Learning to constrain new physics

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NYU

MSDSE
Moore - Sloan
Data Science Environments

LHC legacy measurements

- What's hiding in the electroweak sector?

  ⇒ precision constraints on dimension-6 EFT operators
  (or Pseudo-Observables, non-linear EFT, …)

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  1. Many parameters

$$S = \int \mathrm{d}^4 x \left[\mathcal{L}_{\mathrm{SM}} + \frac{f_{\phi,2}}{\Lambda^2} \frac{1}{2} \partial_\mu (\phi^\dagger \phi) \partial^\mu (\phi^\dagger \phi) + \frac{f_{\phi,3}}{\Lambda^2} \frac{1}{3} (\phi^\dagger \phi)^3 \right.$$
$$+ \frac{f_{GG}}{\Lambda^2} (\phi^\dagger \phi) G^a_{\mu\nu} G^{\mu\nu\, a} - \frac{f_{BB}}{\Lambda^2} \frac{g'^2}{4} (\phi^\dagger \phi) B_{\mu\nu} B^{\mu\nu} - \frac{f_{WW}}{\Lambda^2} \frac{g^2}{4} (\phi^\dagger \phi) W^a_{\mu\nu} W^{\mu\nu\, a}$$
$$+ \frac{f_B}{\Lambda^2} \frac{\mathrm{i} g'}{2} (D^\mu \phi)^\dagger D^\nu \phi \, B_{\mu\nu} + \frac{f_W}{\Lambda^2} \frac{\mathrm{i} g}{2} (D^\mu \phi)^\dagger \sigma^a D^\nu \phi \, W^a_{\mu\nu}$$
$$+ \frac{f_\ell}{\Lambda^2} (\phi^\dagger \phi) \bar{L}_L \phi \, \ell_R + \frac{f_u}{\Lambda^2} (\phi^\dagger \phi) \overline{Q}_L \tilde{\phi} \, u_R + \frac{f_d}{\Lambda^2} (\phi^\dagger \phi) \overline{Q}_L \phi \, d_R$$
$$\left. + \frac{f_{G\widetilde{G}}}{\Lambda^2} (\phi^\dagger \phi) G^a_{\mu\nu} \widetilde{G}^{\mu\nu\, a} - \frac{f_{B\widetilde{B}}}{\Lambda^2} \frac{g'^2}{4} (\phi^\dagger \phi) B_{\mu\nu} \widetilde{B}^{\mu\nu} - \frac{f_{W\widetilde{W}}}{\Lambda^2} \frac{g^2}{4} (\phi^\dagger \phi) W^a_{\mu\nu} \widetilde{W}^{\mu\nu\, a} \right]$$

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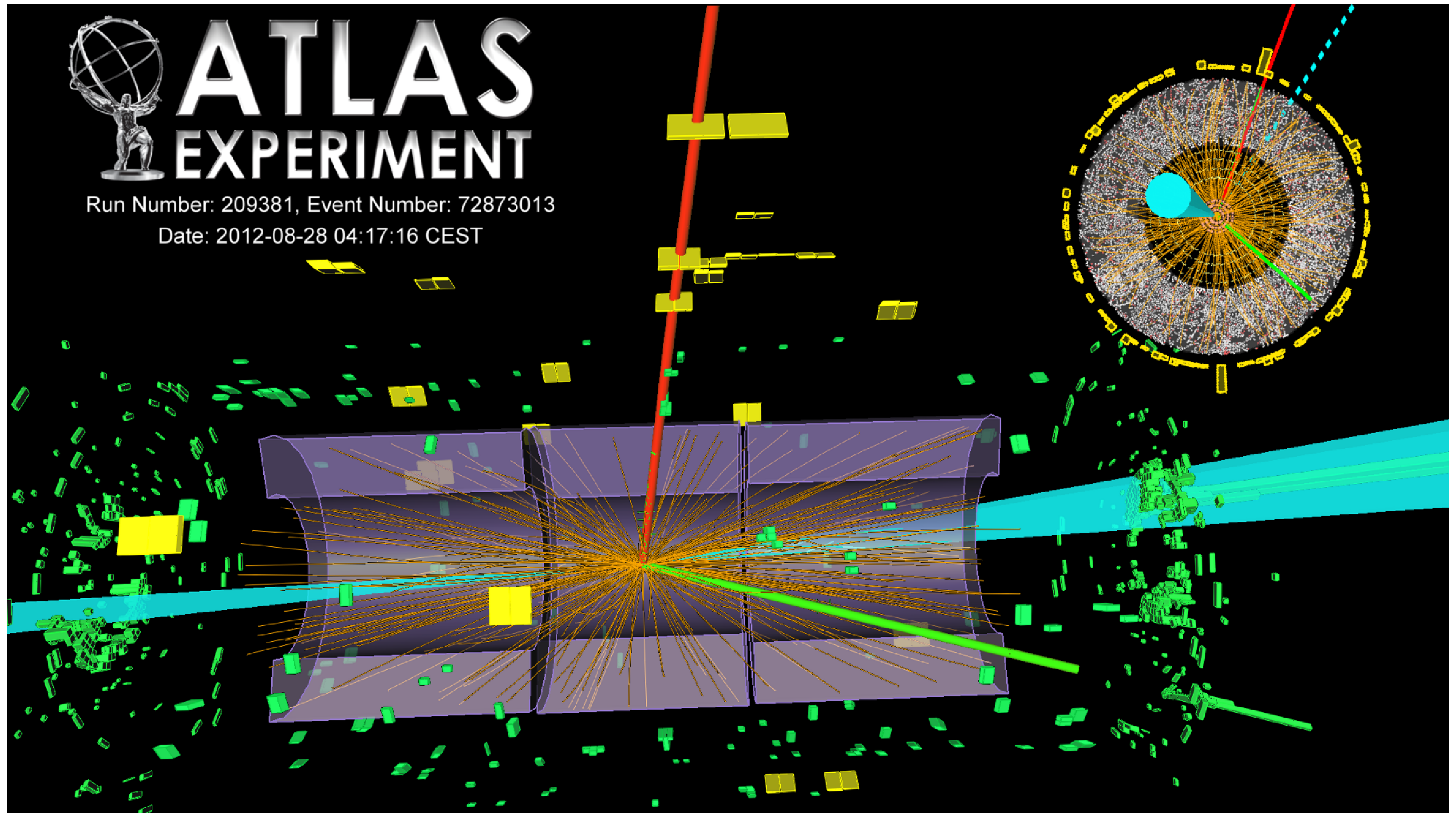
  2. Many observables



[ATLAS 1501.04943]

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

LHC legacy measurements

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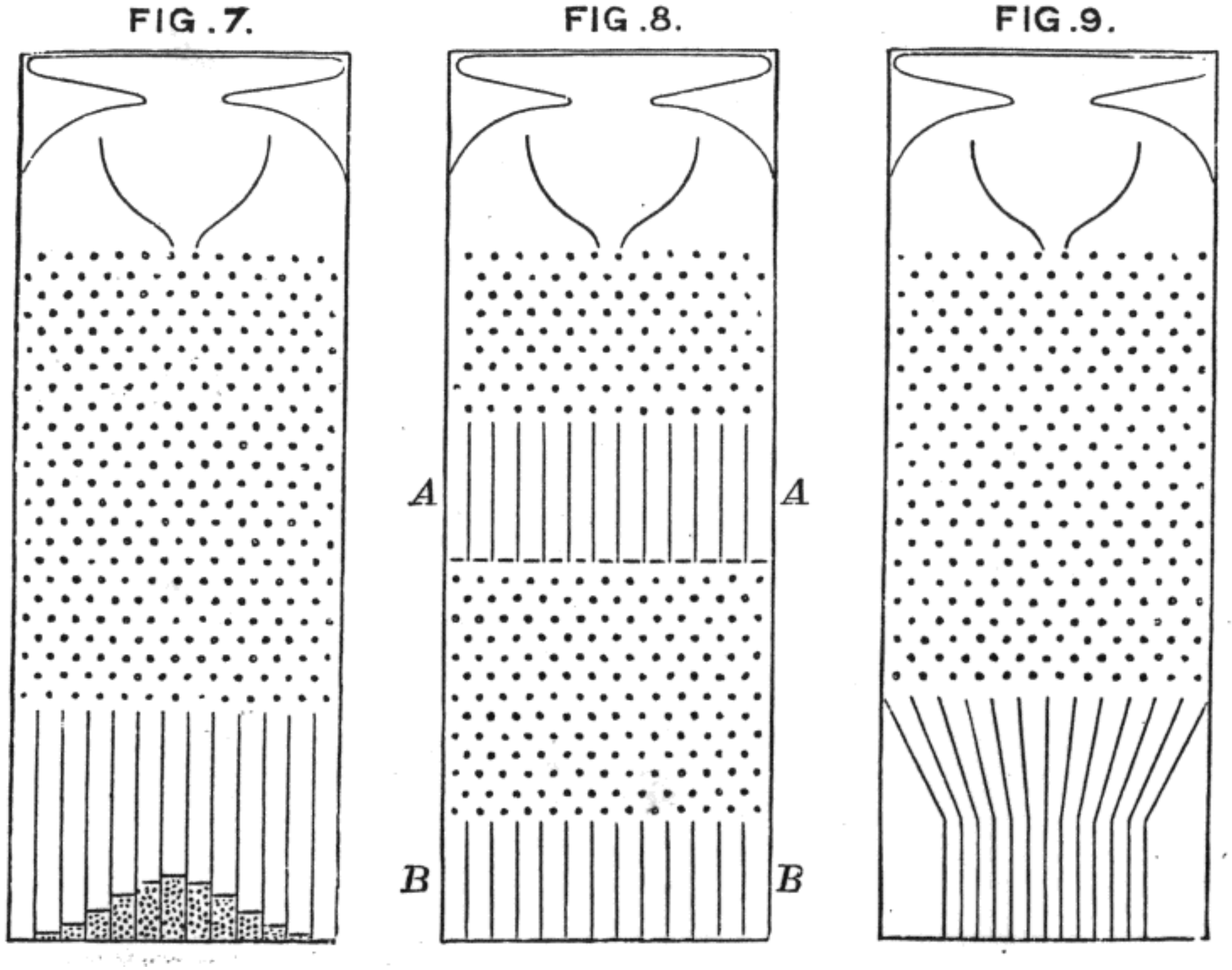
- Established data analysis methods struggle…
  New ideas can improve the sensitivity to new physics!

Likelihood-free inference

The Galton board

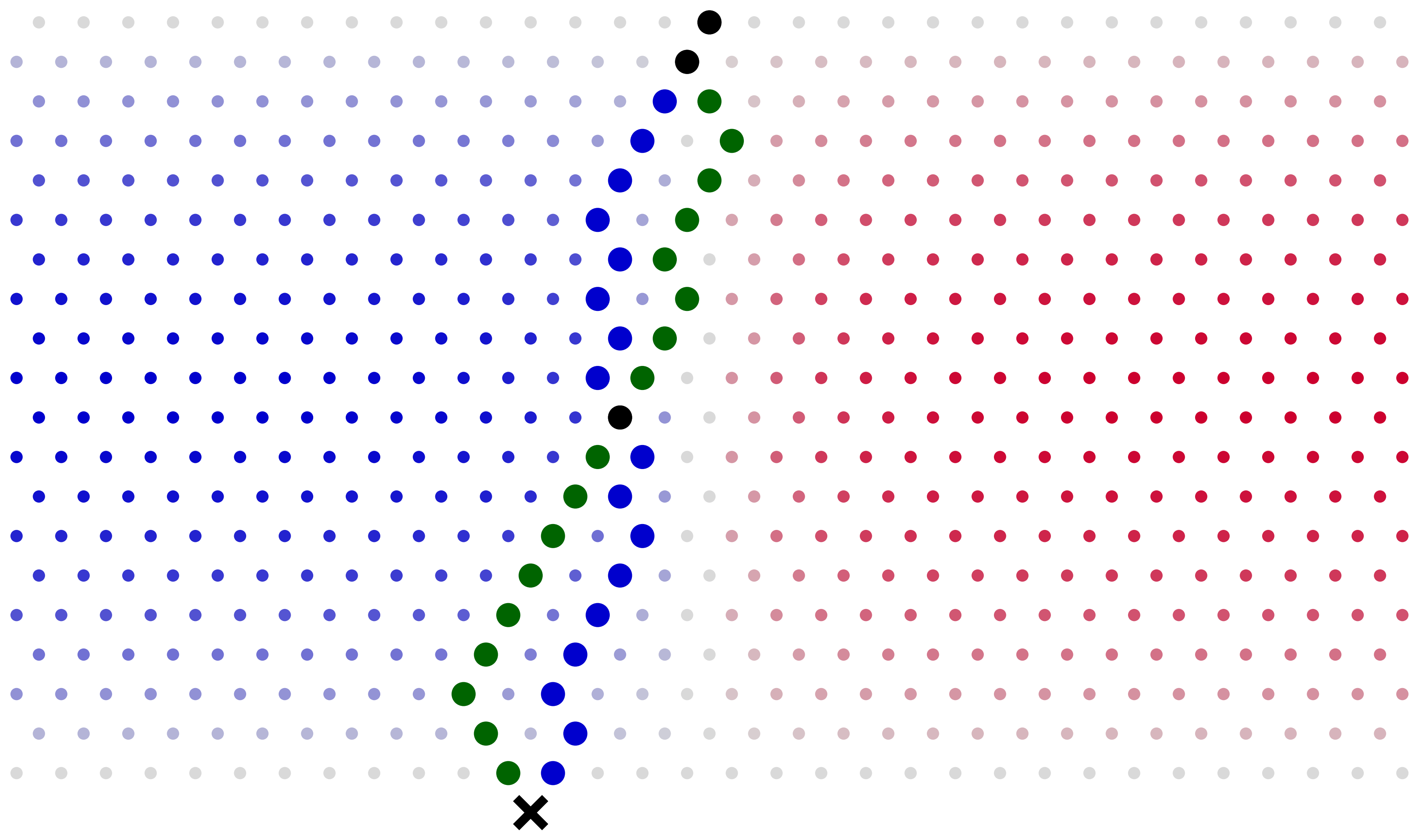
[galtonboard.com]

The Galton board



[F. Galton 1889]

Probabilities from integrating trajectories



Probability of ending in bin x : $p(x) = \int \mathrm{d}z \; p(x, z)$

Sum over all trajectories ("latent variables")

Probability of each path z from start to x

The generalized Galton board

What if probability to go left at a nail is not always 0.5, but some (known) function of some parameters θ ?

- Prediction: given θ, generate samples of observations $\{x_i\}$.

  Simple: just drop balls!

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- Prediction: given θ, generate samples of observations $\{x_i\}$.

  Simple: just drop balls!

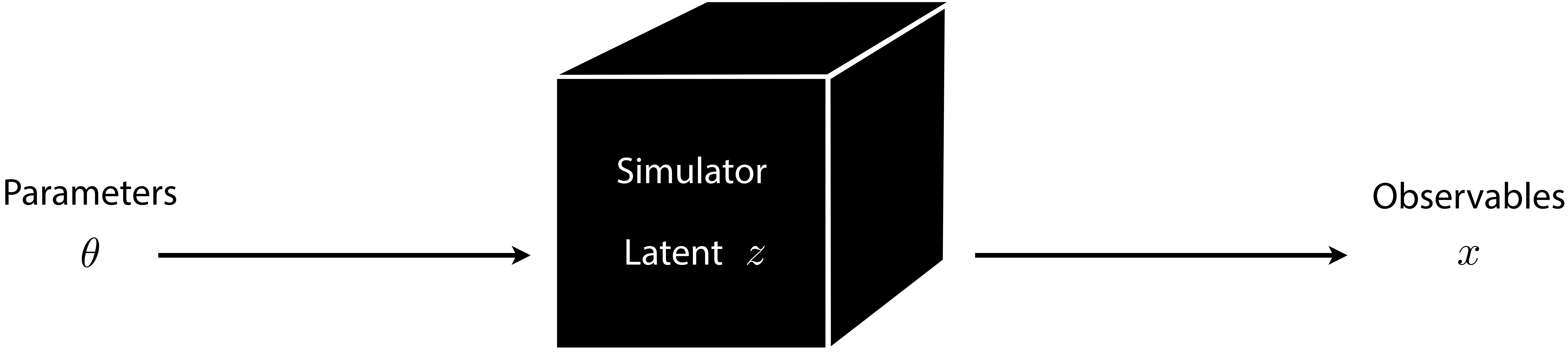
- Inference: given observations $\{x_i\}$, what are the most likely values for θ ?

  "Easy" problem if we can evaluate likelihood

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

  But the number of possible paths z can be huge, and it becomes impossible to calculate the integral!

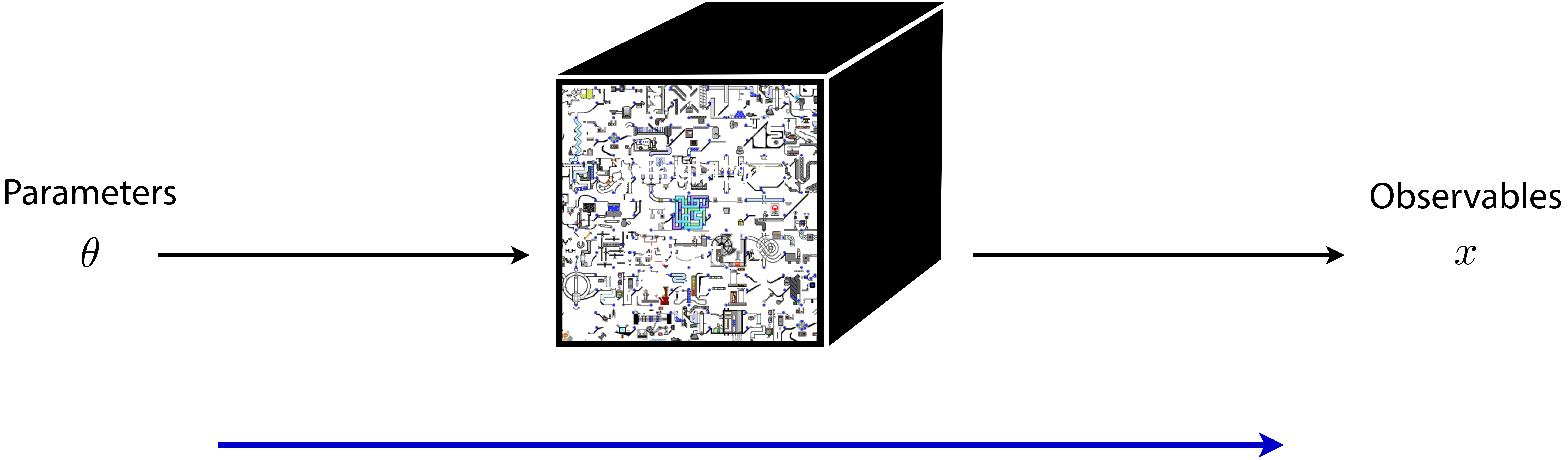
“Likelihood-free inference”



Prediction:

- Well-understood mechanistic model
- Simulator can generate samples

“Likelihood-free inference”



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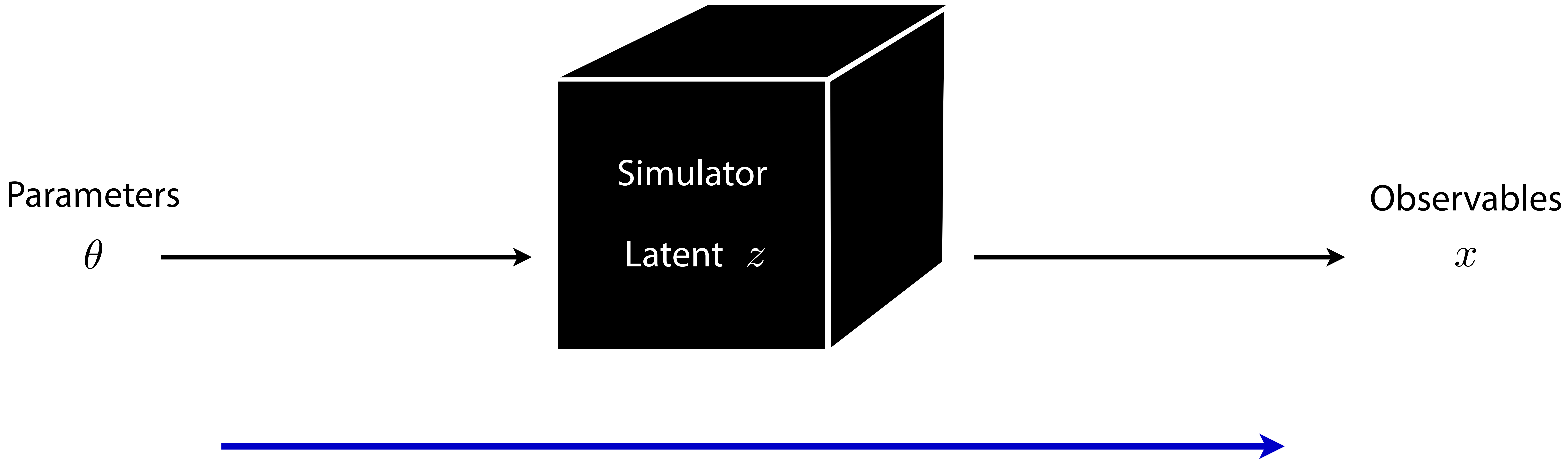

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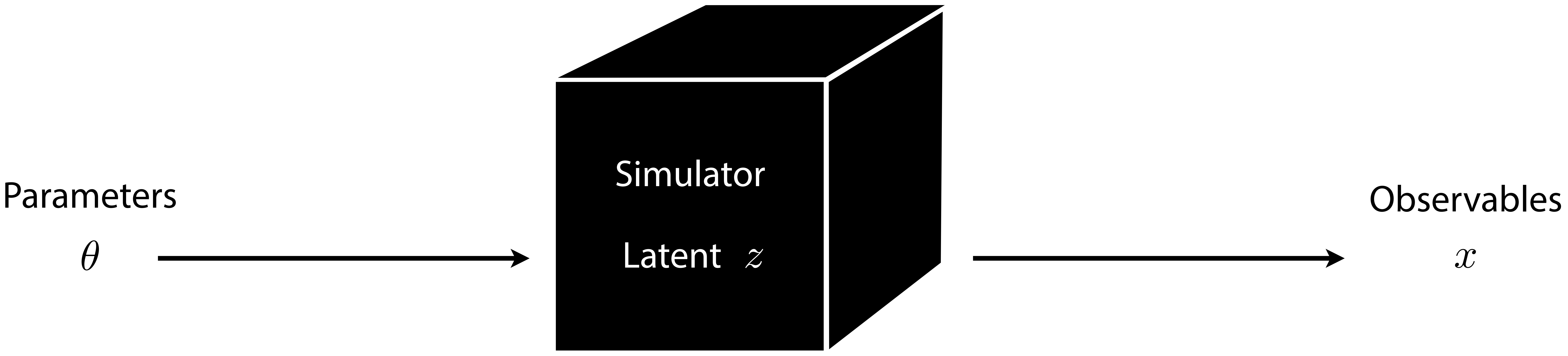
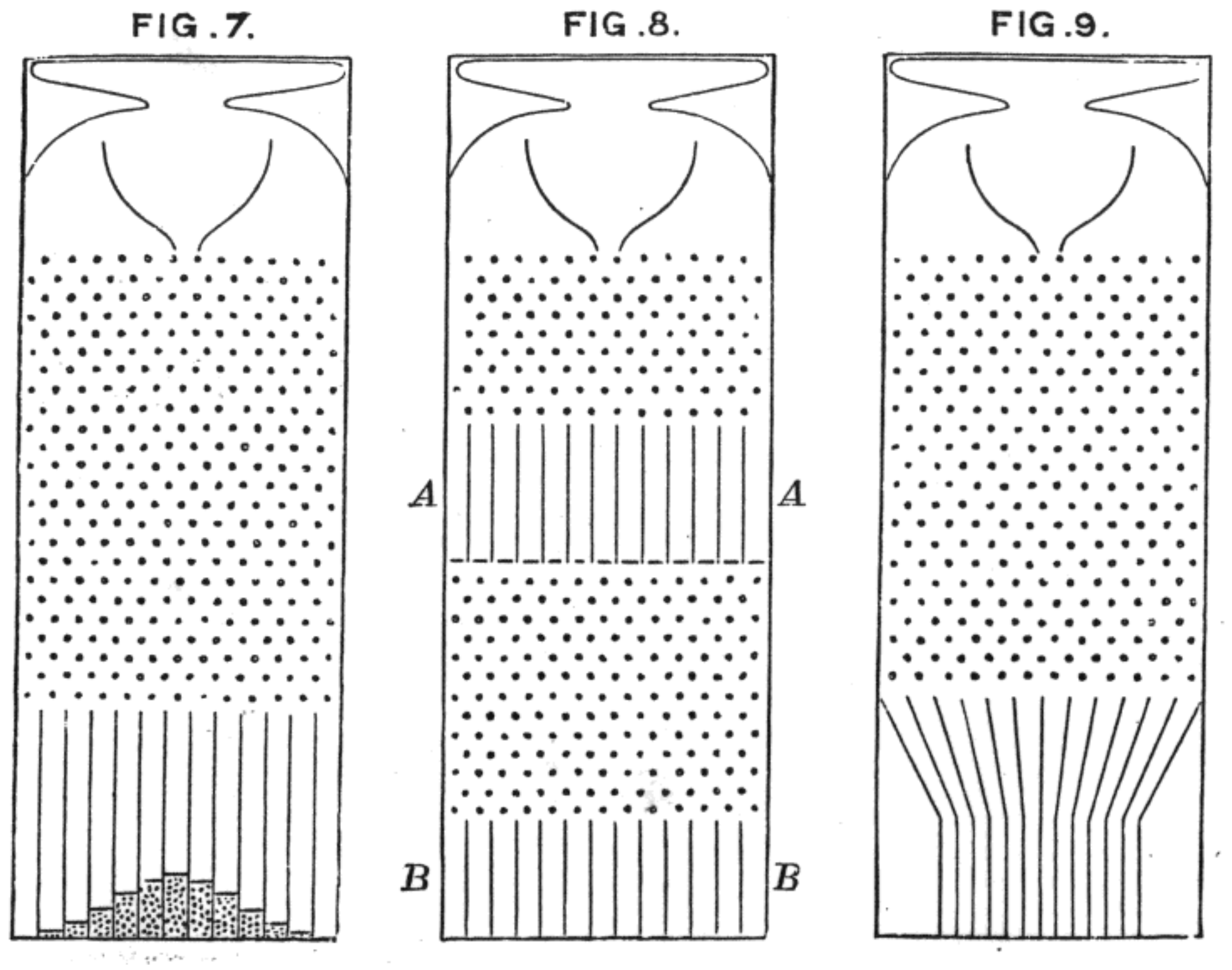


