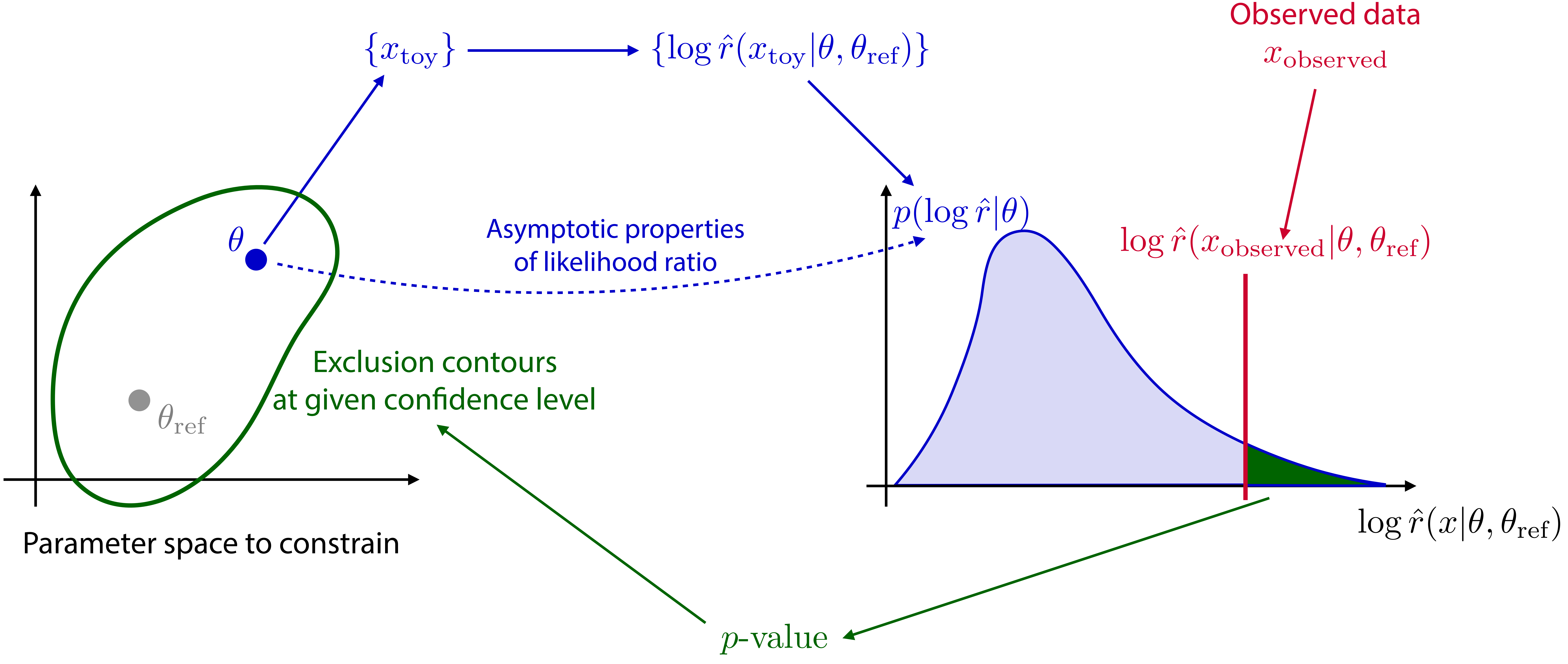