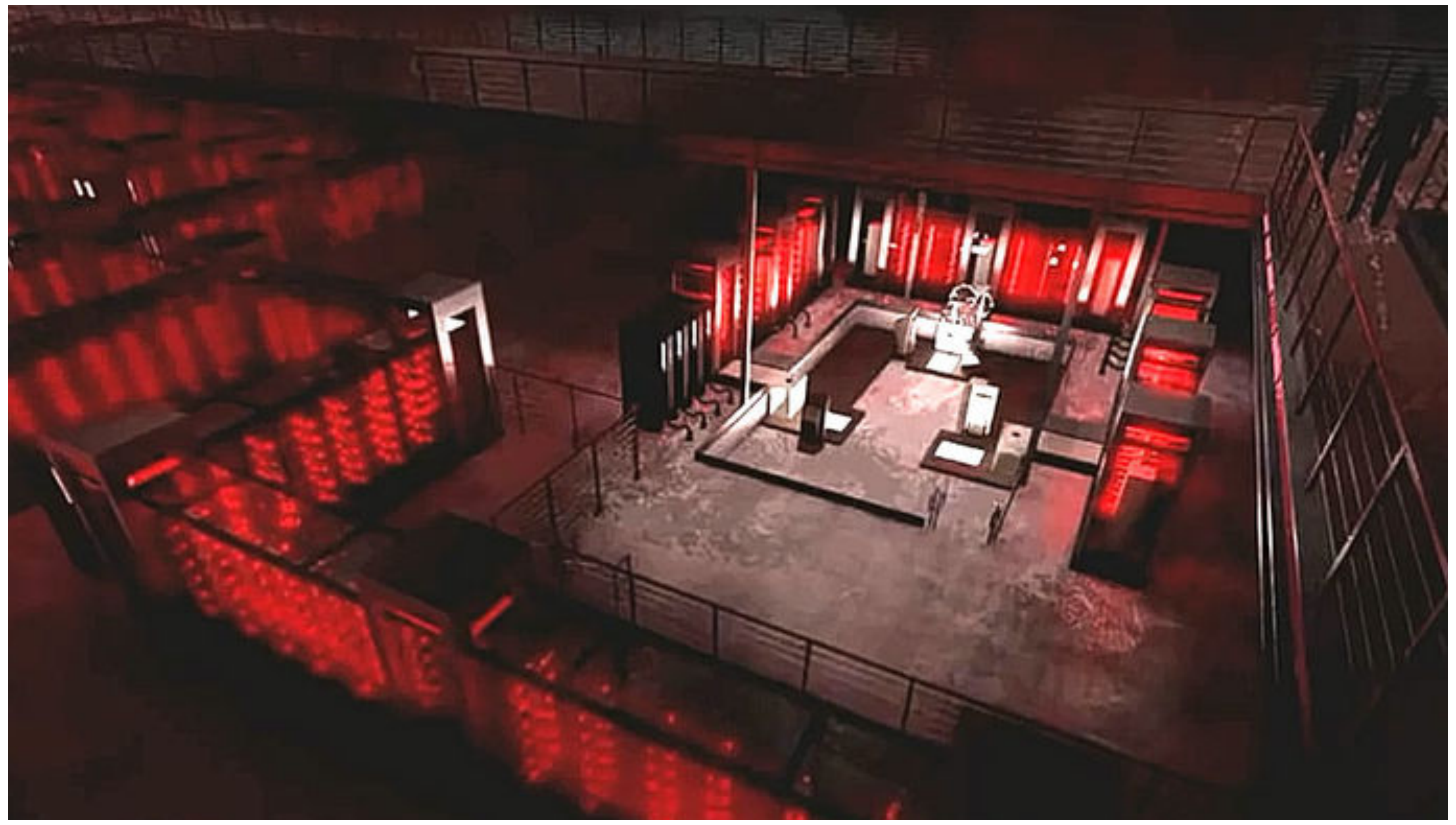
Prediction:
- Well-understood mechanistic model
- Simulator can generate samples

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

Galton board: metaphor for simulator-based science



[F. Galton 1889]



[HBO 2018]

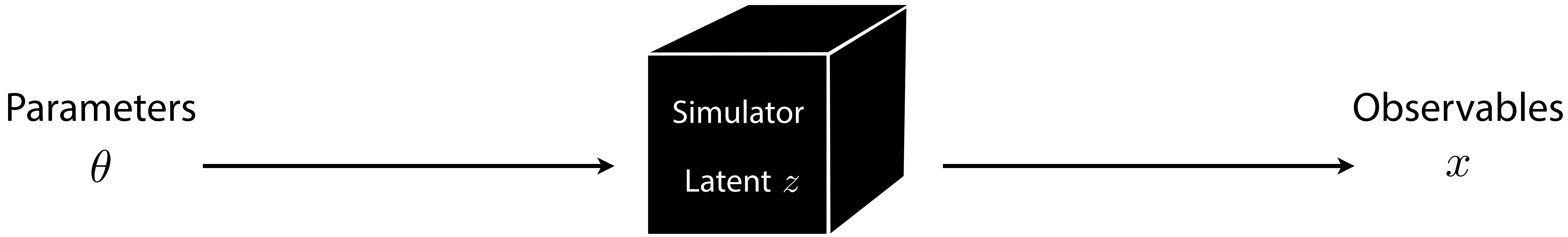
Galton board device $\longrightarrow$ Computer simulation

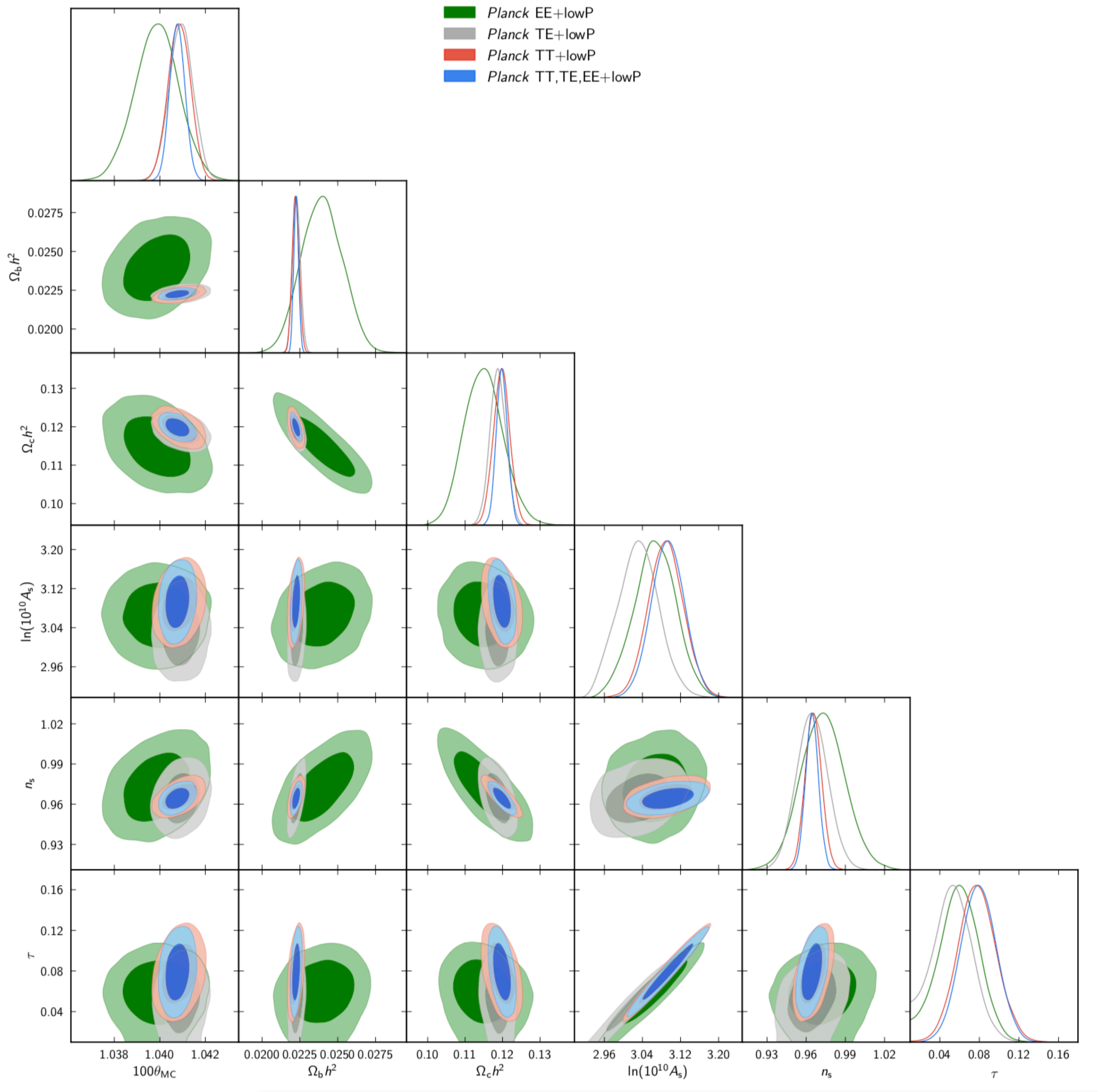
Parameters θ $\longrightarrow$ Model parameters θ

Bins x $\longrightarrow$ Observables x

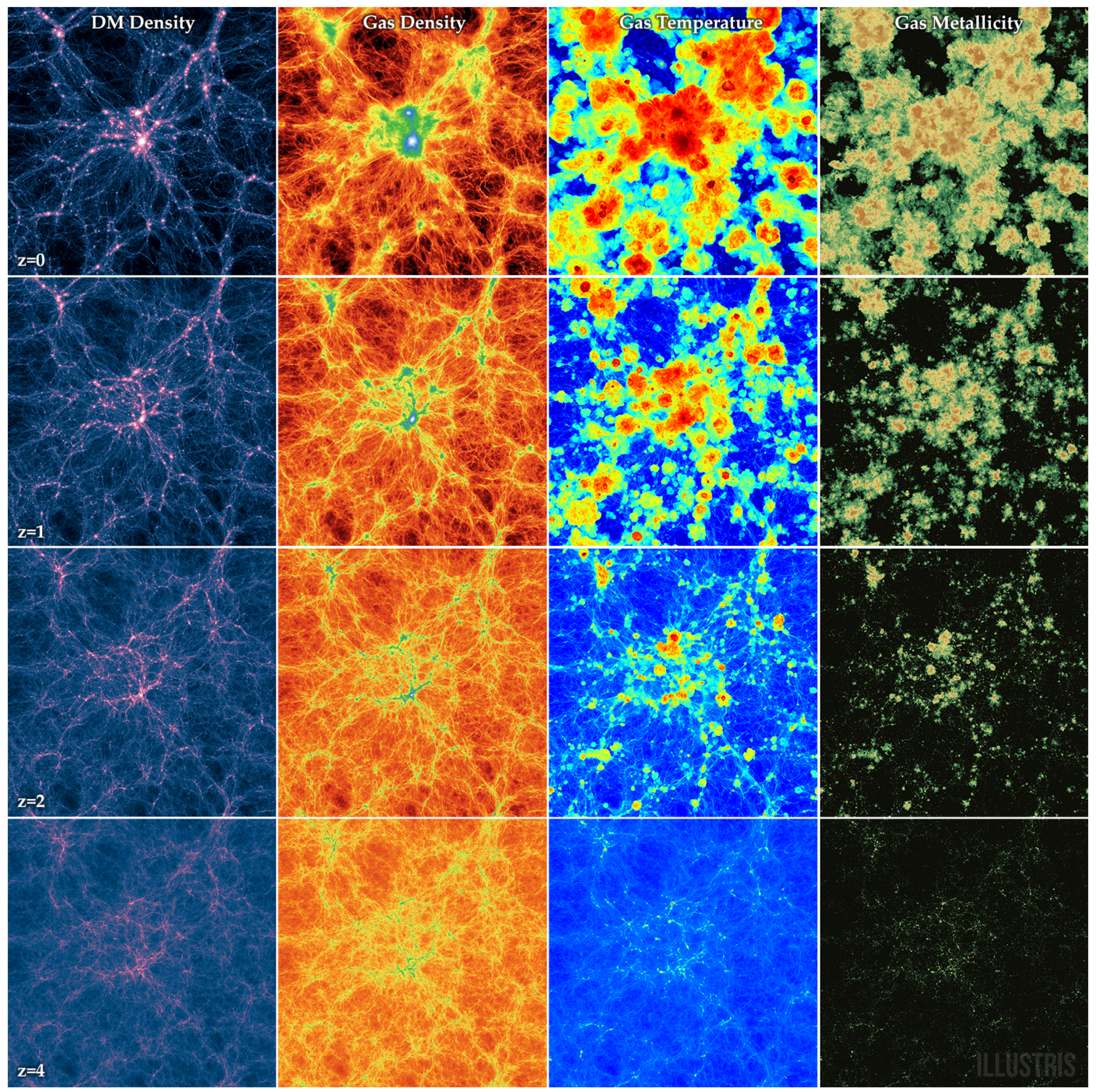
Path z $\longrightarrow$ Latent variables z
(stochastic execution trace through simulator)

Cosmological N-body simulations

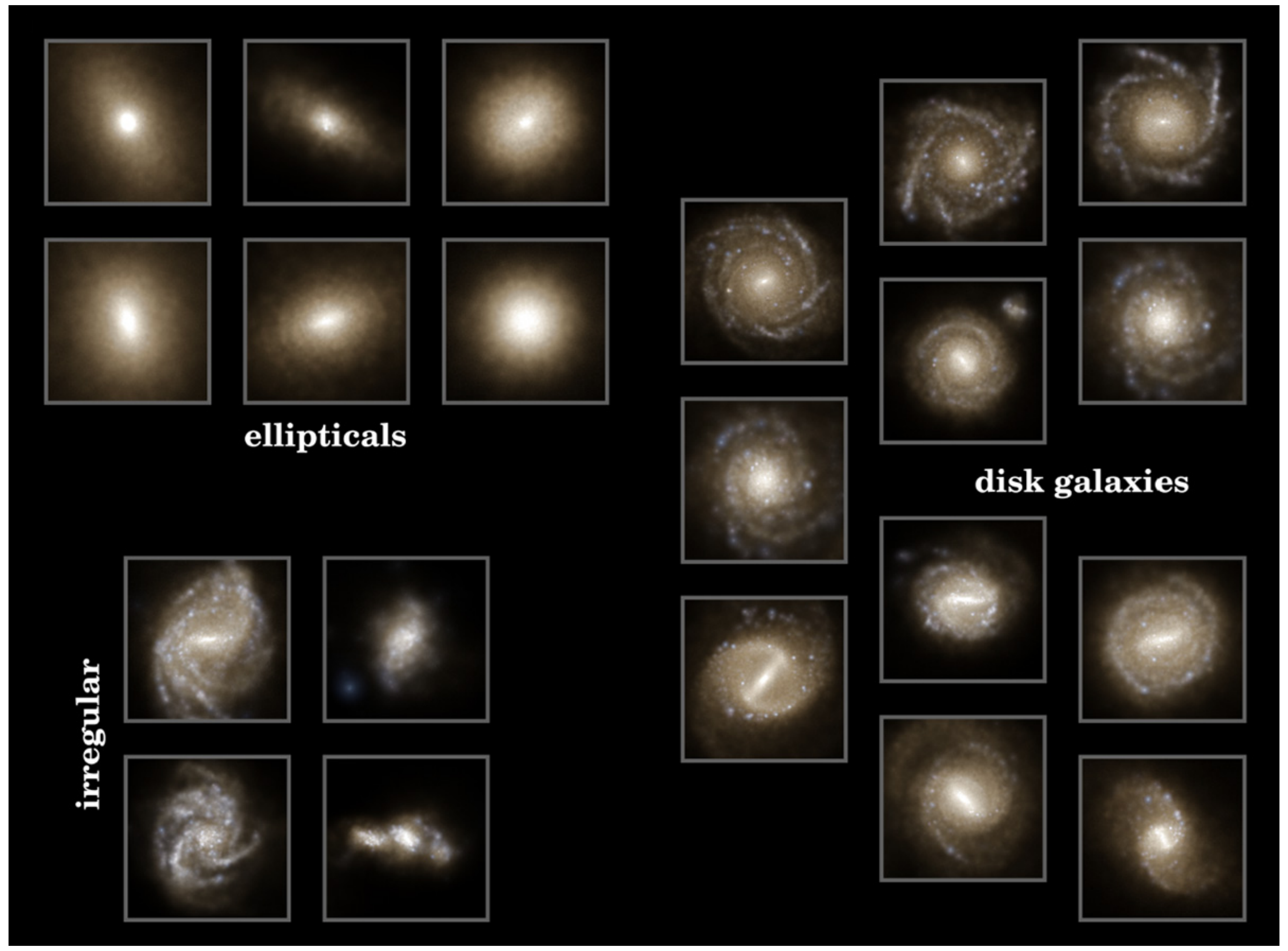




[Planck 1502.01589]



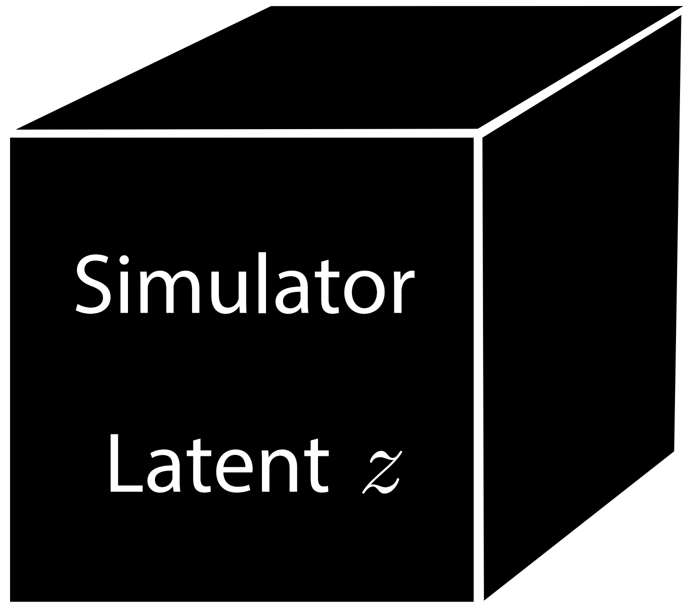
[Illustris 1405.2921]



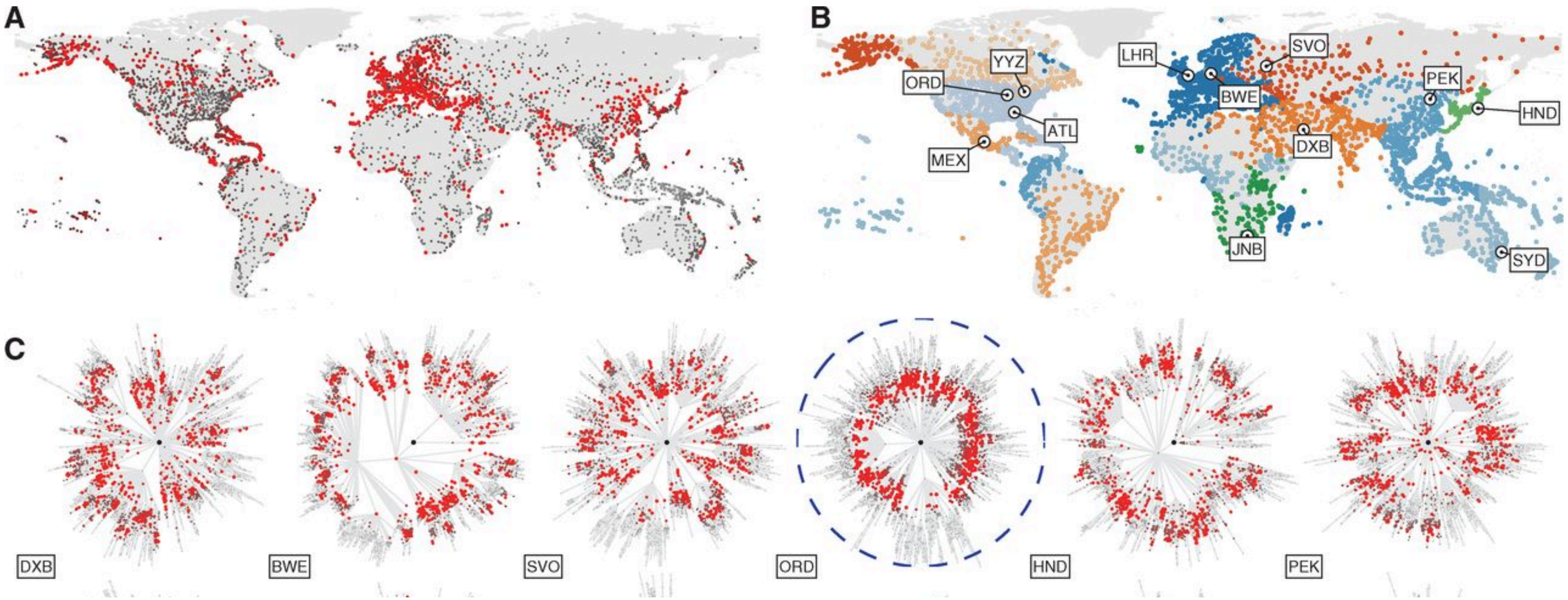
[Illustris 1405.2921]

Epidemiology

Parameters
θ



Observables
x



[D. Brockmann, D. Helbing 2013]

Particle physics

Theory
parameters
θ

Evolution

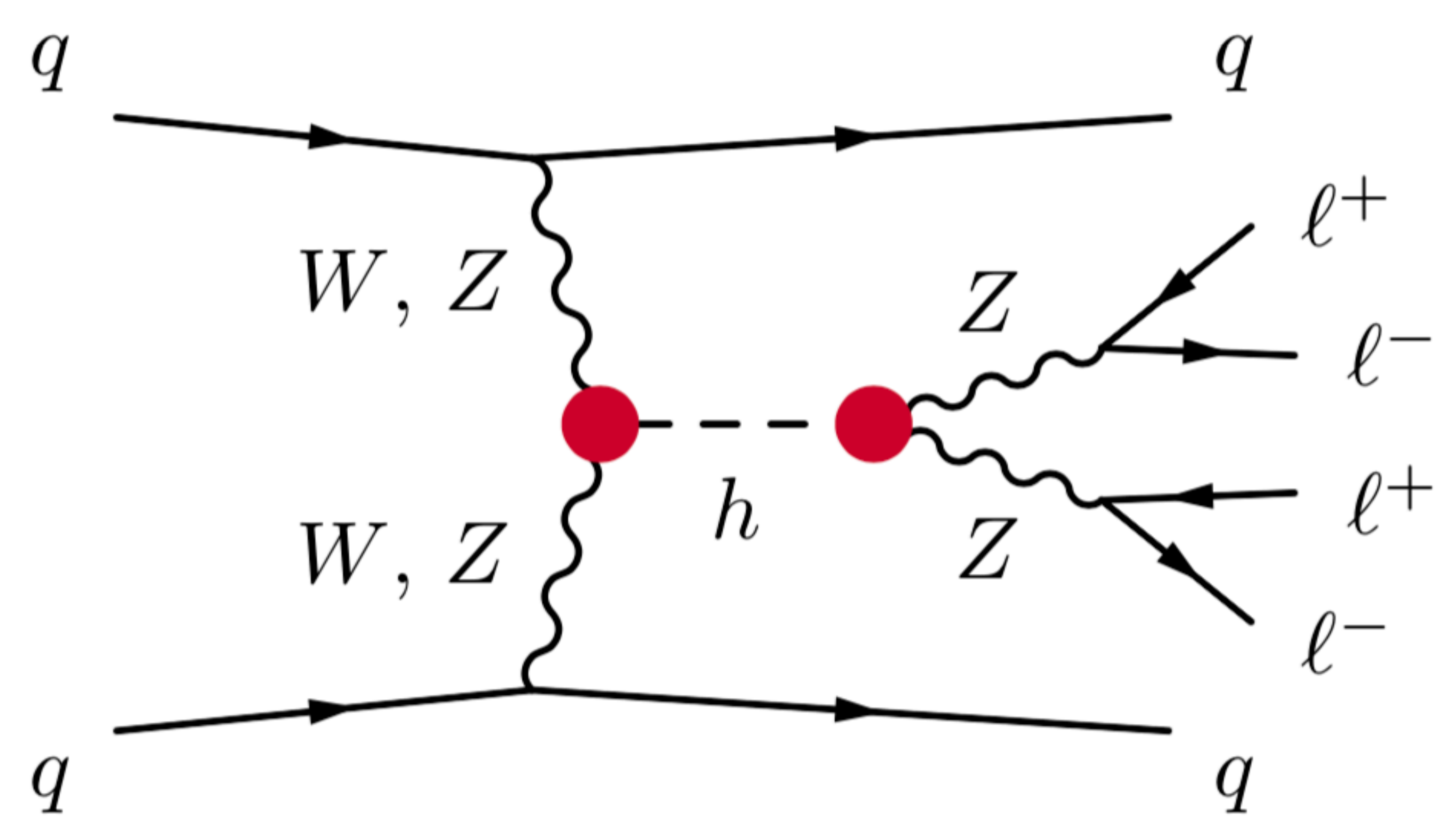
Particle physics

Latent variables

Parton-level momenta

Theory parameters

$z_p \longleftarrow \theta$



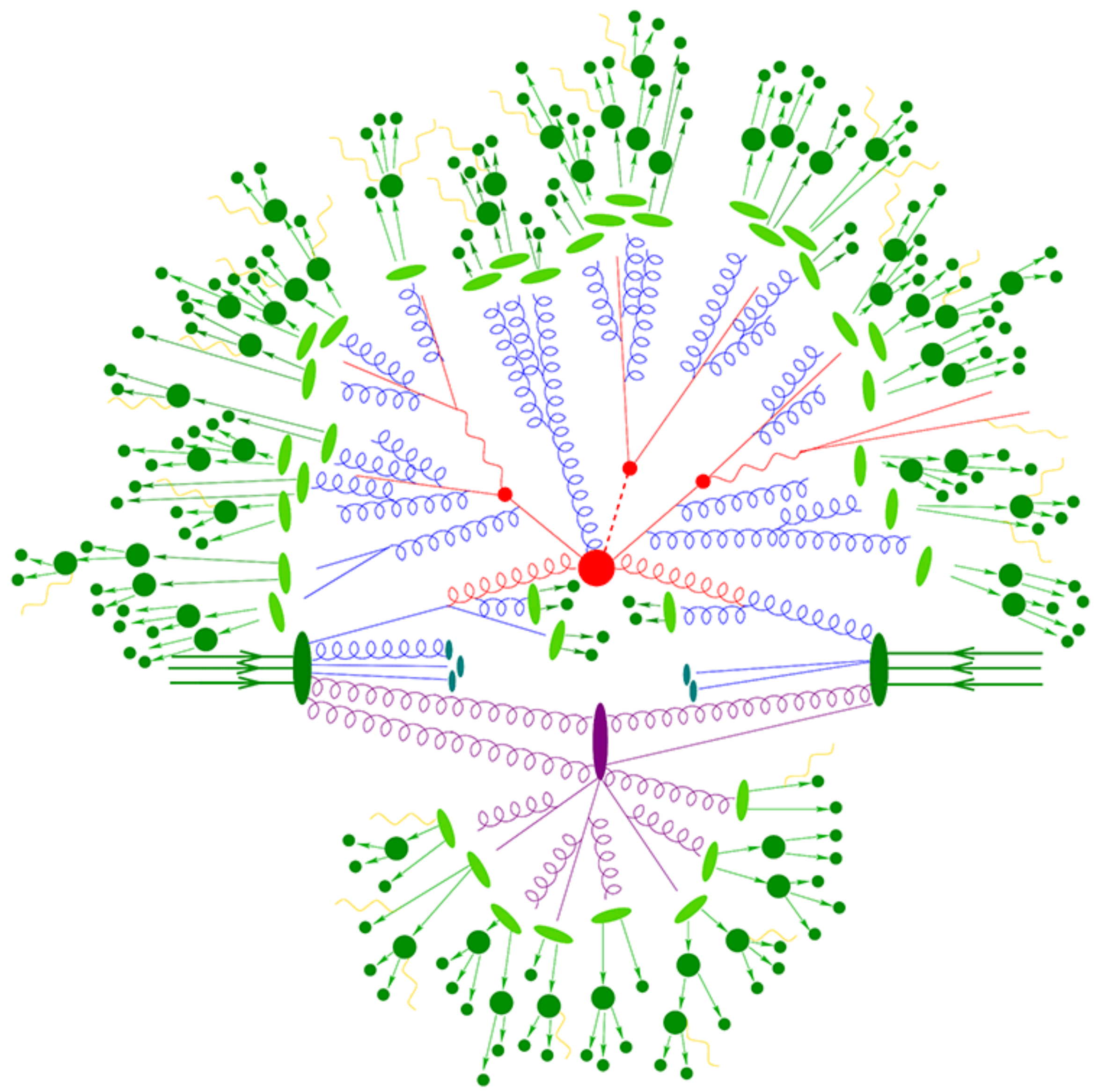
Evolution

Particle physics

Latent variables

Shower splittings	Parton-level momenta	Theory parameters
z_s	z_p	θ

$$z_s \leftarrow z_p \leftarrow \theta$$



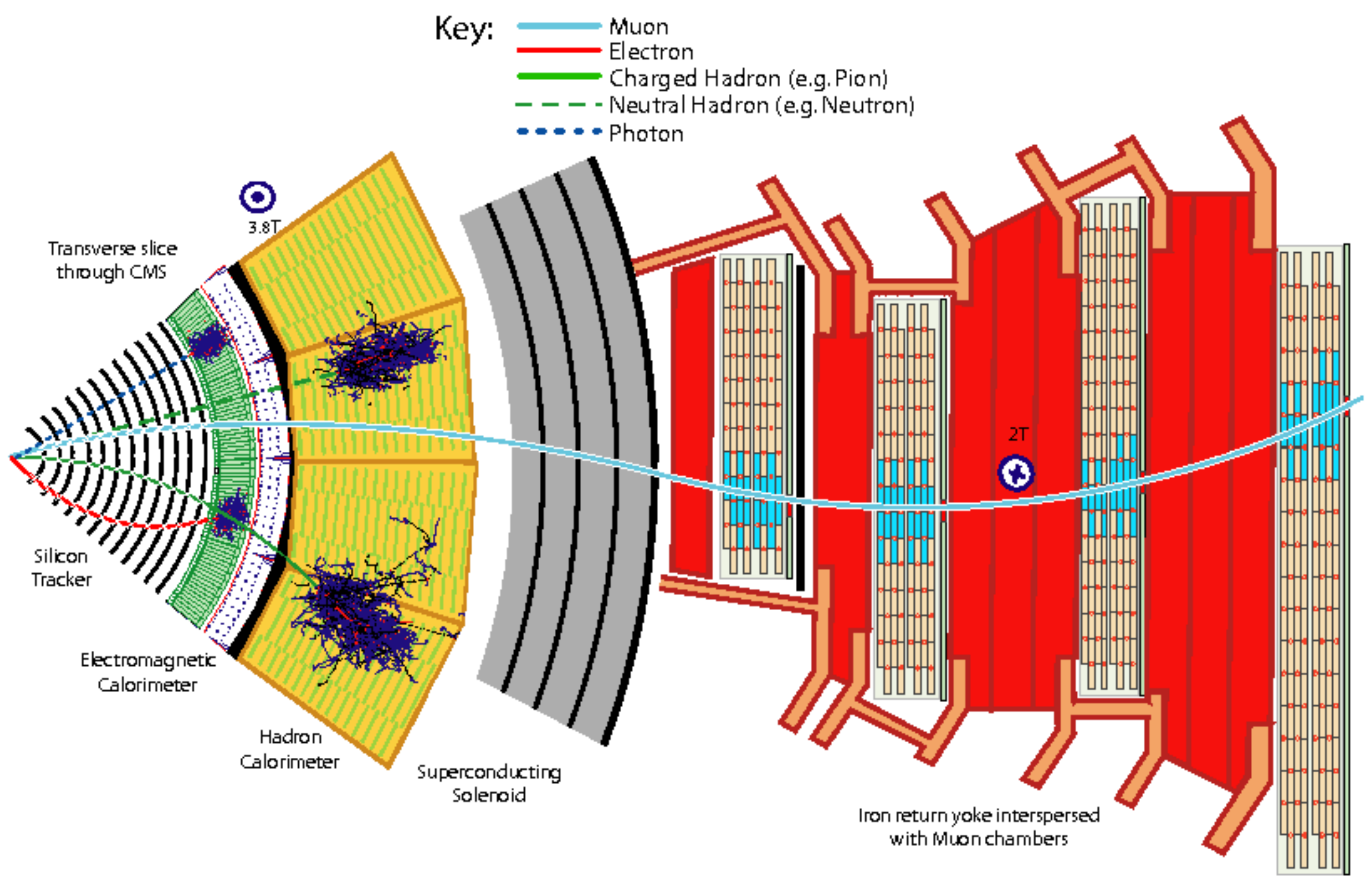
[F. Krauss]

Evolution

Particle physics

Latent variables

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



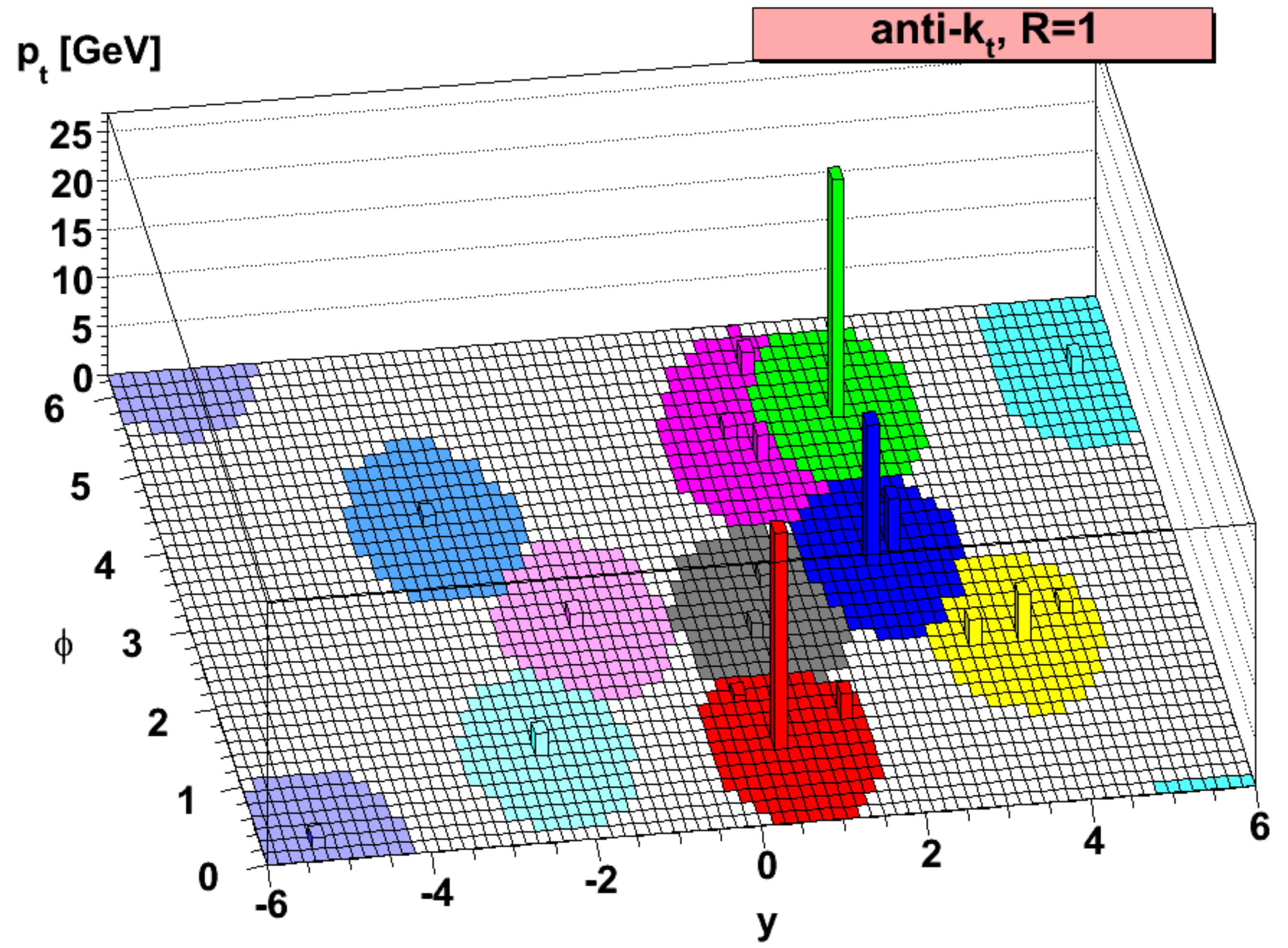
[CMS]

Evolution

Particle physics

Latent variables

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



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

$\longleftarrow$ Evolution

Particle physics

Latent variables

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

Particle physics

Latent variables

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

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

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

Inference $\longrightarrow$

Particle physics

Latent variables

Observables — Detector interactions — Shower splittings — Parton-level momenta — Theory parameters

$$x \leftarrow z_d \leftarrow z_s \leftarrow z_p \leftarrow \theta$$

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

Infeasible to calculate the integral over this enormous space!

Inference →

Why has that not stopped us so far?

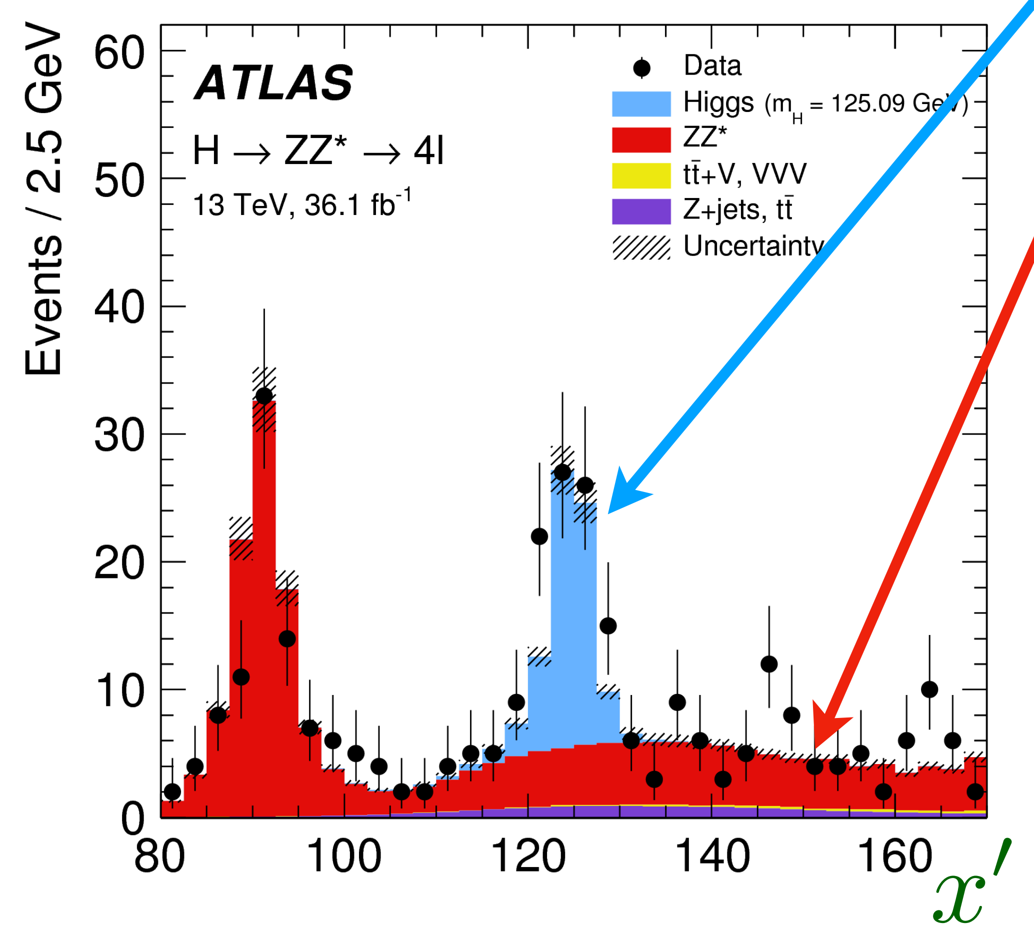
Solve it by histogramming summary statistics

- Most physicists' solution:

Solve it by histogramming summary statistics

- Most physicists' solution:

$$\hat{p}(x|\theta) = p(x'|\theta) =$$

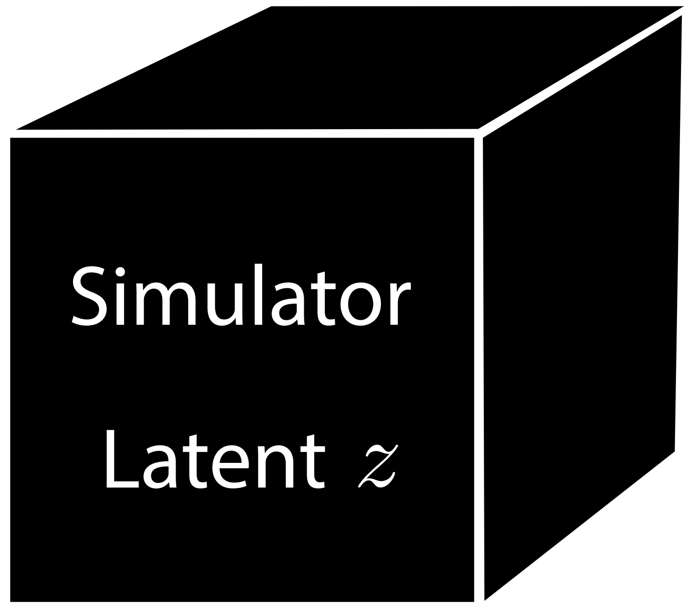


[ATLAS 1712.02304]

Run simulator for different θ, fill histograms

Solve it by histogramming summary statistics

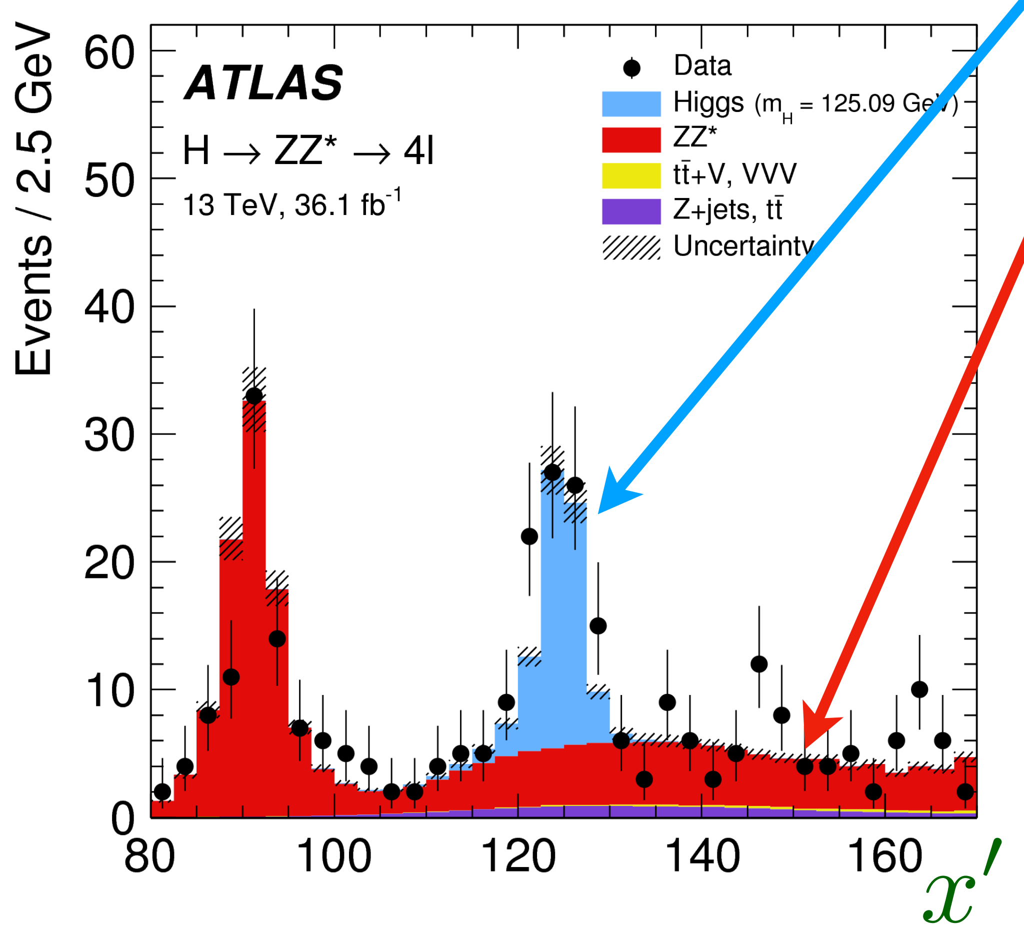
- Most physicists' solution:

Parameters θ → 

→ Observables x → Summary statistics x'

Run simulator for different θ, fill histograms

$$\hat{p}(x|\theta) = p(x'|\theta) =$$



[ATLAS 1712.02304]