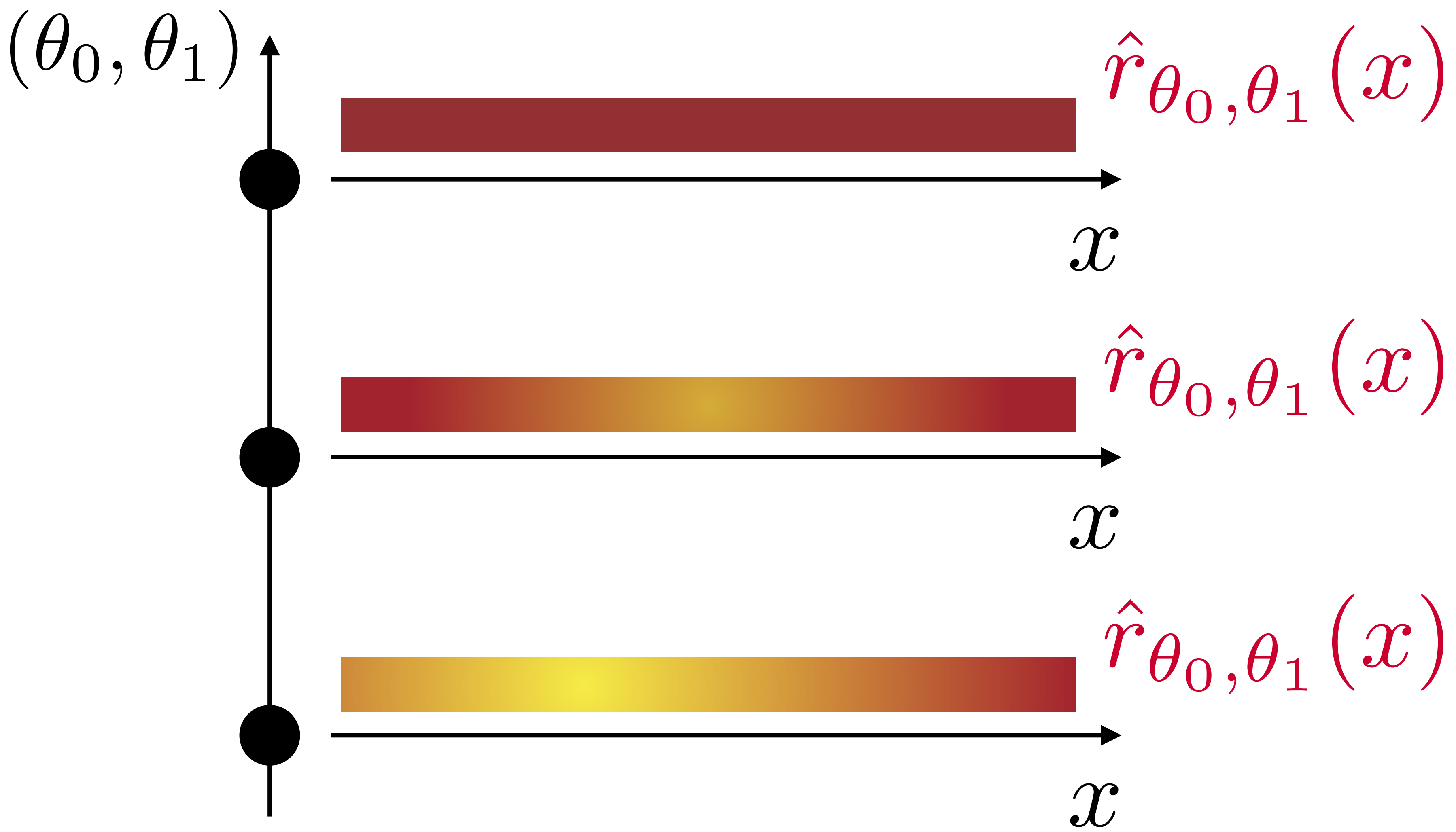