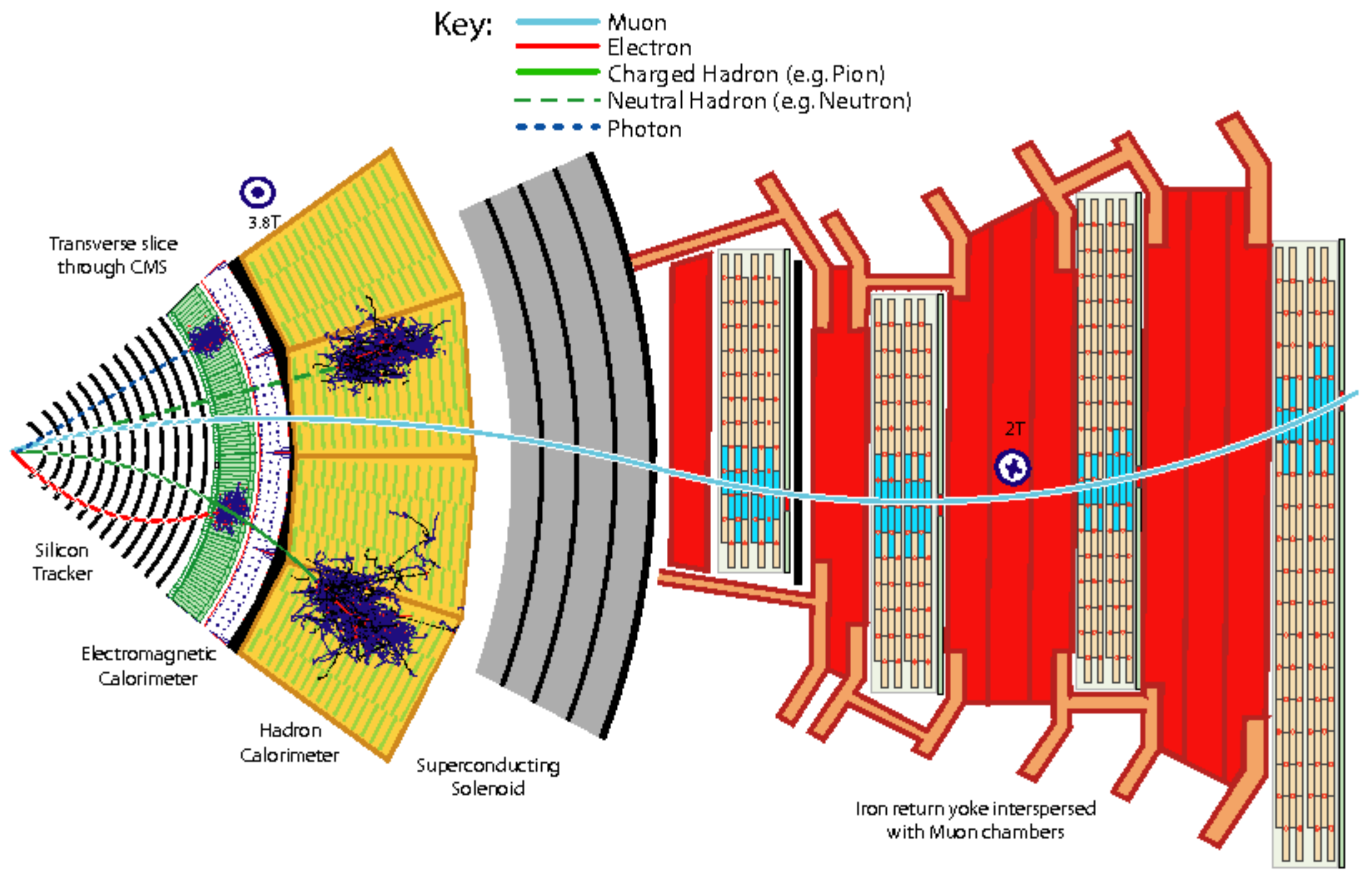
- How to choose x' ? Standard variables often lose information
  [JB, K. Cranmer, F. Kling, T. Plehn 1612.05261; JB, F. Kling, T. Plehn, T. Tait 1712.02350]

- "Curse of dimensionality": Histograms don't scale to high-dimensional x

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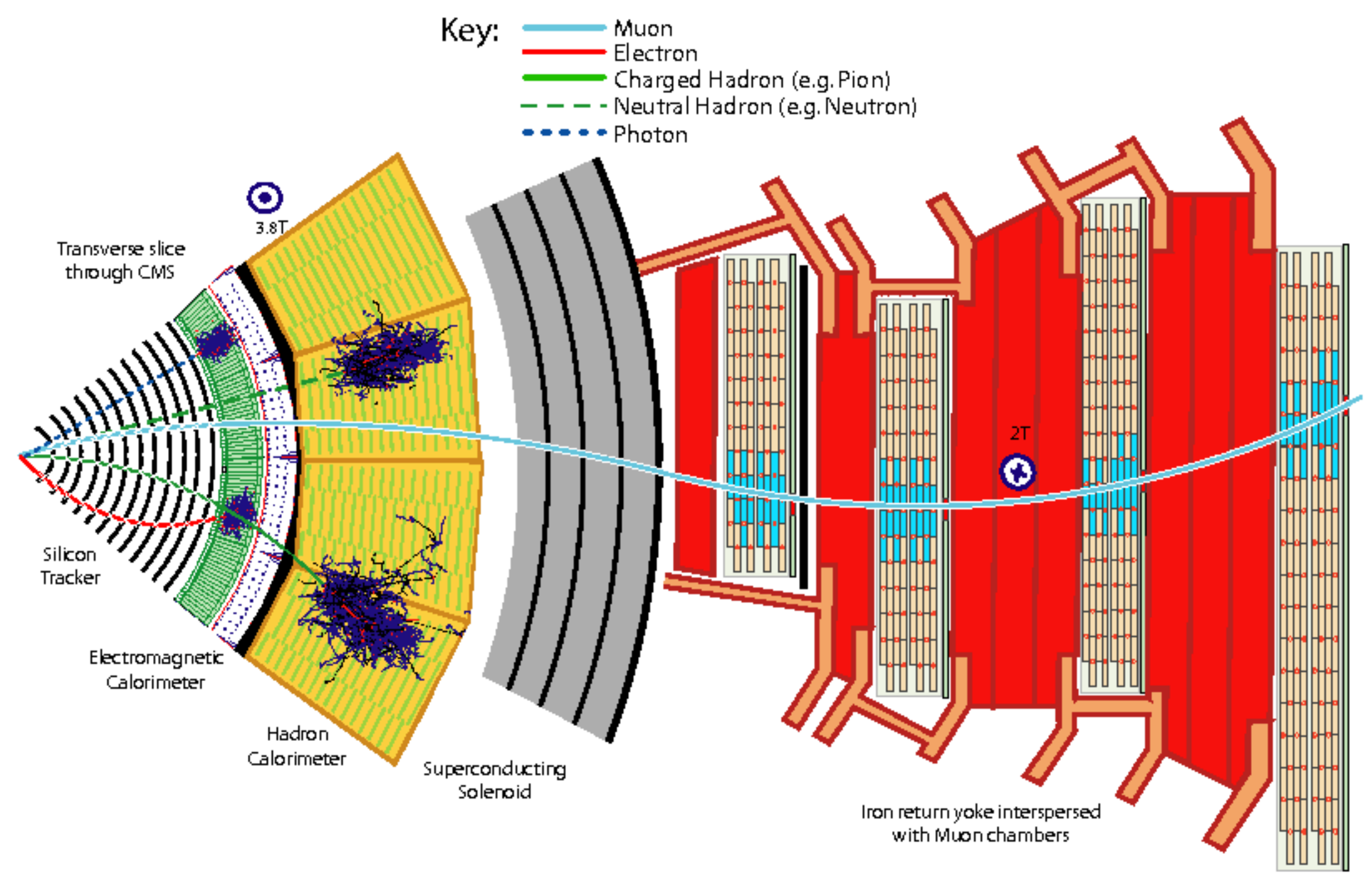
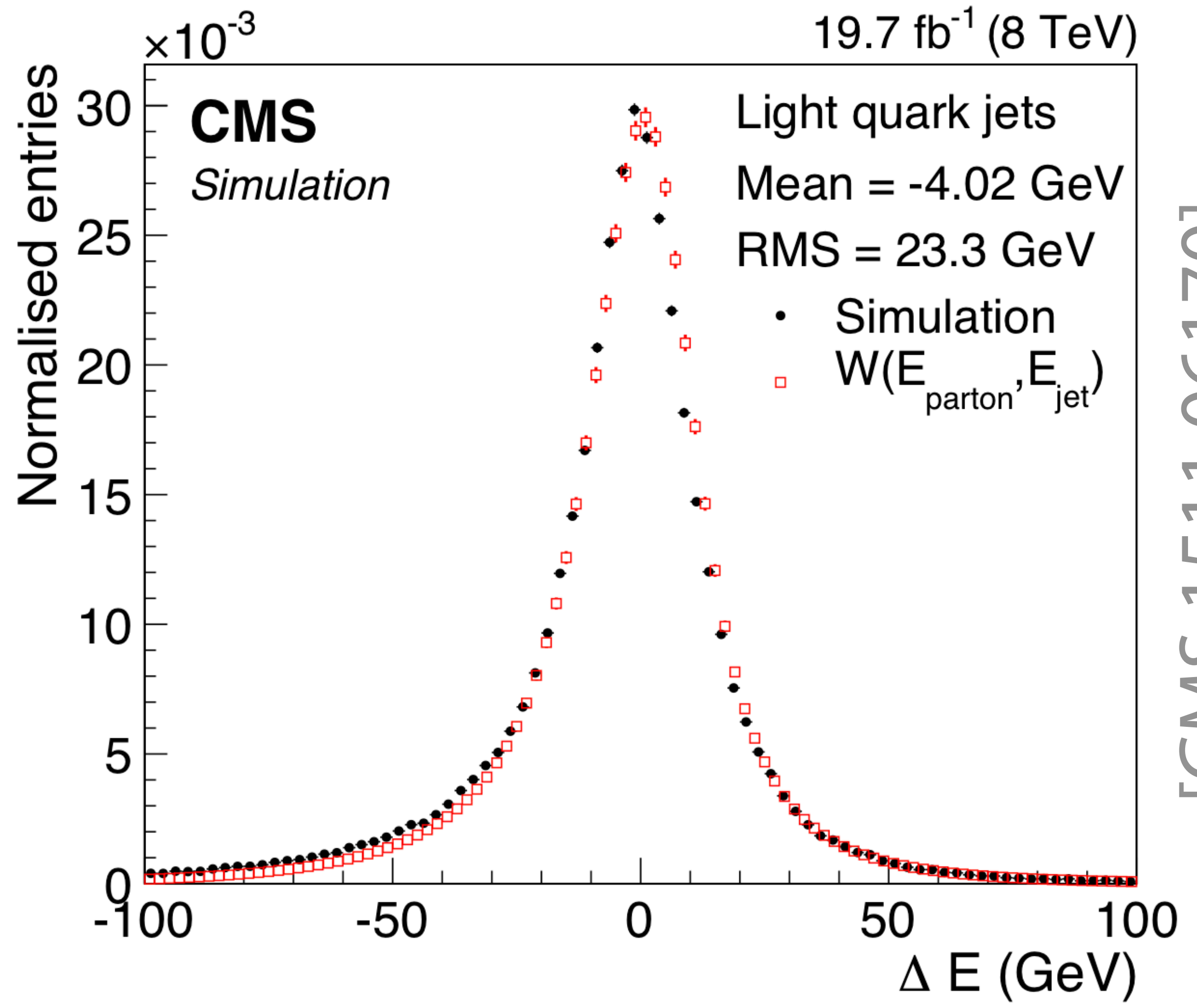
- Matrix Element Method: [K. Kondo 1988]
  - approximate shower + detector effects into transfer function $\hat{p}(x|z_p)$
  - explicitly calculate remaining integral

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

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



[CMS]



[CMS 1511.06170]

Solve it by approximating the integral

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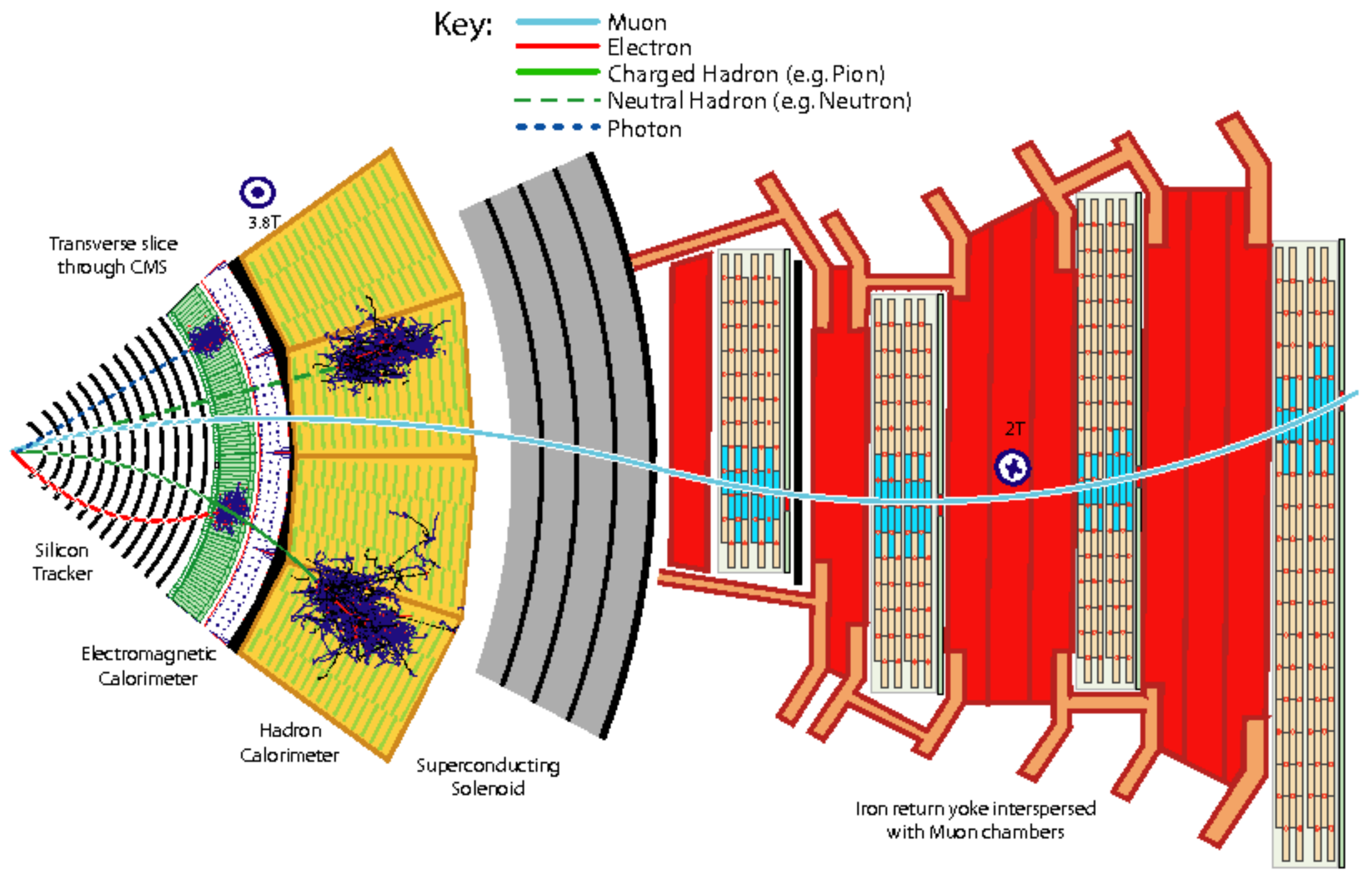

[CMS]

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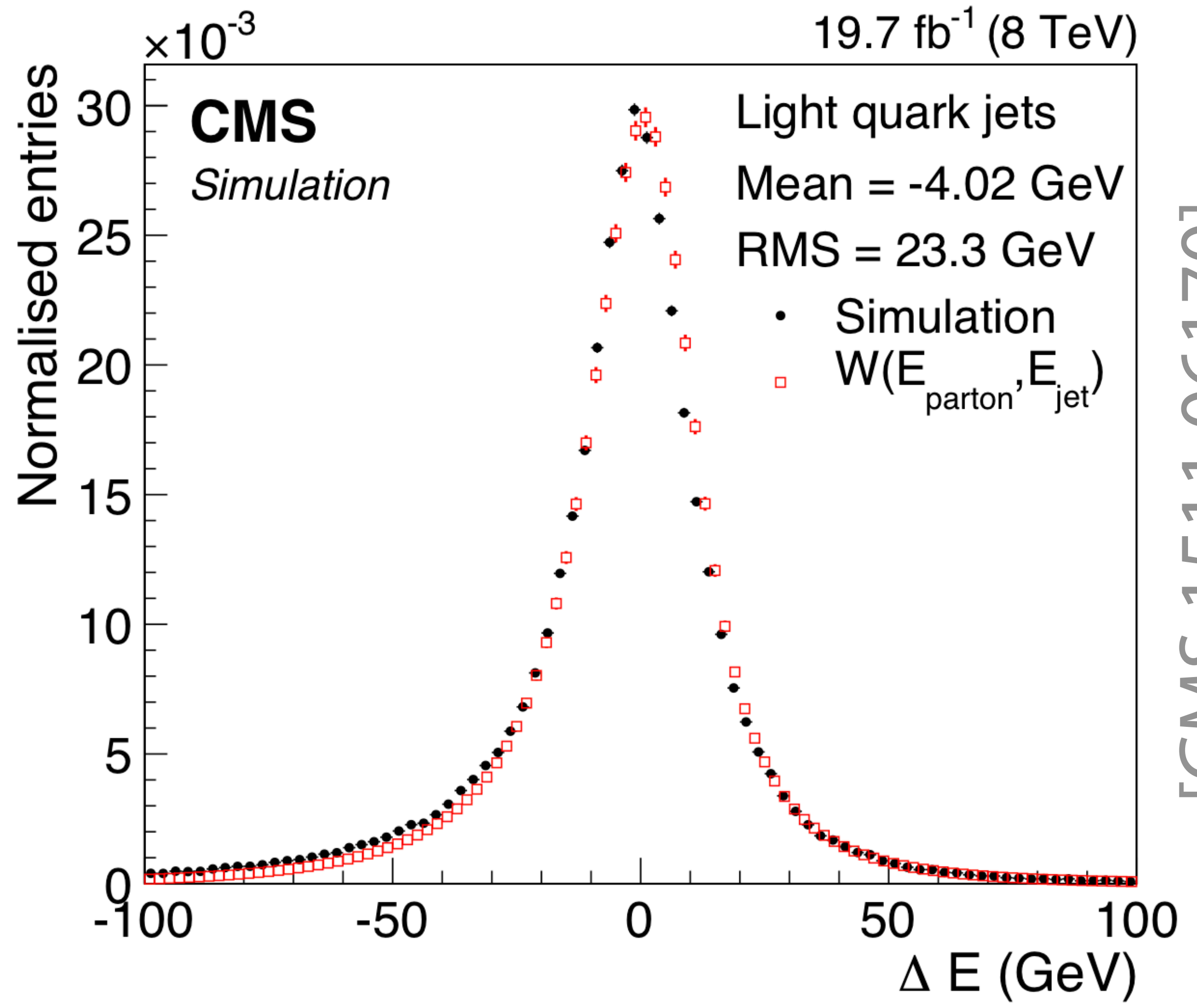


[CMS 1511.06170]

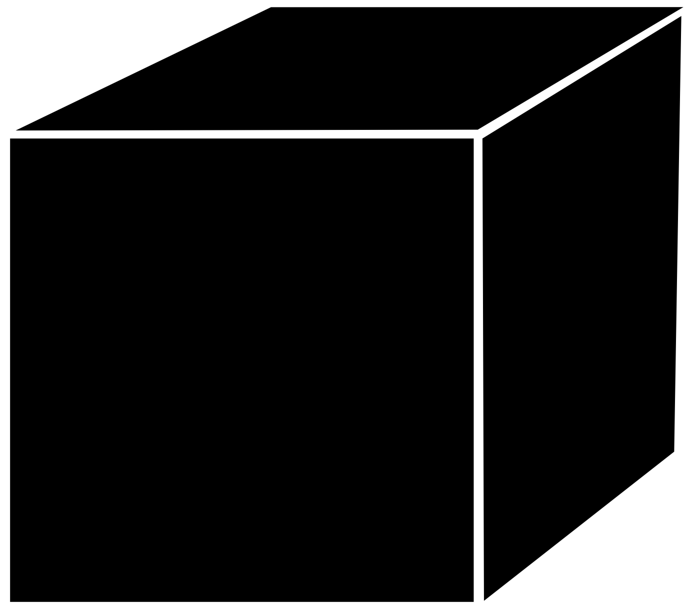
- Uses matrix-element information, no summary statistics necessary, but:
  - ad-hoc transfer functions
  - evaluation still requires calculating an expensive integral

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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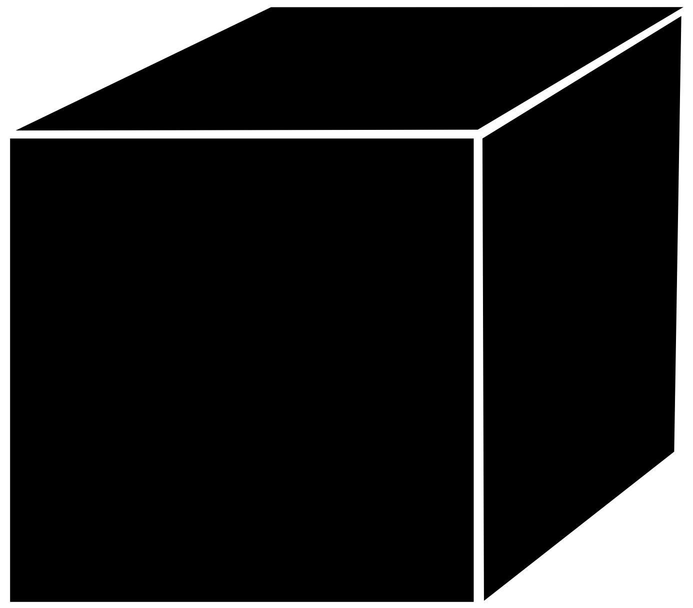

Use latent structure:

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

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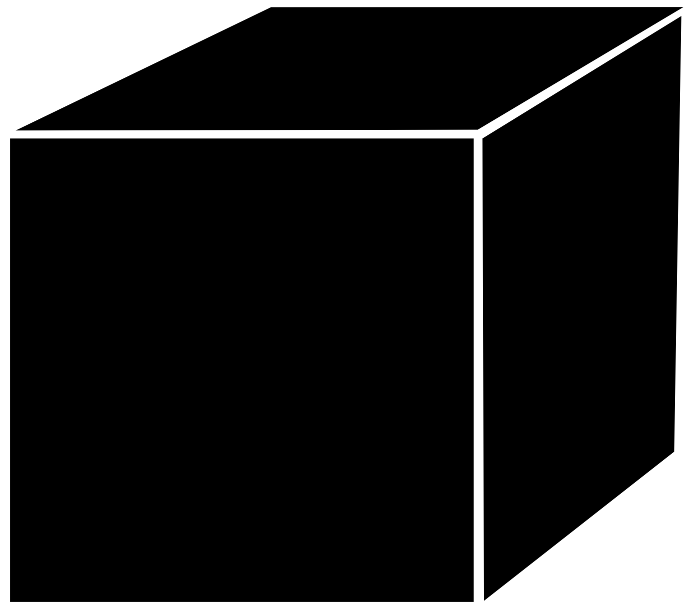

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  Neglect or approximate shower + detector, explicitly calculate z integral

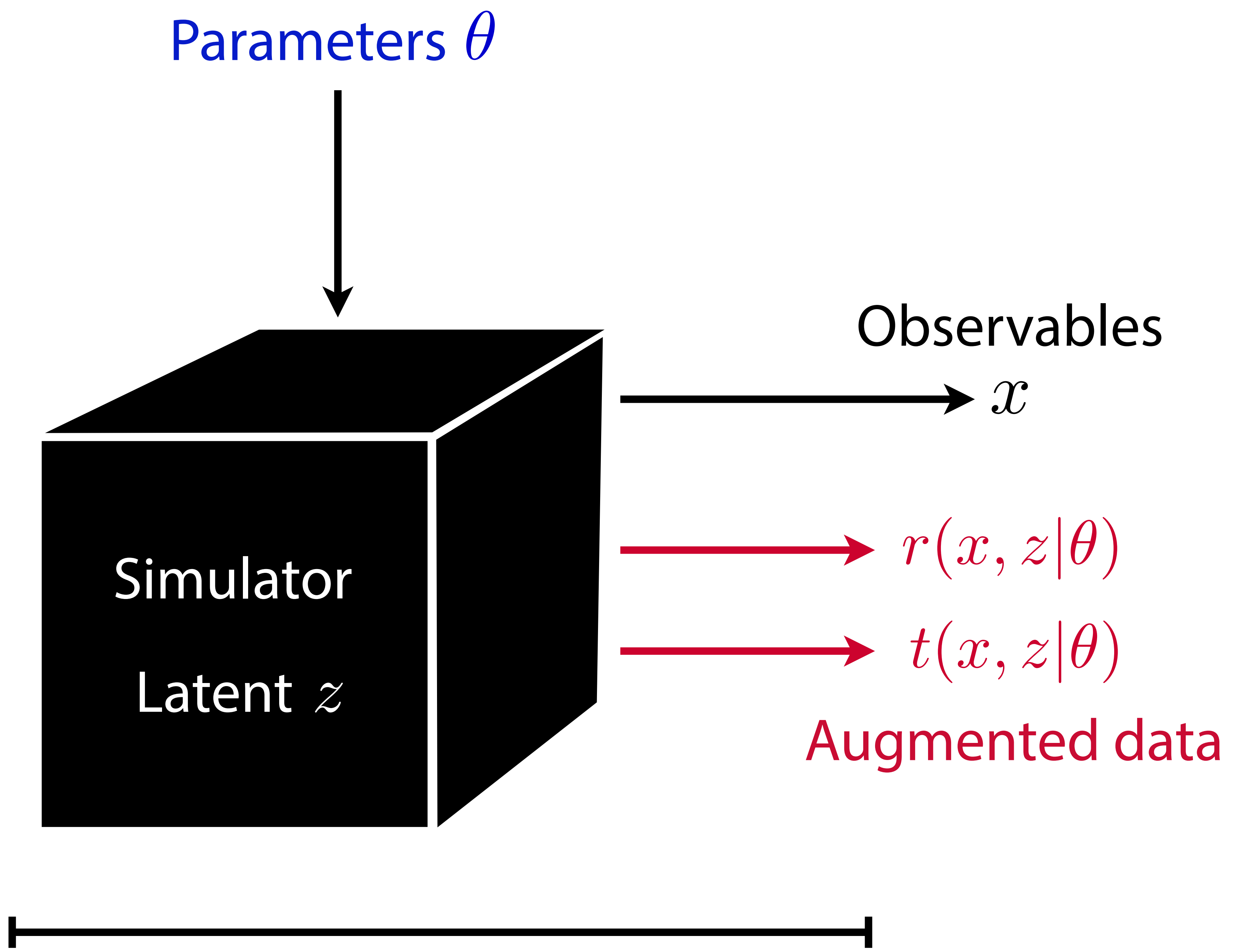
New!

- 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;
with M. Stoye 1808.00973; with F. Kling in progress]

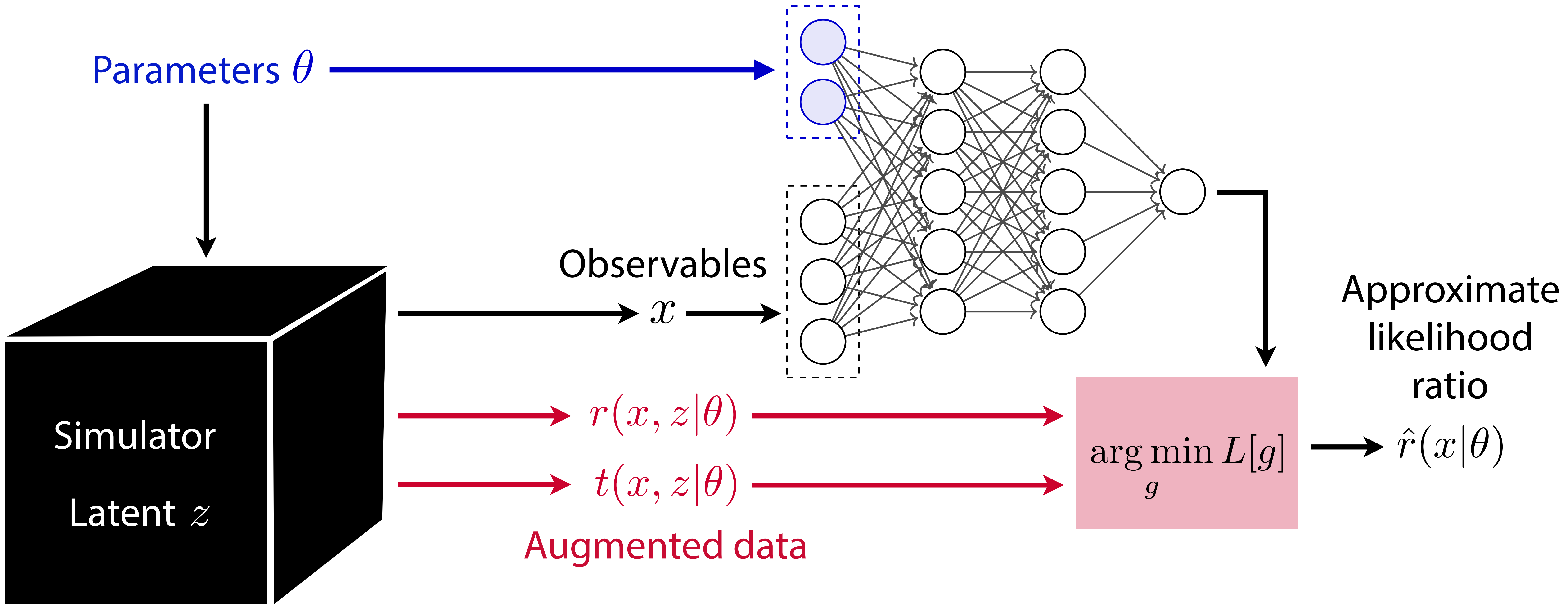
Bird’s-eye view



1. Simulation

“Mining gold”: Extract additional information from simulator

Bird's-eye view



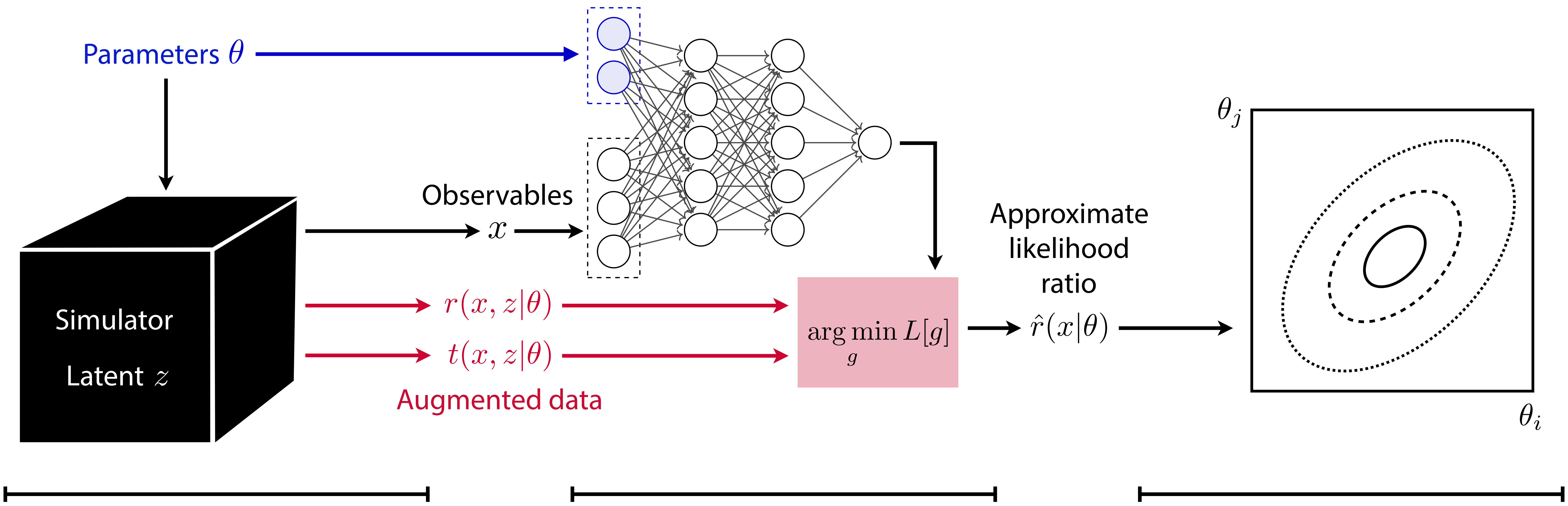
1. Simulation

"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

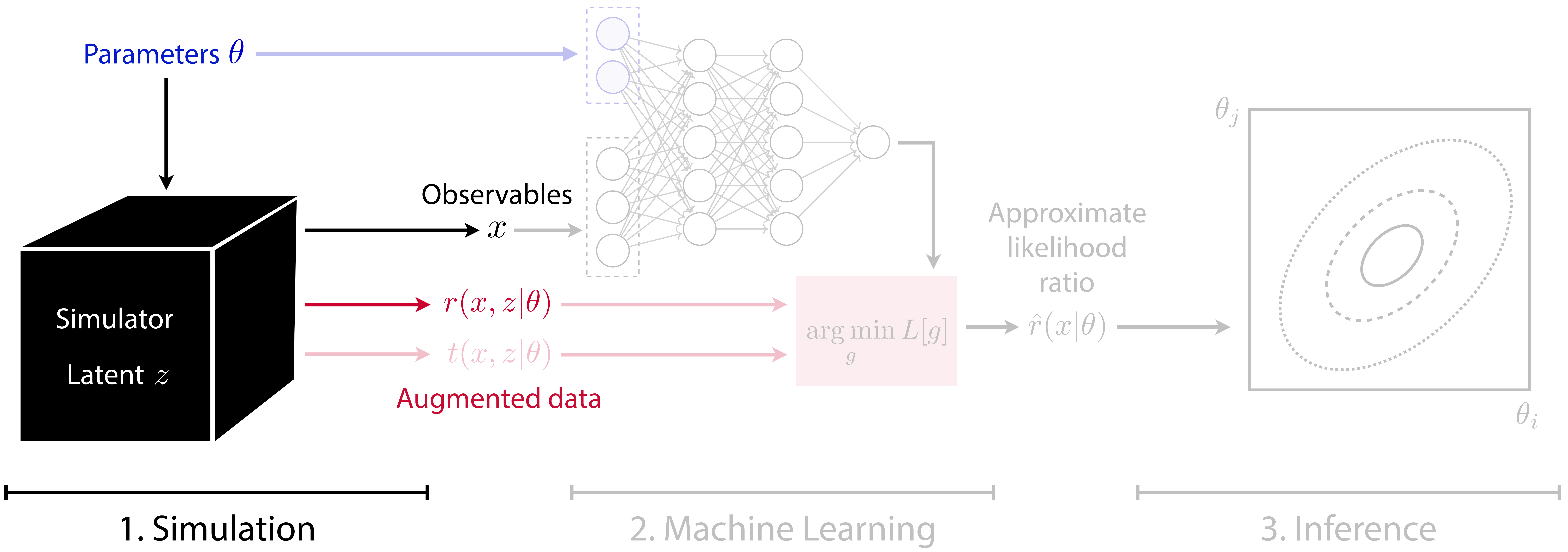
“Mining gold”: Extract additional information from simulator

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	←	z_d ←	z_s ←	z_p ←	θ

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

Intractable integrals

Mining gold from the simulator

Latent variables

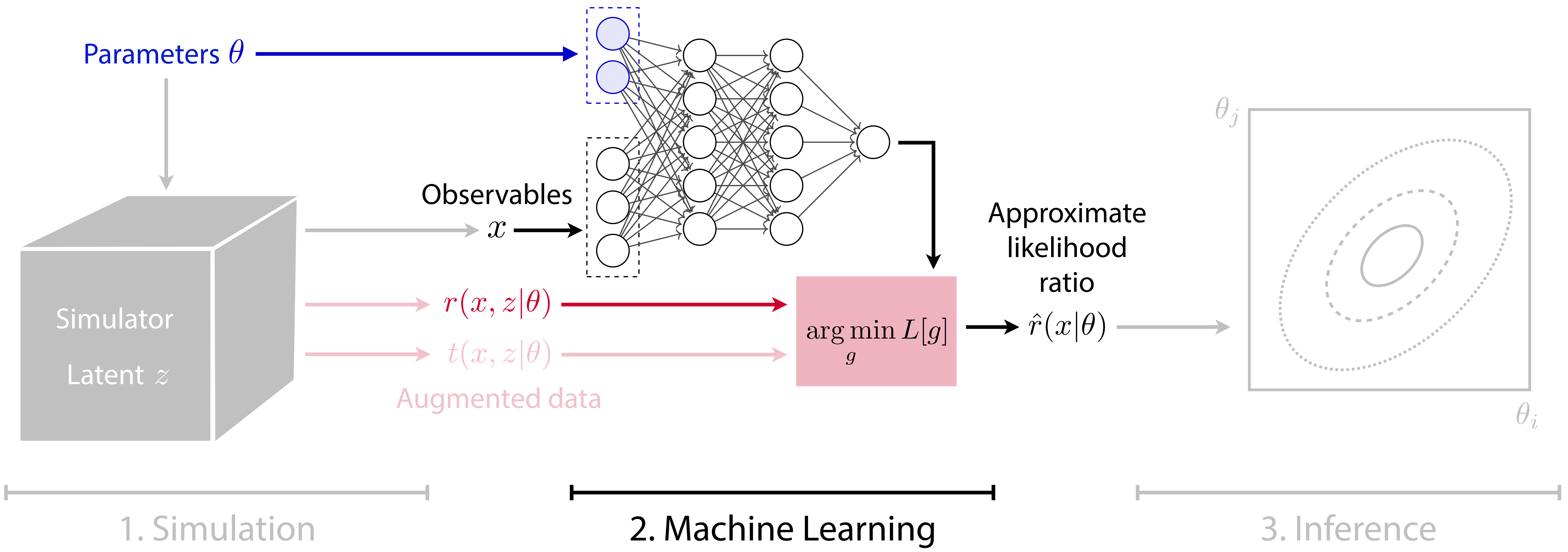
Observables		Detector interactions		Shower splittings		Parton-level momenta		Theory parameters
x	←	z_d	←	z_s	←	z_p	←	θ

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

Parton-level likelihood can be evaluated!

⇒ For each generated event, we can calculate the joint likelihood ratio conditional on its specific evolution:

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


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

The value of gold

We can calculate the joint likelihood ratio

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

↓

We want the likelihood ratio function

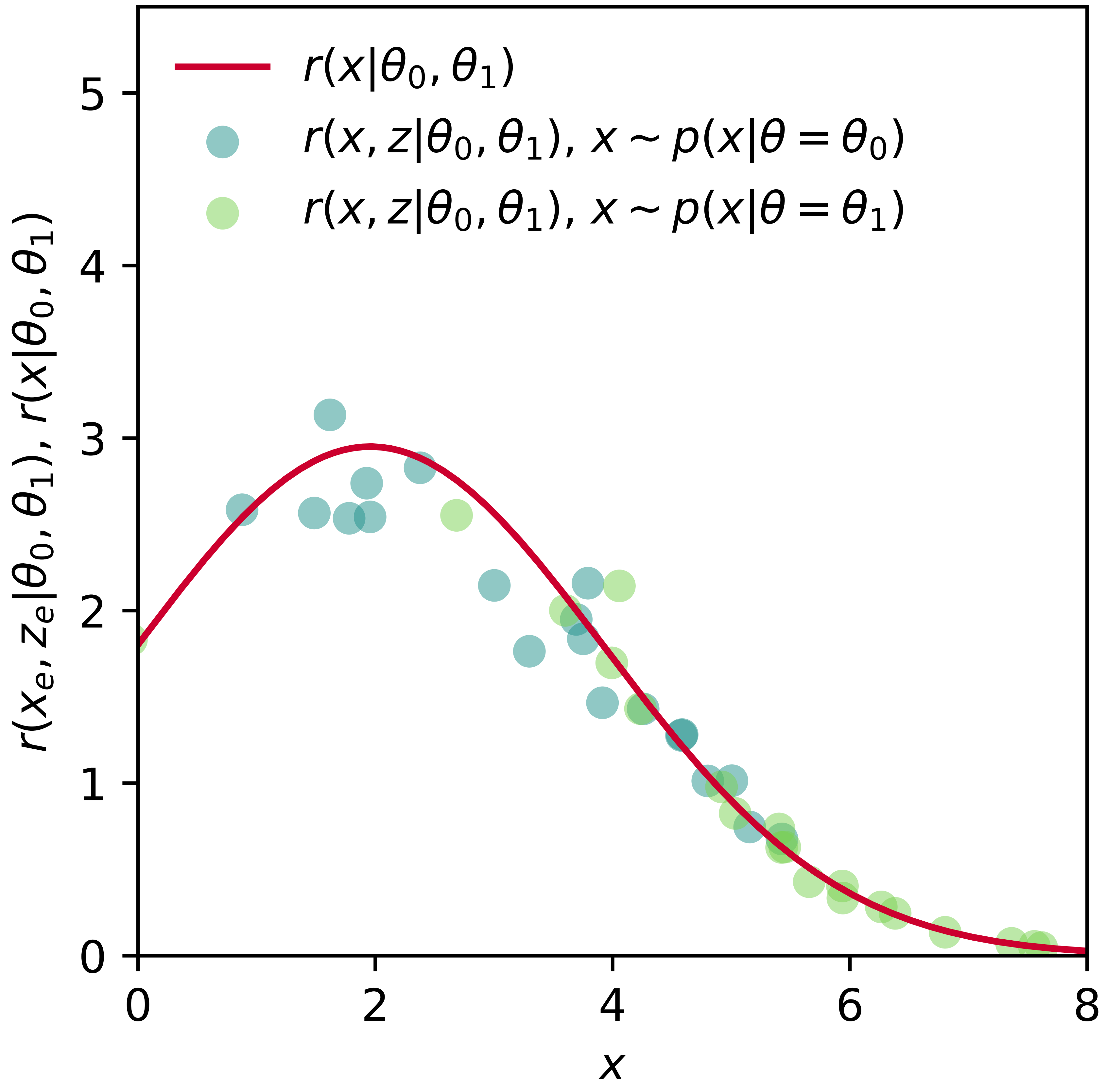
$$r(x|\theta_0, \theta_1) \equiv \frac{p(x|\theta_0)}{p(x|\theta_1)}$$

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 $r(x|\theta_0, \theta_1)$



We want the likelihood ratio function

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One can show it is minimized by

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

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

We can get a precise estimator of the likelihood ratio by numerically mimimizing a functional:

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

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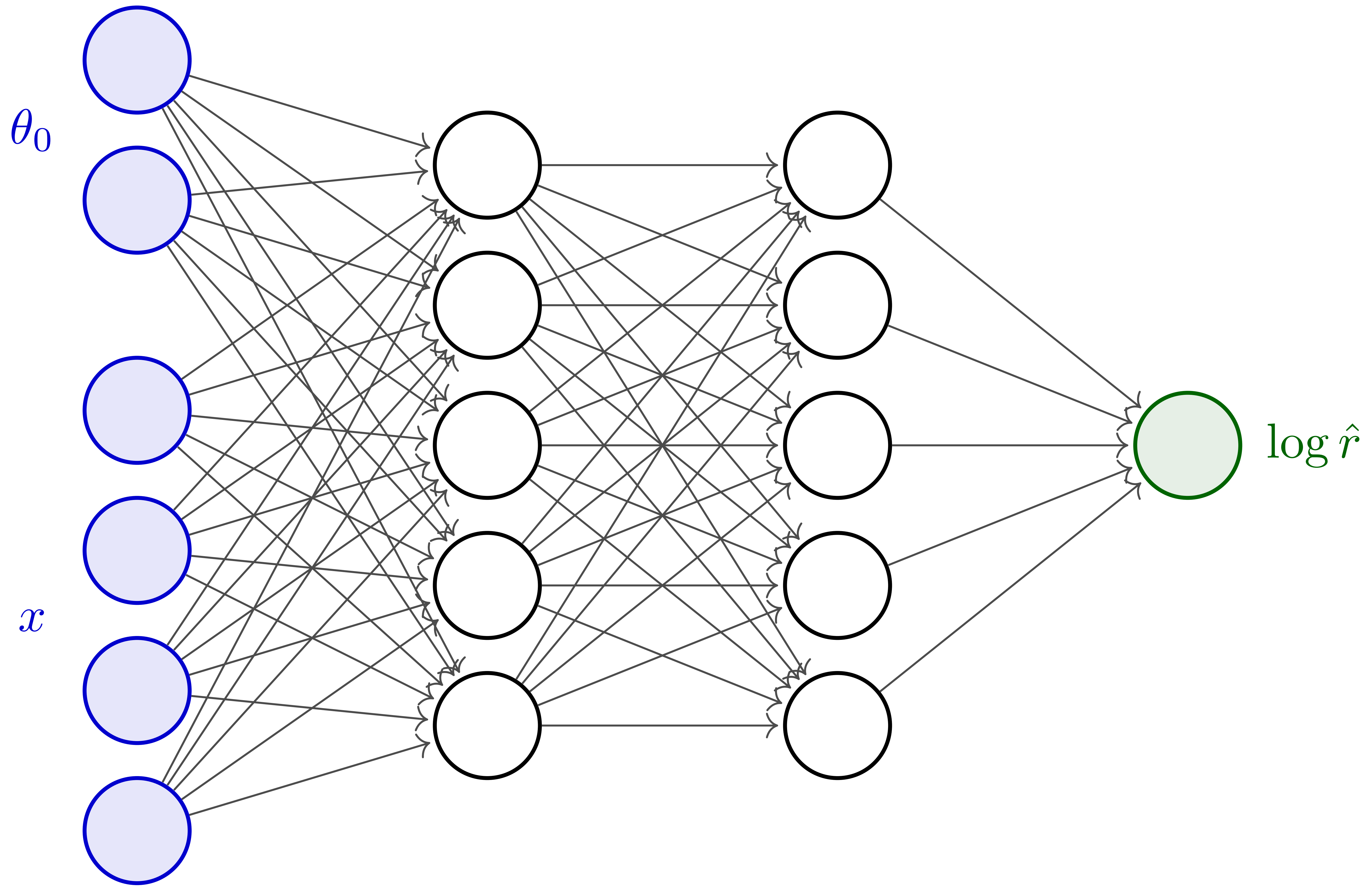
We do this through machine learning:

- Functional L_r $\longrightarrow$ Loss function

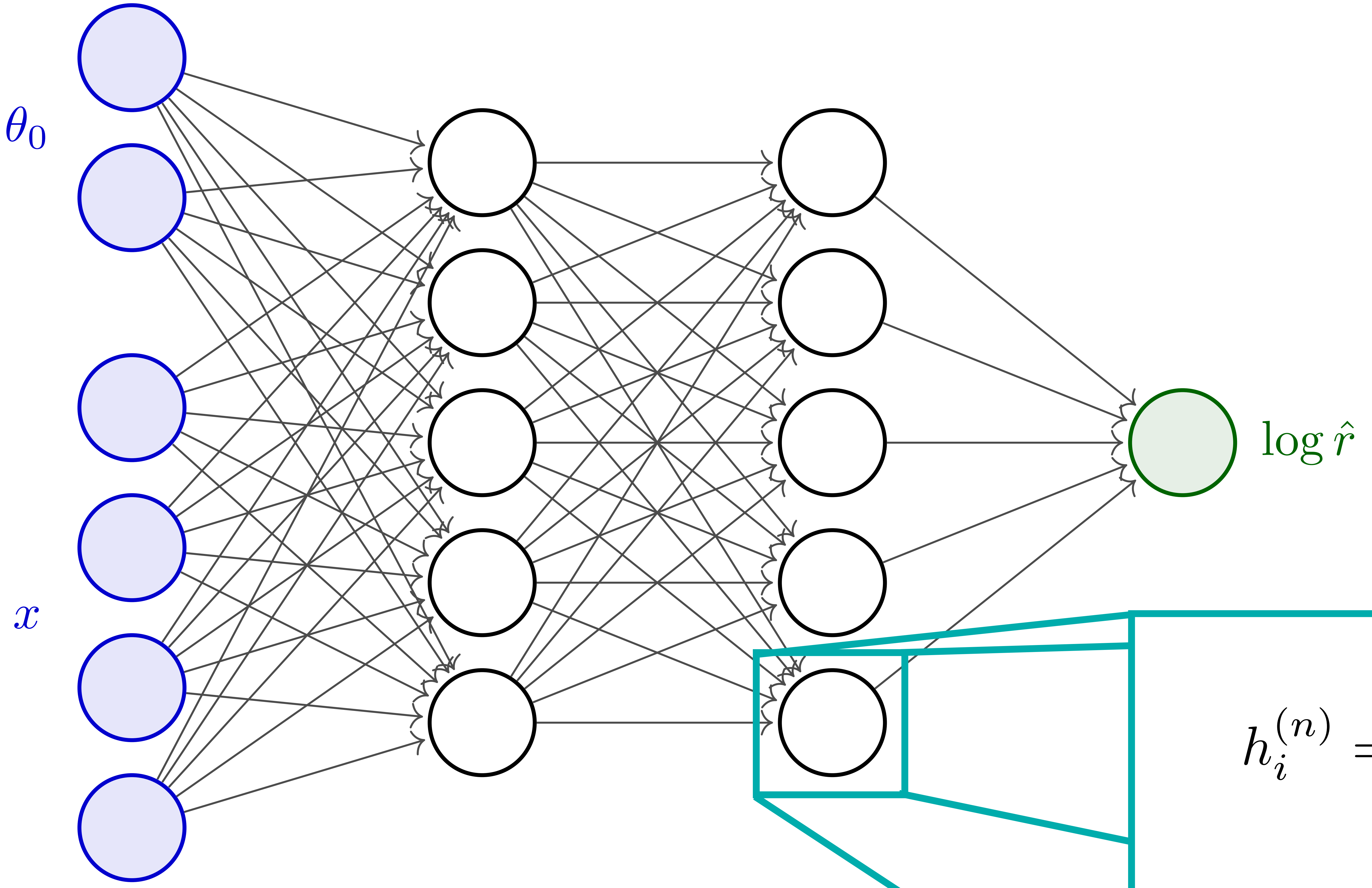
$$\hat{L}_r[\hat{r}(x|\theta_0,\theta_1)] = \frac{1}{N} \sum_{(x_i,z_i)\sim p(x,z|\theta_1)} \left[\hat{r}(x_i|\theta_0,\theta_1) - r(x_i,z_i|\theta_0,\theta_1)\right]^2$$