Two types of likelihood ratio estimators

A) Point by point:

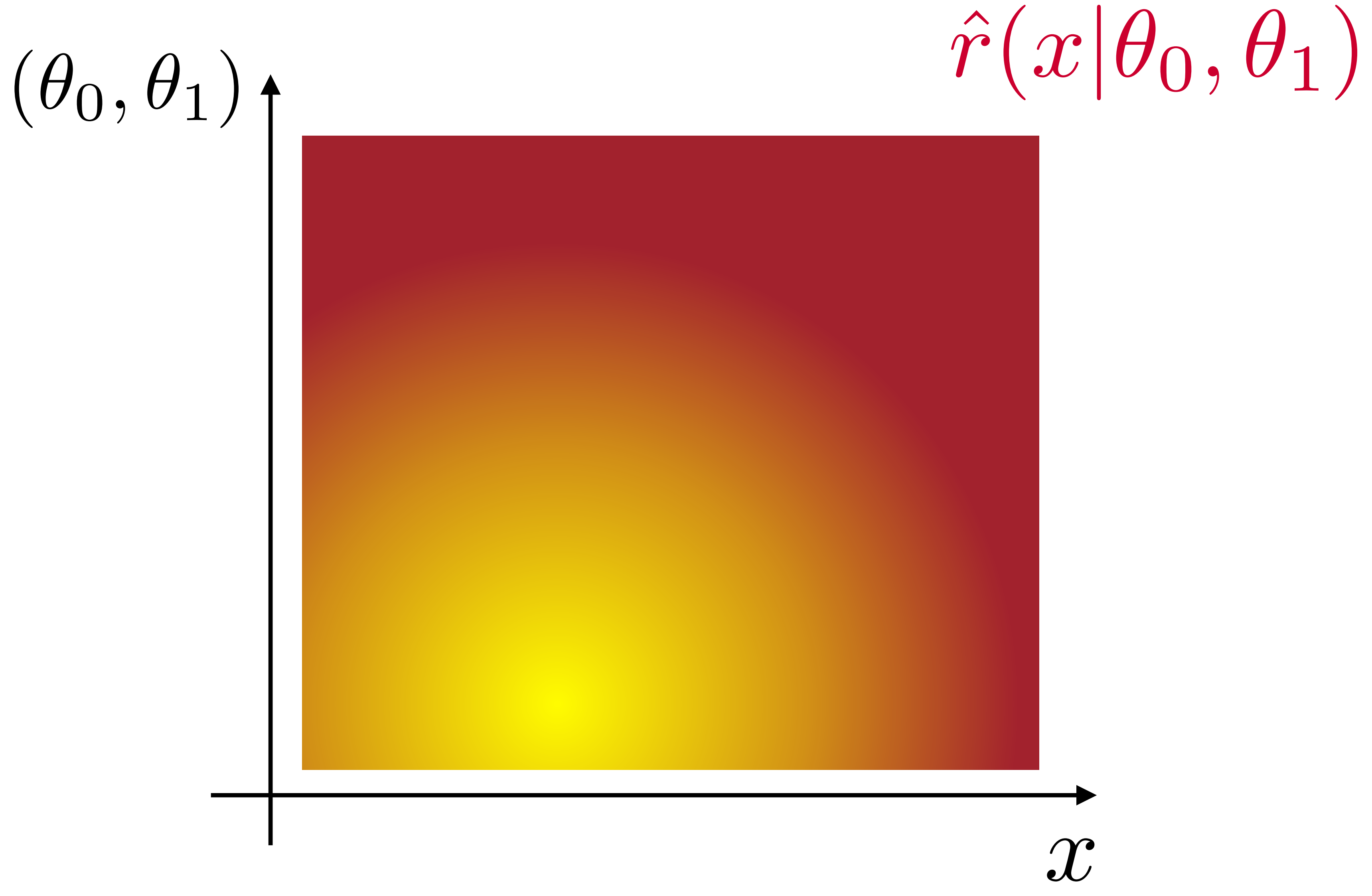
- first, define grid of parameter points $\{(\theta_0, \theta_1)\}$
- for each combination (θ_0, θ_1) ,
  create separate estimator $\hat{r}_{\theta_0,\theta_1}(x)$
- final results can be interpolated between grid points



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



WBF Higgs to four leptons with detector effects