- Variational family $\hat{r}(x|\theta_0,\theta_1)$ $\longrightarrow$ Flexible parametric function (e.g. neural network)
- Exact minimization $\longrightarrow$ Numerical optimization algorithm (e.g. stochastic gradient descent)

Neural networks = universal function approximators

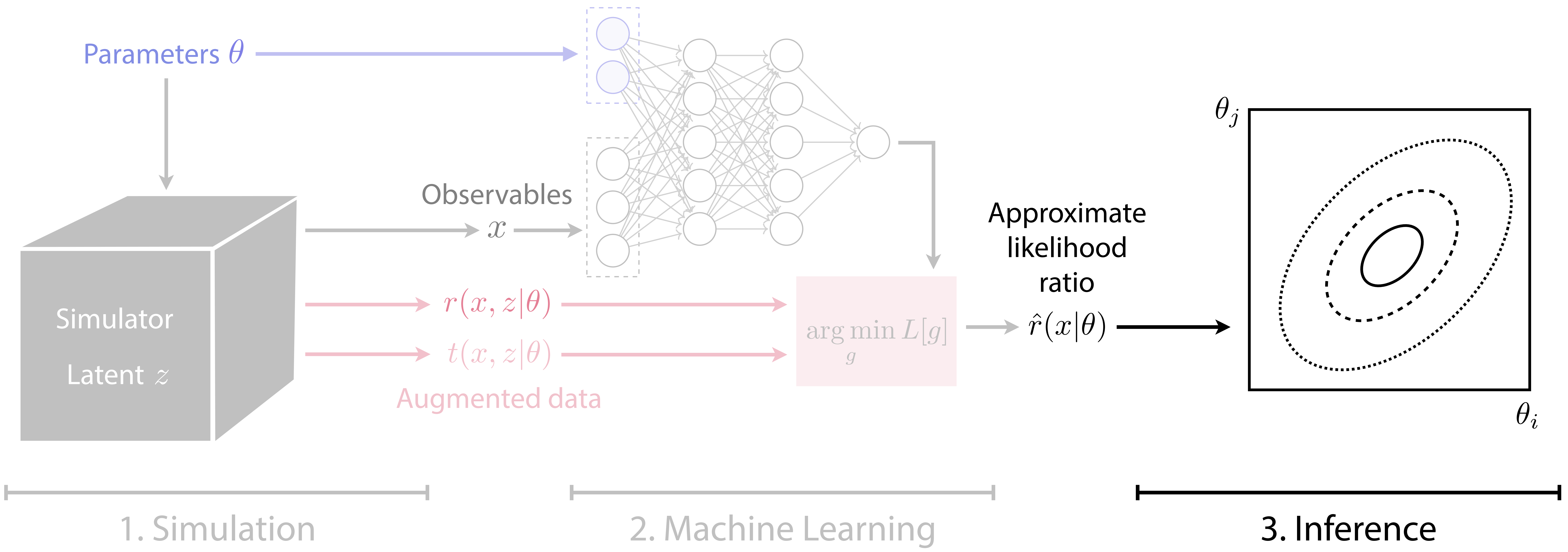


Neural networks = universal function approximators



$$h_i^{(n)} = f\left(\sum_k w_{ik}^{(n)}\, h_k^{(n-1)} + b_i^{(n)}\right)$$

where the weights $w_{ik}^{(n)}$, $b_i^{(n)}$ are parameters "trained" by the optimizer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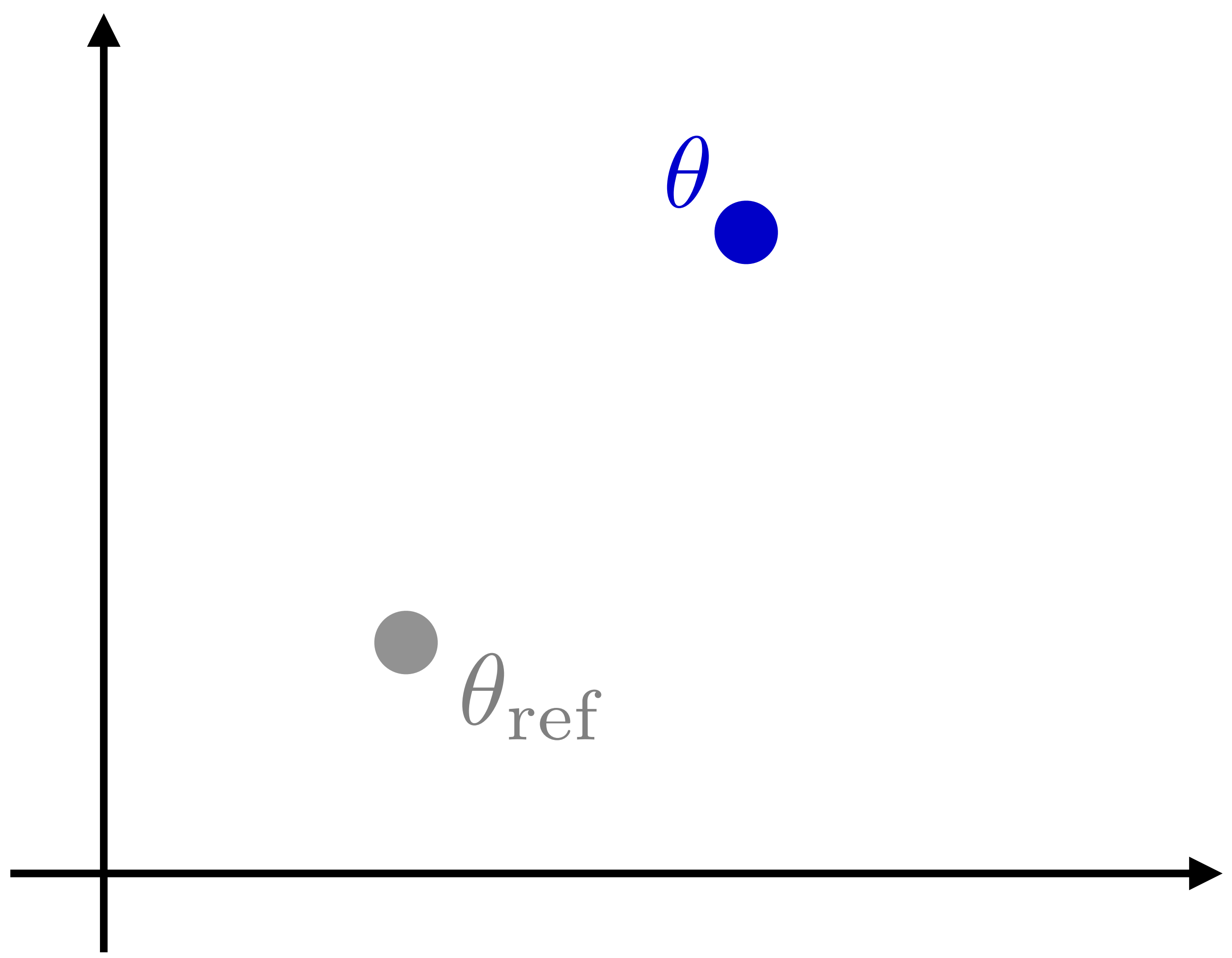
Limit setting (most LHC physicists are frequentists)

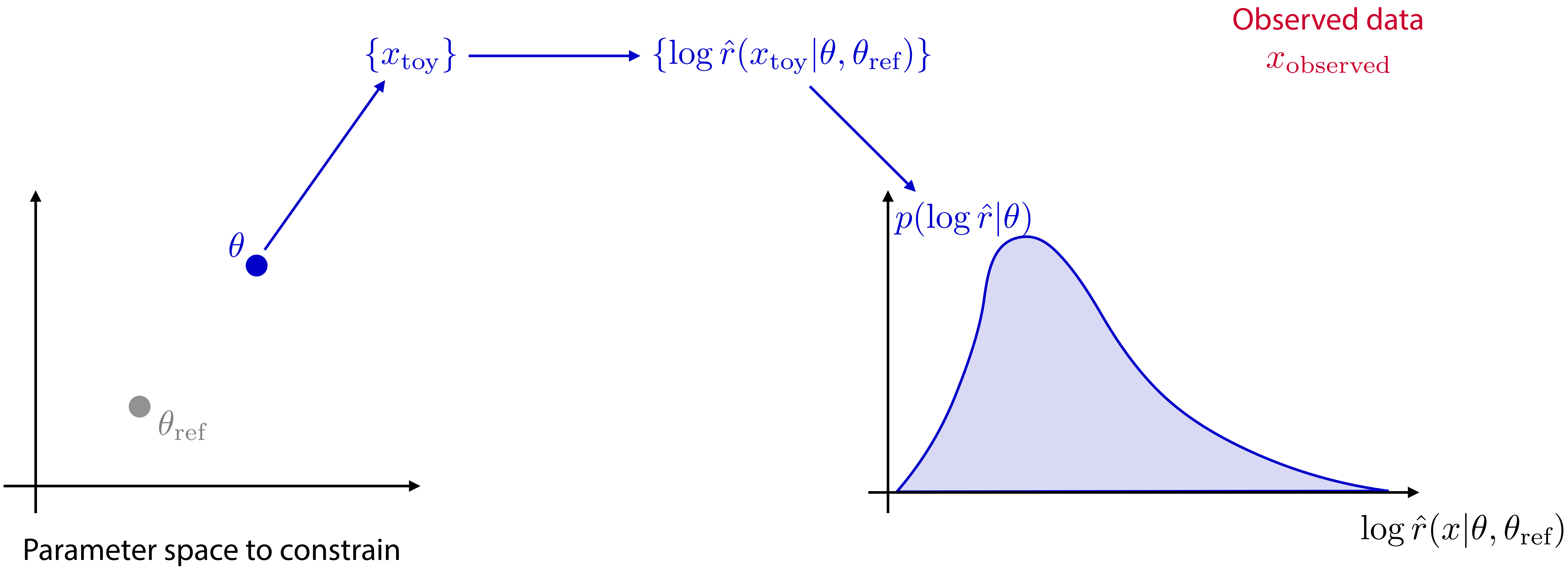
Observed data

x_{observed}



Parameter space to constrain

Limit setting (most LHC physicists are frequentists)



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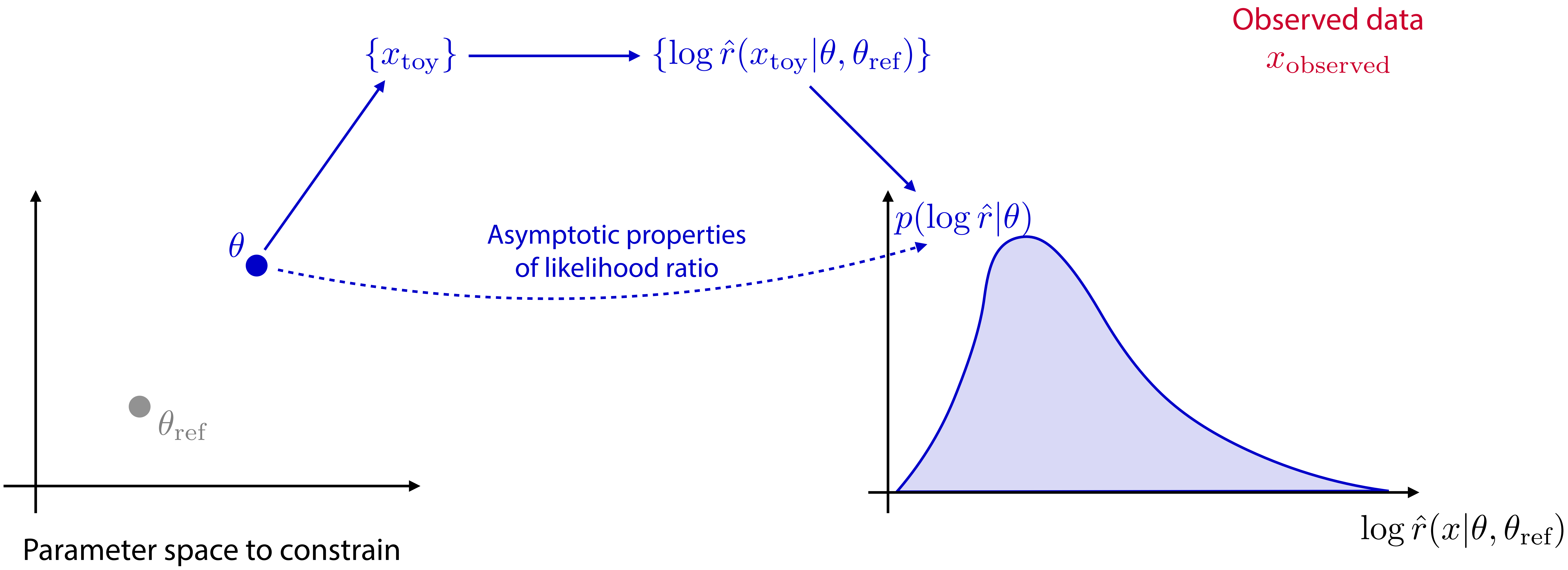

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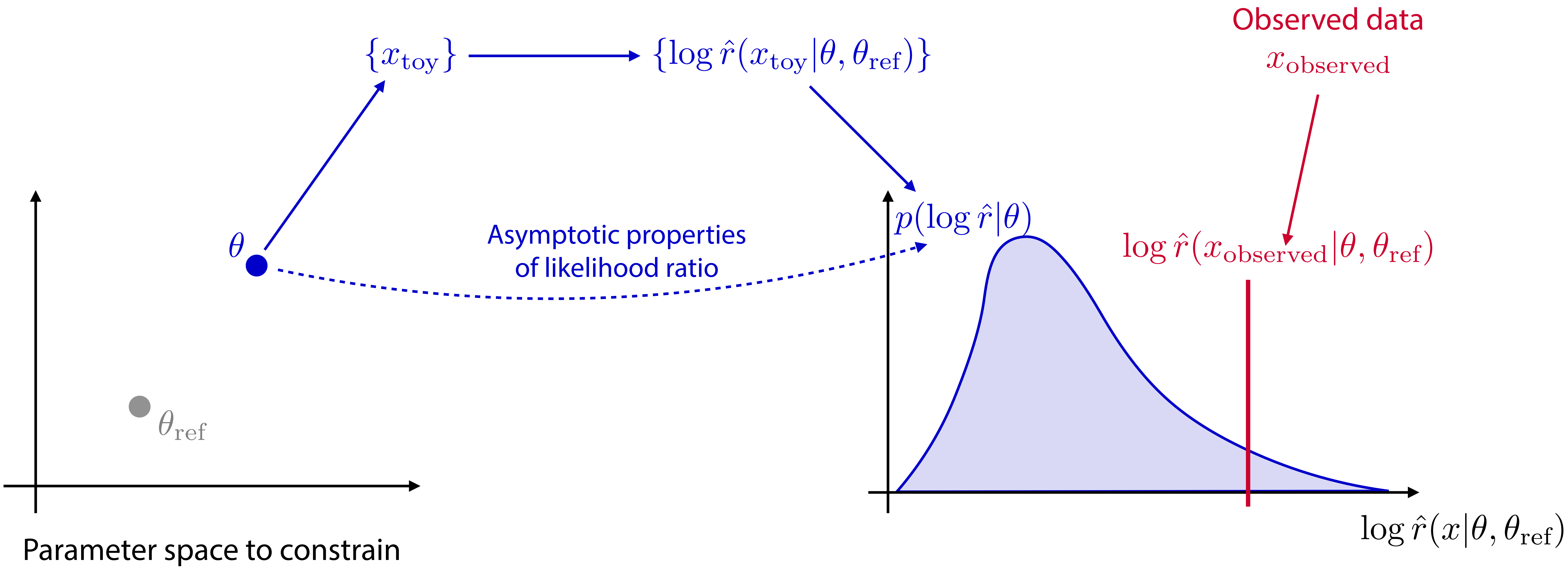

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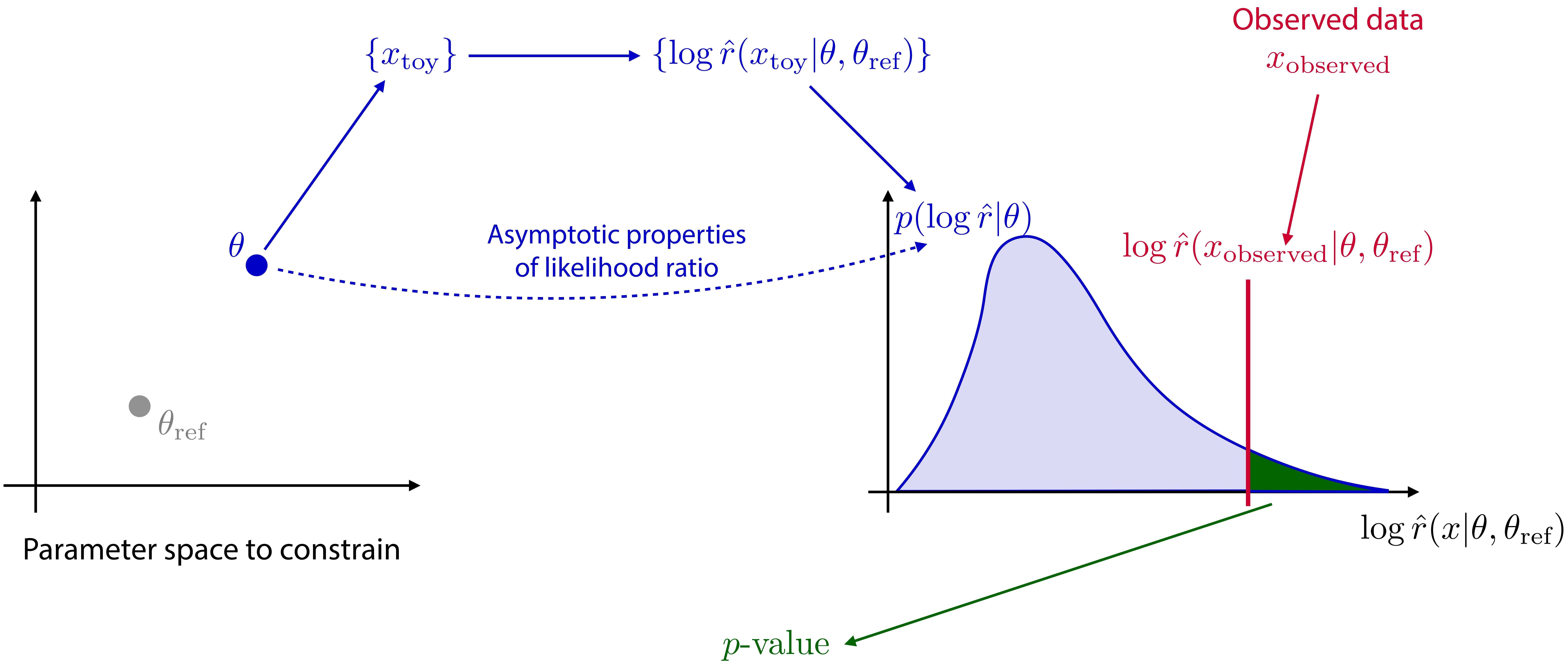

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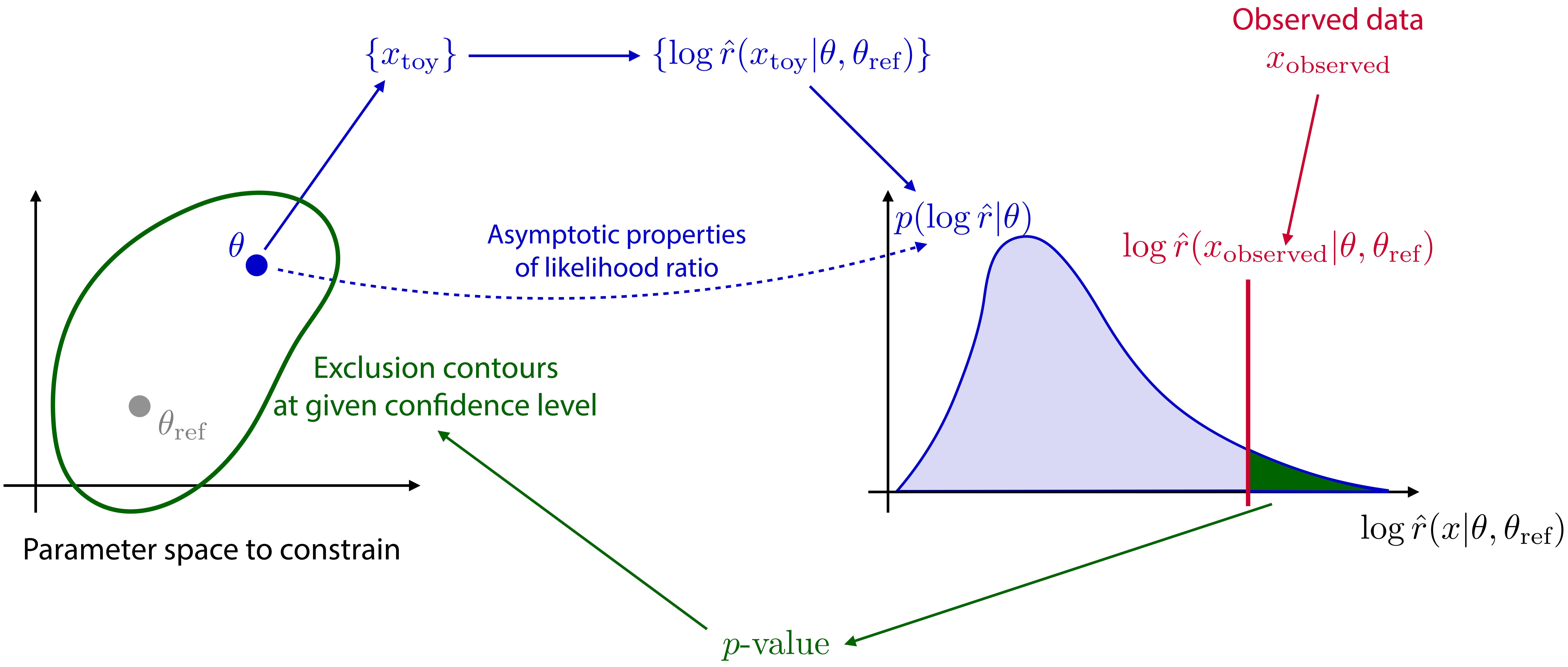

The likelihood ratio is the most powerful test statistic

IX. *On the Problem of the most Efficient Tests of Statistical Hypotheses.*

By J. NEYMAN, *Nencki Institute, Soc. Sci. Lit. Varsoviensis, and Lecturer at the Central College of Agriculture, Warsaw, and* E. S. PEARSON, *Department of Applied Statistics, University College, London.*

(*Communicated by* K. PEARSON, *F.R.S.*)

(Received August 31, 1932.—Read November 10, 1932.)

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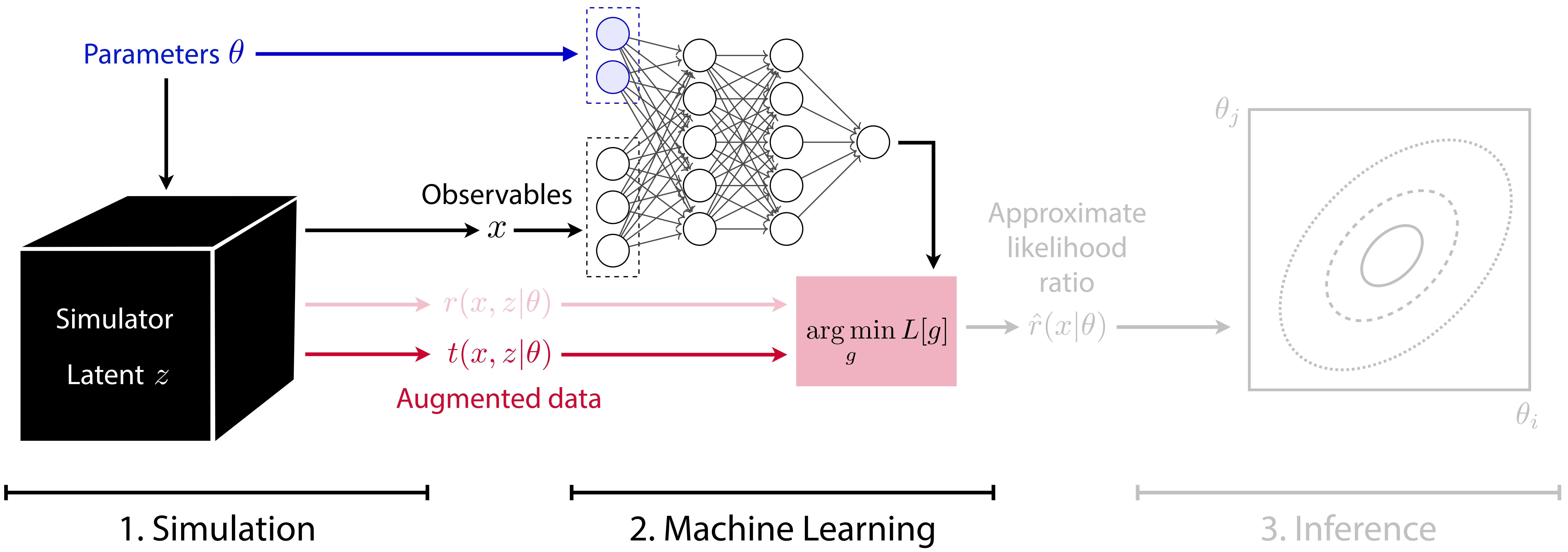
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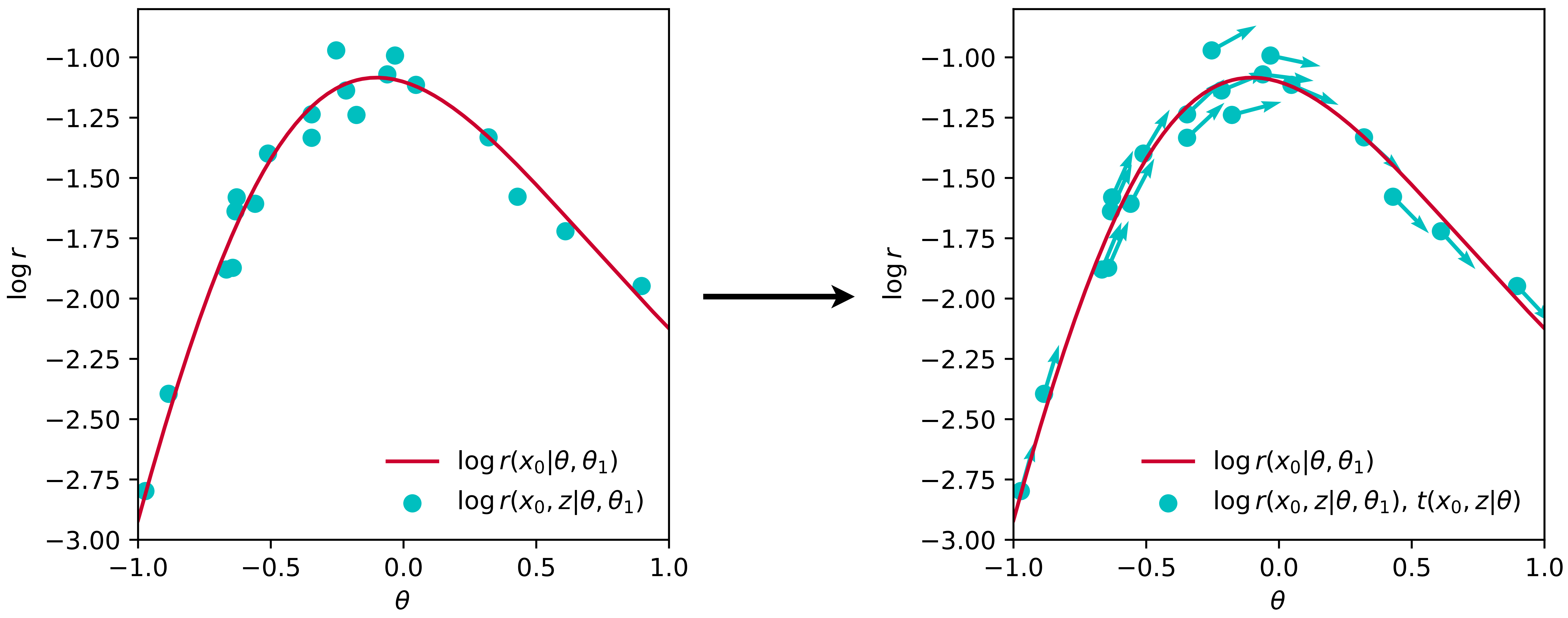
One more piece: the score

- Knowing derivative often helps fitting:



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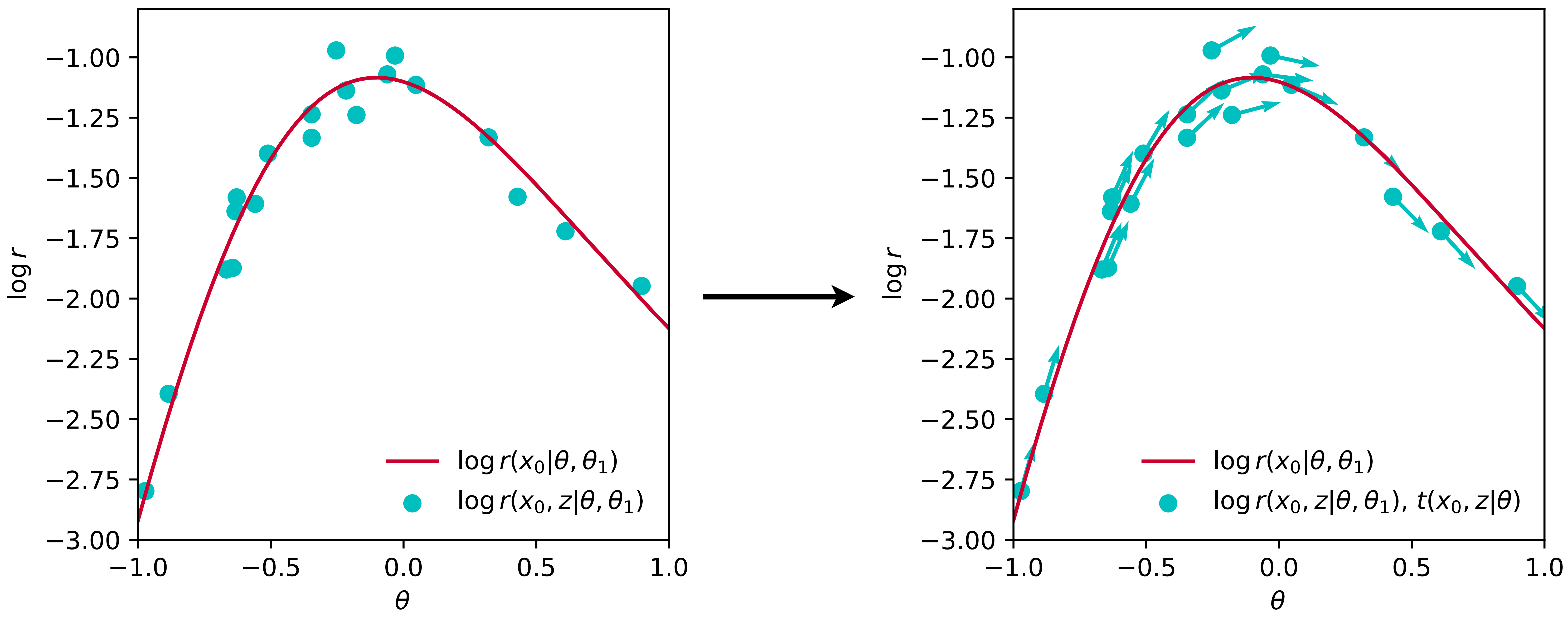

- In our case, the relevant quantity is the score $t(x|\theta_0) \equiv \nabla_\theta \log p(x|\theta)\Big|_{\theta_0}$.
  - The score fully characterizes the likelihood function in the neighborhood of θ_0
  - The score itself is intractable. But…

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

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

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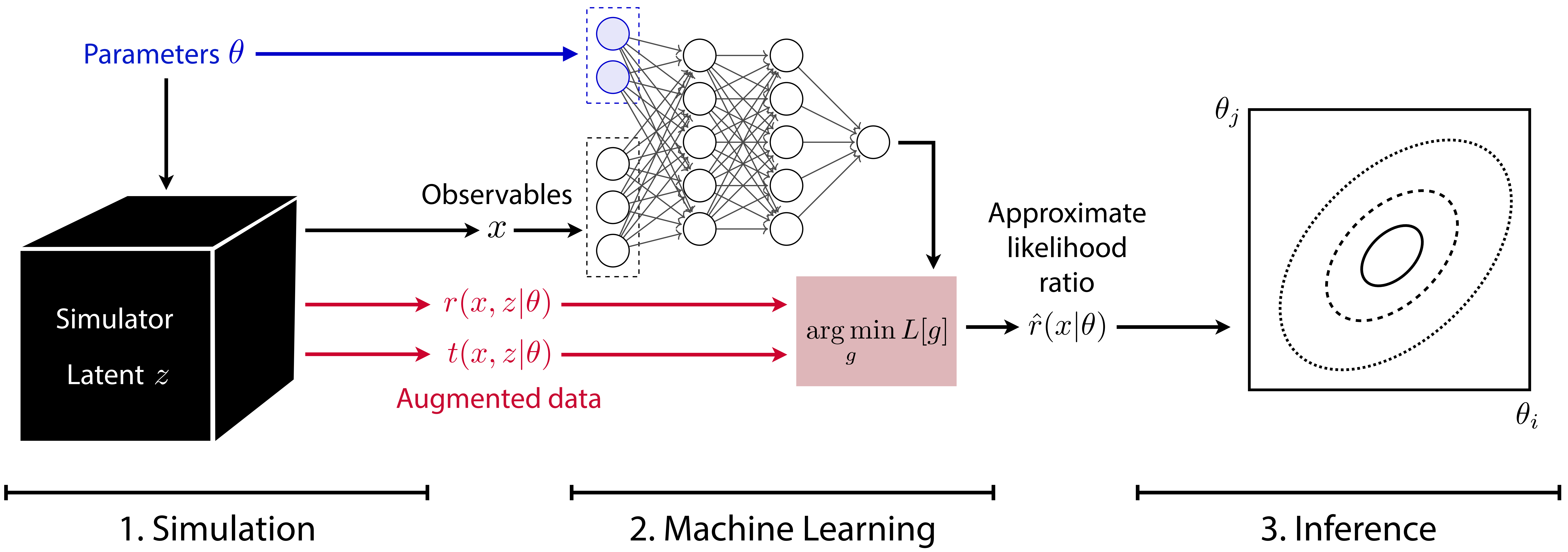
$$L_t[\hat{t}(x|\theta_0)] = \int \mathrm{d}x \int \mathrm{d}z \; p(x,z|\theta_0) \left[\left(\hat{t}(x|\theta_0) - t(x,z|\theta_0)\right)^2\right].$$

One can show it is minimized by

$$t(x|\theta_0) = \arg\min_{\hat{t}(x|\theta_0)} L_t[\hat{t}(x|\theta_0)] \;!$$

Again, we implement this minimization through machine learning

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



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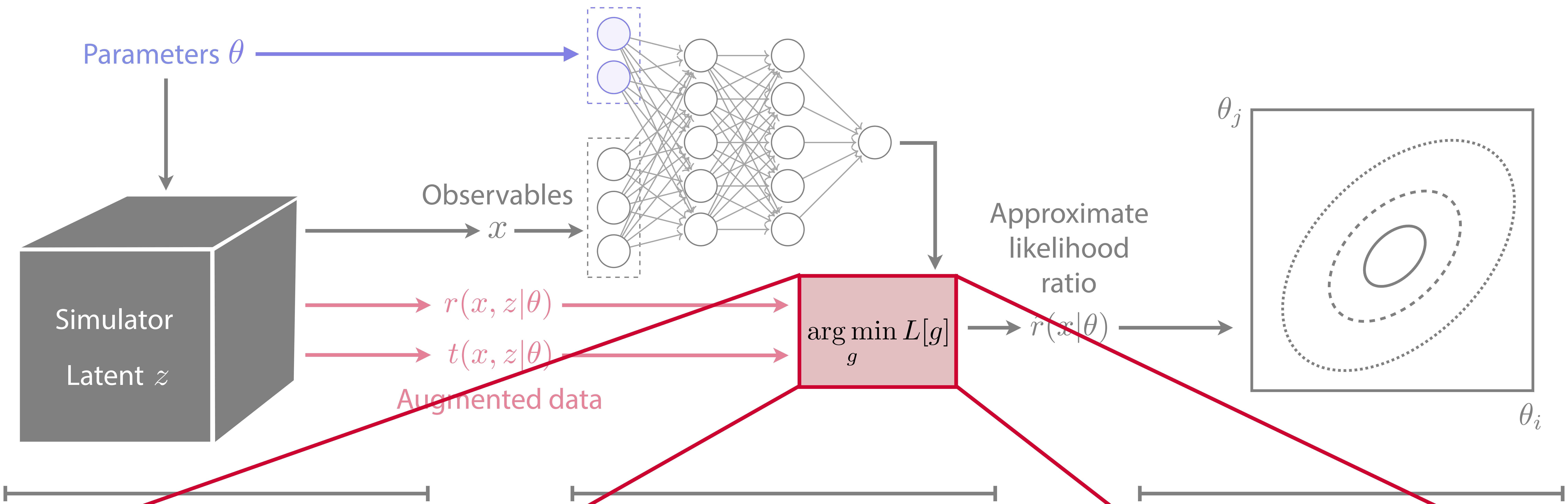
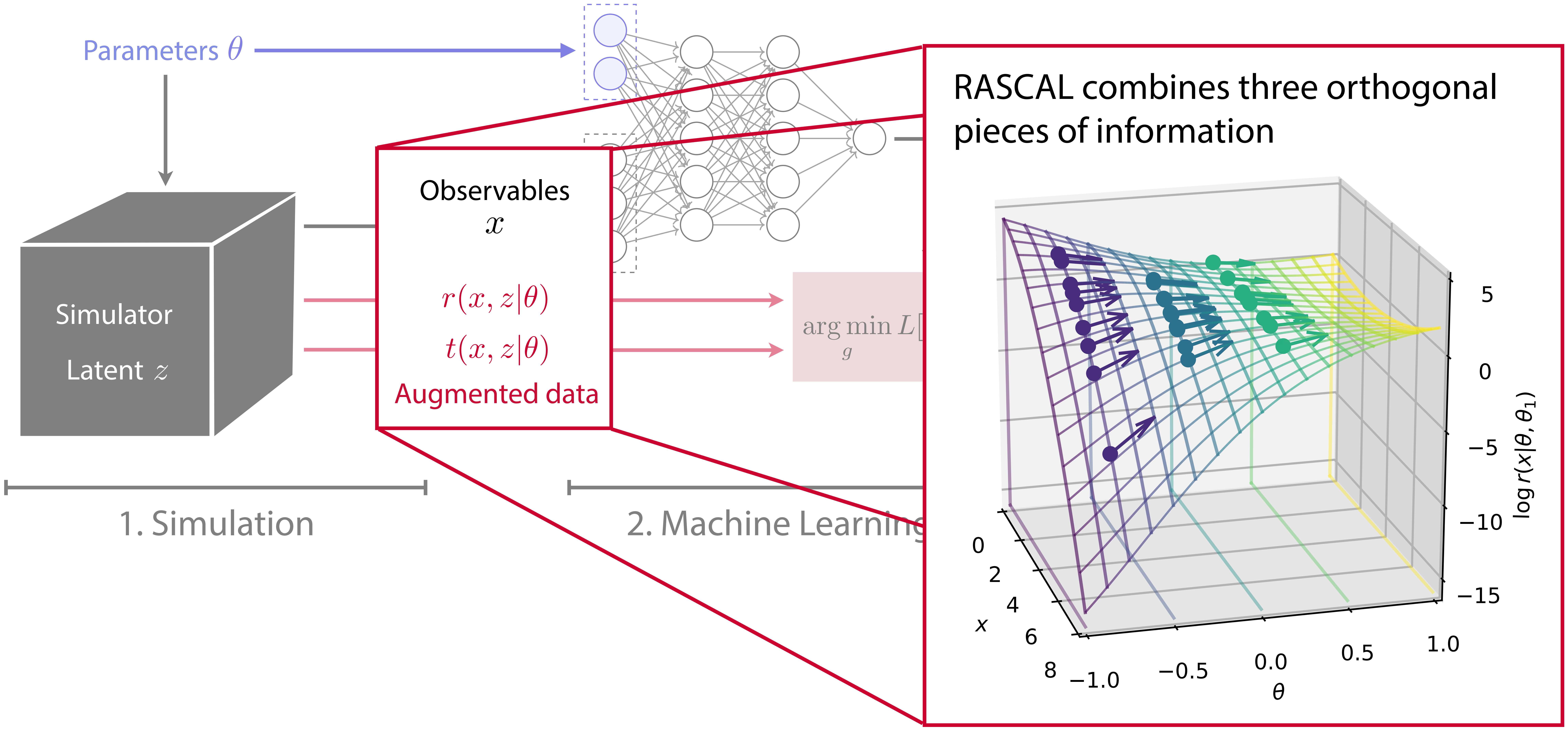


Combining ratio and score information:

- If ratio estimator is differentiable, we can calculate the estimated score $\hat{t}(x|\theta_0) = \nabla_{\theta_0} \log \hat{r}(x|\theta_0, \theta_1)$
- Minimize combined loss function:

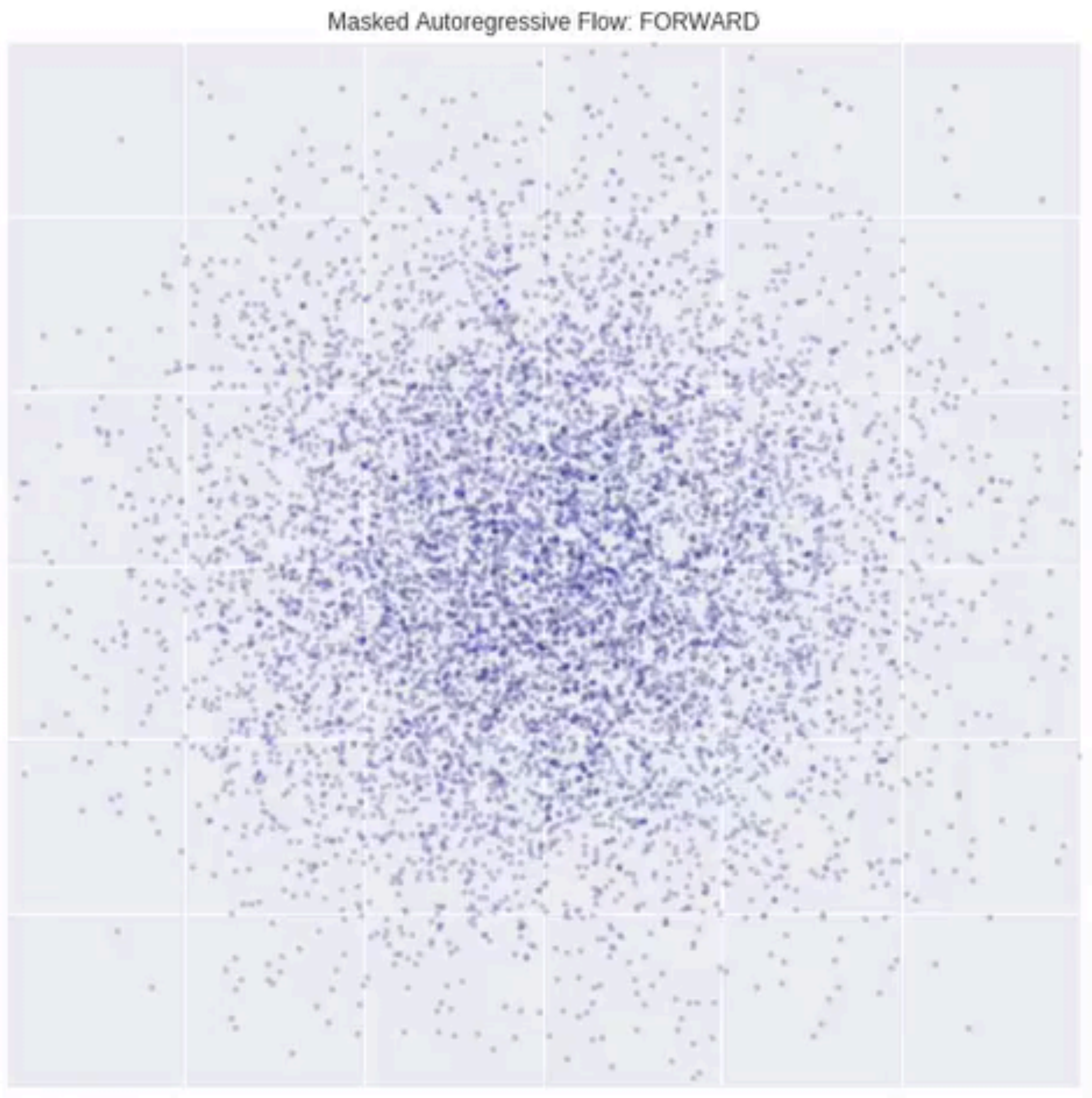
$$L_{\text{RASCAL}}[\hat{r}(x|\theta_0, \theta_1)] = L_r[\hat{r}(x|\theta_0, \theta_1)] + \alpha\, L_t[\nabla_{\theta_0} \log \hat{r}(x|\theta_0, \theta_1)]$$

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



Alternatives and extensions

- More than one way to the likelihood (ratio)!
  - ALICE: use cross entropy instead of squared error loss
  - SCANDAL: combine with neural density estimators, e.g. Masked Autoregressive Flows
    [G. Papamakarios, T. Pavlakou, I. Murray 1705.07057]
  - SALLY / SALLINO: use estimated score as “optimal observable”



[Alex Mordvintsev]

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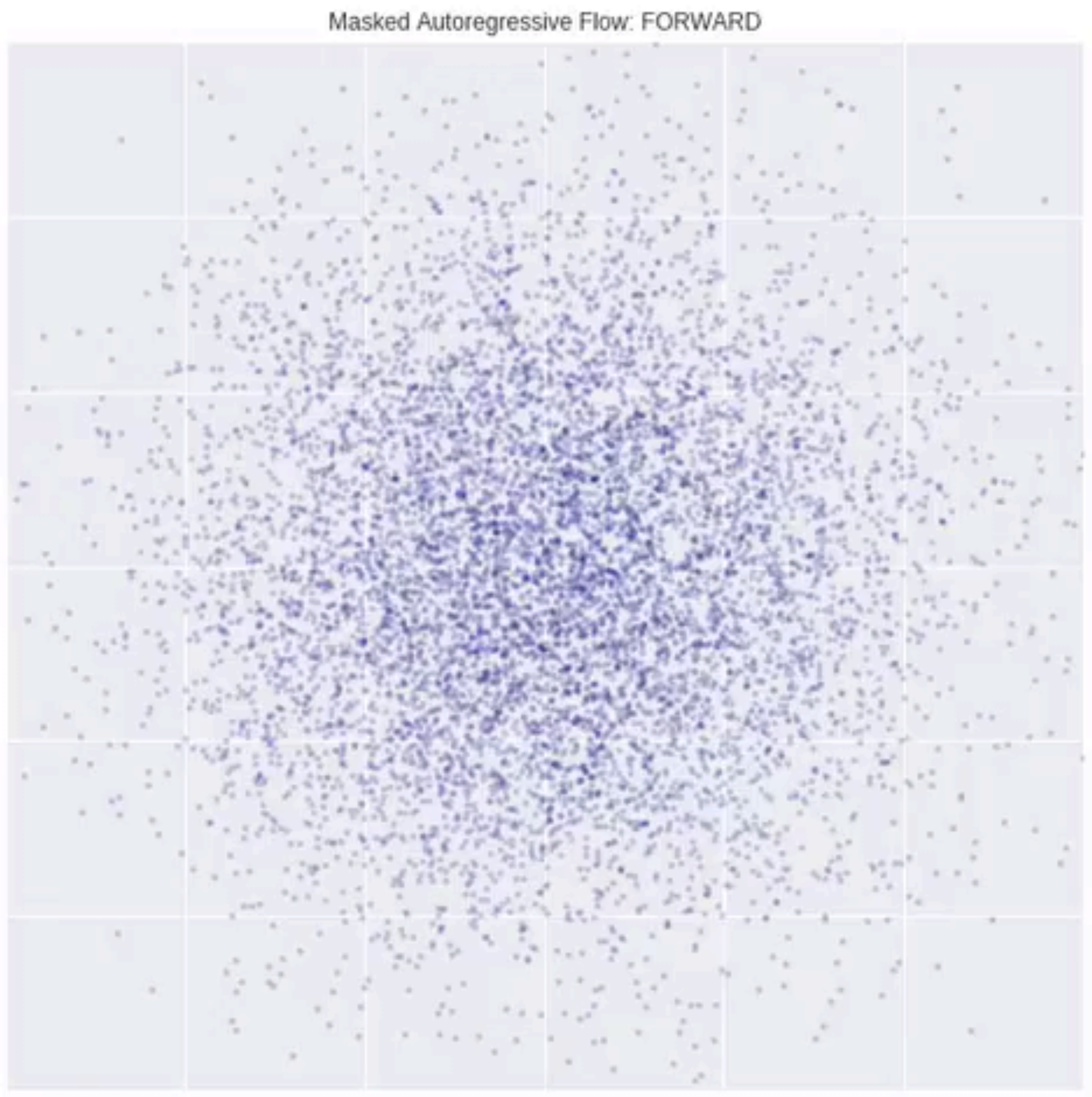
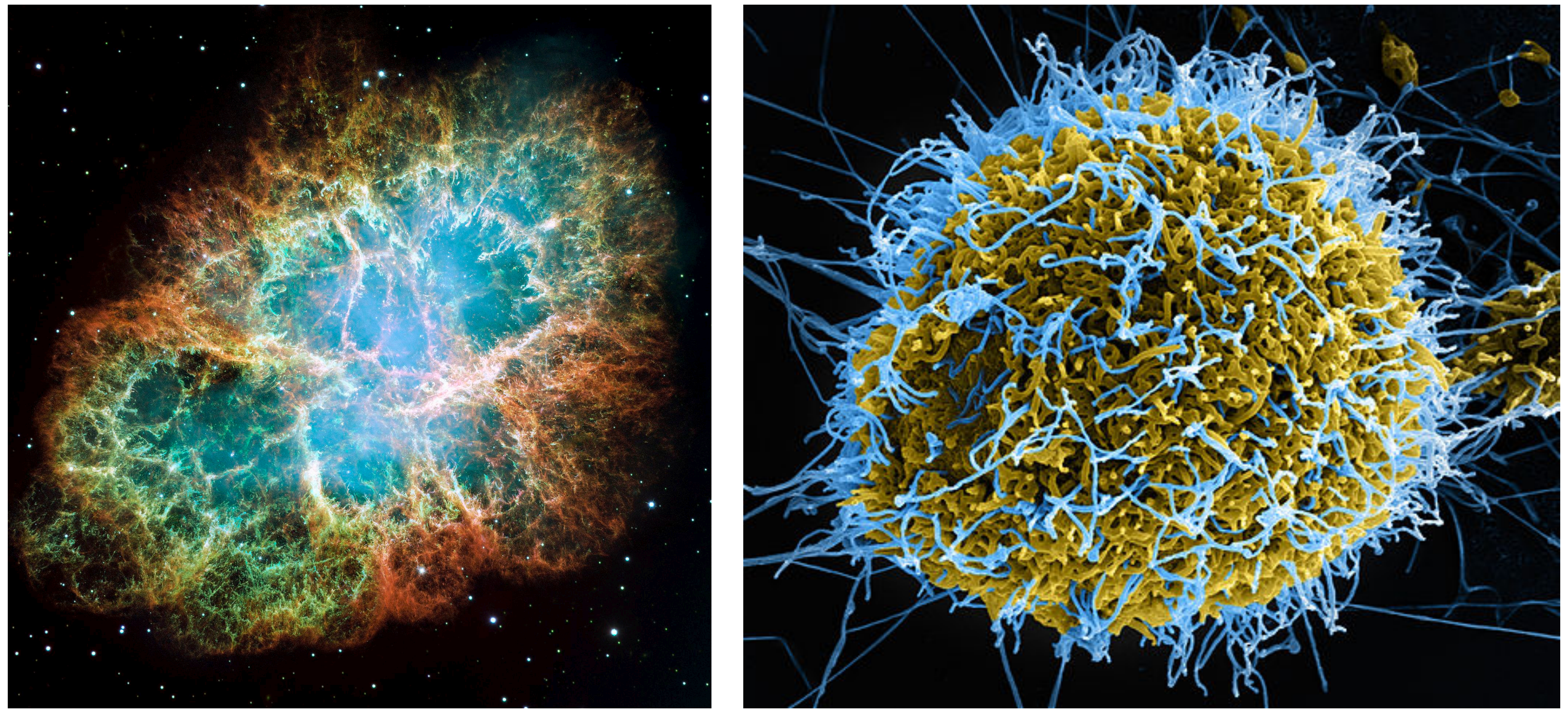


[Alex Mordvintsev]

- What if we don't fully trust the simulator?
  - Nuisance parameters to model systematic uncertainties
  - Learn robustness with adversarial training
    [G. Louppe, M. Kagan, K. Cranmer 1611.01046]

- More general than particle physics
  - Currently being adapted to cosmology and epidemiology



[NASA, NIAID]

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, …

Use latent structure:

- Matrix Element Method, Optimal Observables, Shower Deconstruction
  Neglect or approximate shower + detector, explicitly calculate z integral
- Mining gold from the simulator (New!)
  Leverage matrix-element information + machine learning

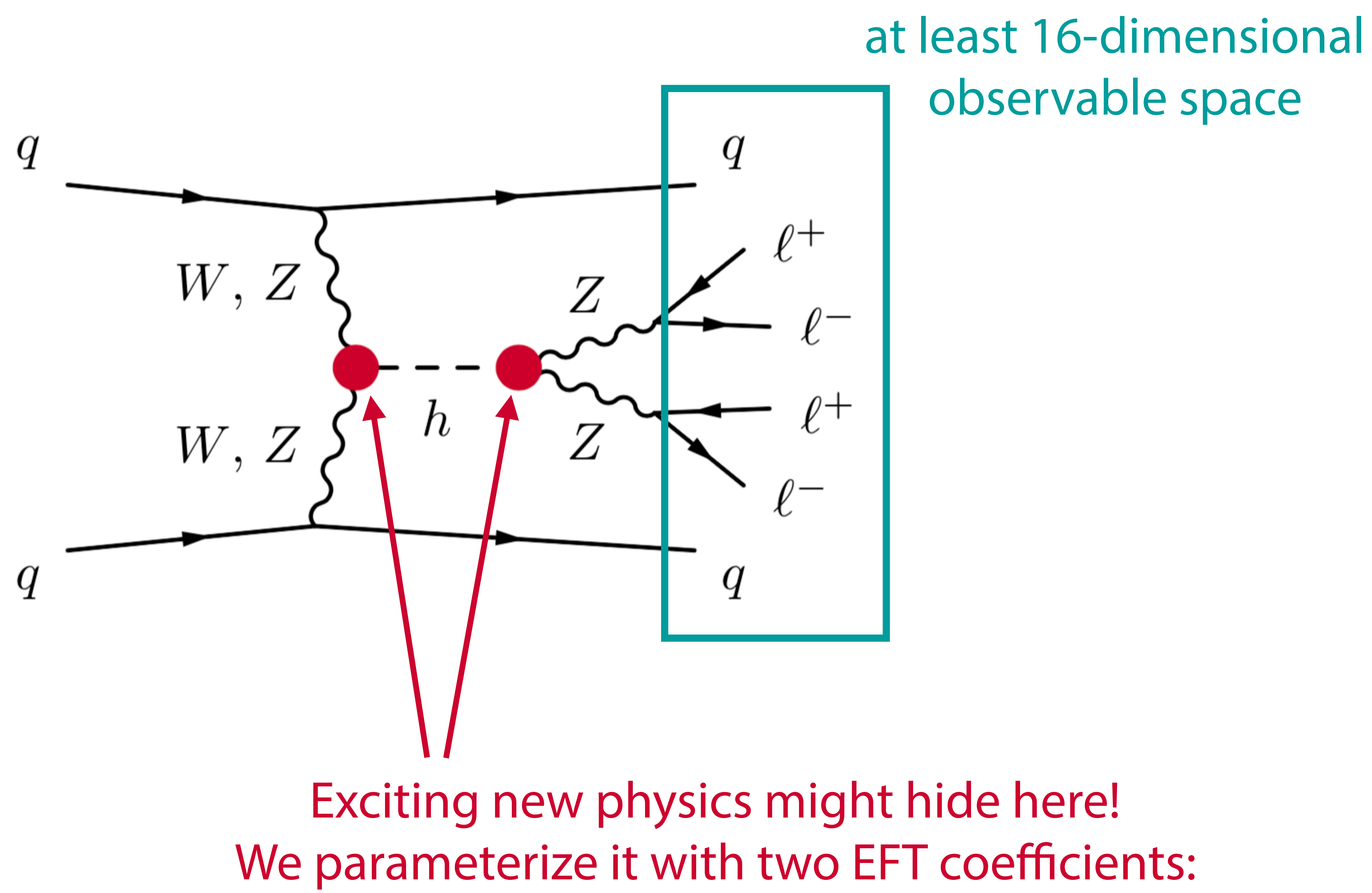
	Histograms, ABC	Neural density est.	Matrix-Element Method	RASCAL etc
High-dimensional observables		✓	✓	✓
Realistic shower, detector sim.	✓	✓	transfer fns.	✓
Uses matrix element information			✓	✓
Evaluation	fast	fast	expensive	fast

EFT example

[JB, K. Cranmer, G. Louppe, J. Pavez 1805.00013, 1805.00020, 1805.12244;
with M. Stoye 1808.00973]

Proof of concept

Higgs production in weak boson fusion:

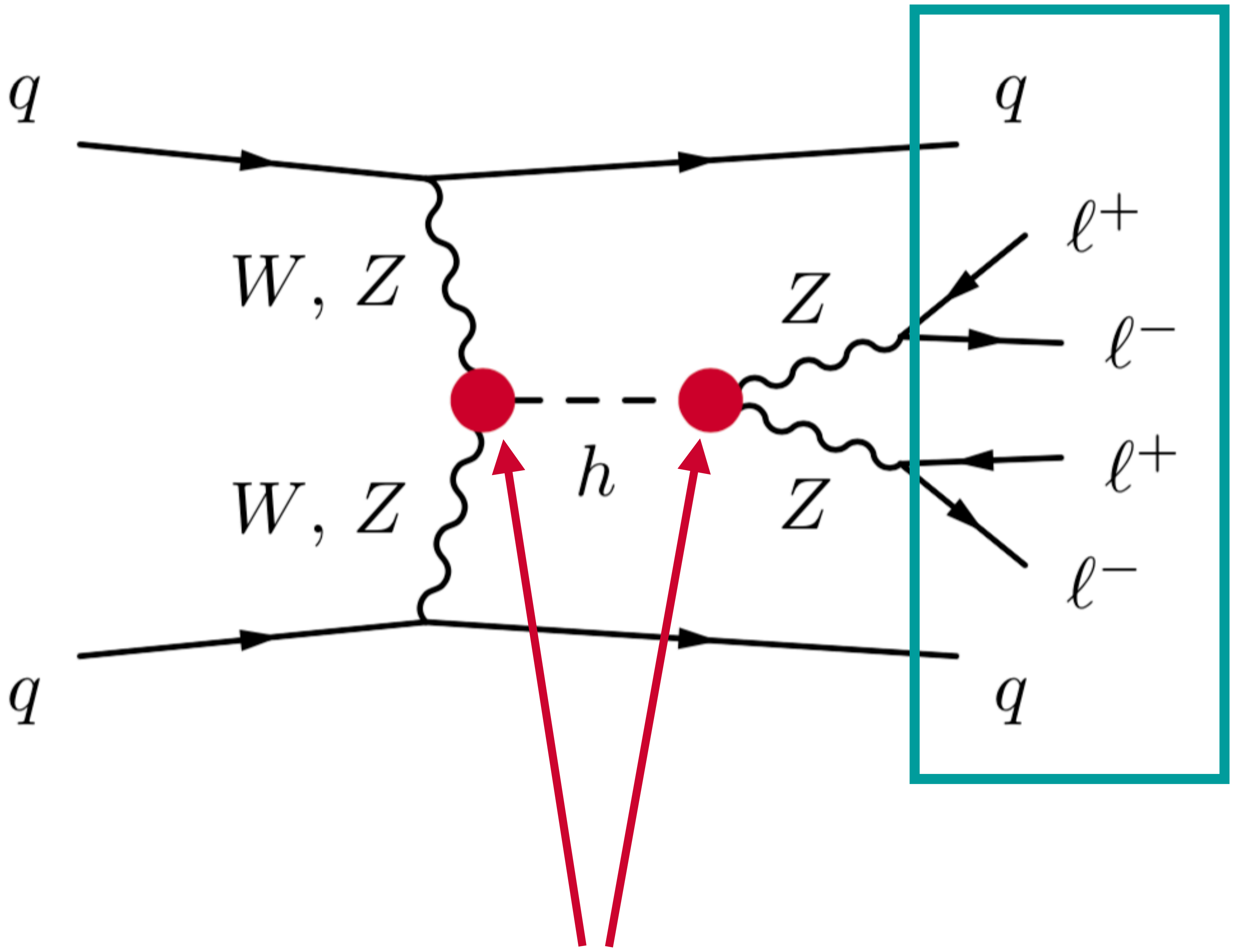


$$\mathcal{L} = \mathcal{L}_{\text{SM}} + \boxed{\frac{f_W}{\Lambda^2}} \underbrace{\frac{\mathrm{i}g}{2} (D^\mu \phi)^\dagger \sigma^a D^\nu \phi \, W^a_{\mu\nu}}_{\mathcal{O}_W} - \boxed{\frac{f_{WW}}{\Lambda^2}} \underbrace{\frac{g^2}{4} (\phi^\dagger \phi) \, W^a_{\mu\nu} W^{\mu\nu\, a}}_{\mathcal{O}_{WW}}$$

Proof of concept

Higgs production in weak boson fusion:

at least 16-dimensional observable space



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

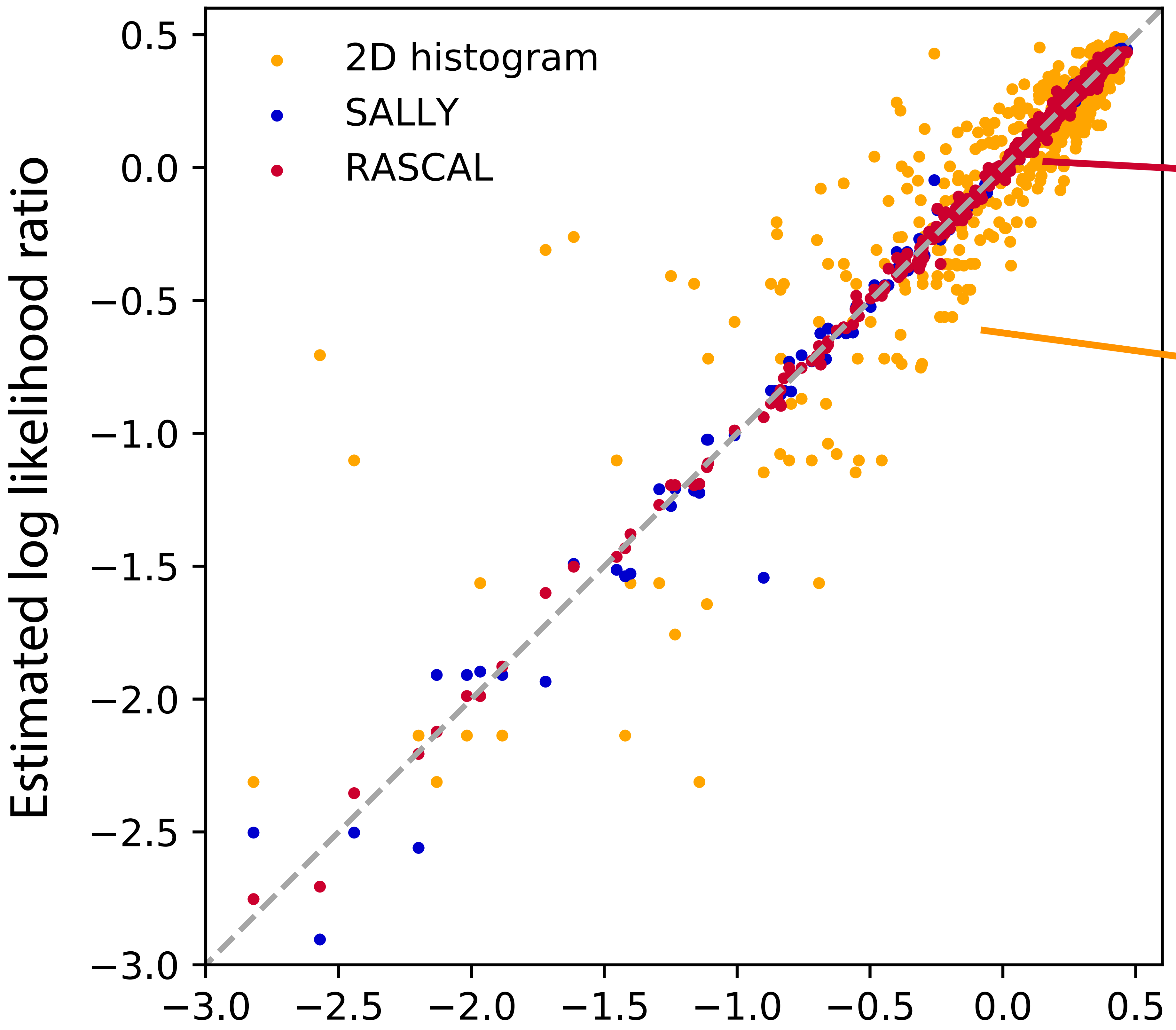
$$\mathcal{L} = \mathcal{L}_{\text{SM}} + \boxed{\frac{f_W}{\Lambda^2}} \underbrace{\frac{ig}{2} \, (D^\mu \phi)^\dagger \, \sigma^a \, D^\nu \phi \, W^a_{\mu\nu}}_{\mathcal{O}_W} - \boxed{\frac{f_{WW}}{\Lambda^2}} \underbrace{\frac{g^2}{4} \, (\phi^\dagger \phi) \, W^a_{\mu\nu} \, W^{\mu\nu\, a}}_{\mathcal{O}_{WW}}$$

- 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
- Simulation: MadGraph + MadMax

  [J. Alwall et al. 1405.0301; K. Cranmer, T. Plehn hep-ph/0605268; T. Plehn, P. Schichtel, D. Wiegand 1311.2591]

More precise likelihood ratio estimates with less training data

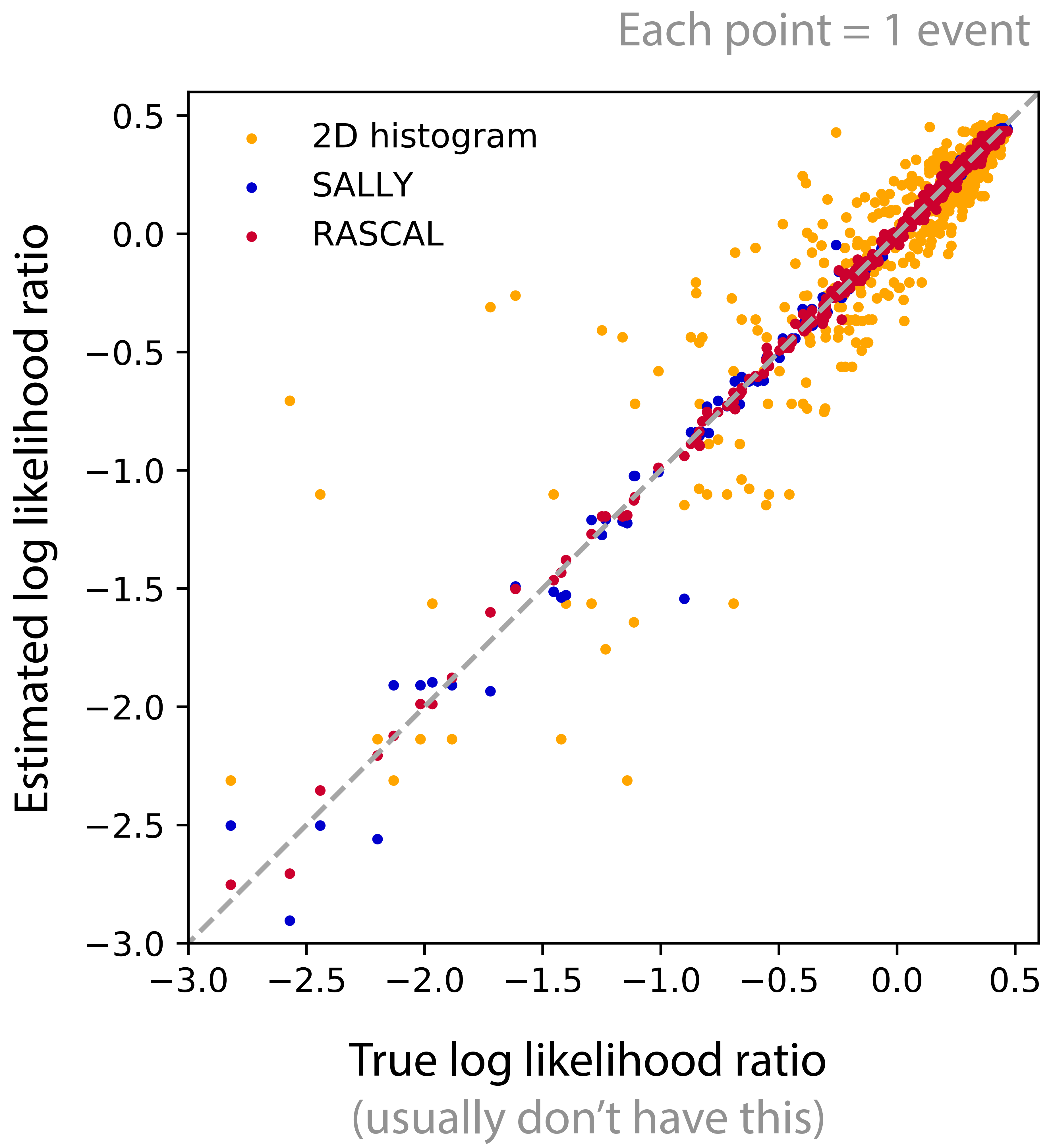
Each point = 1 event

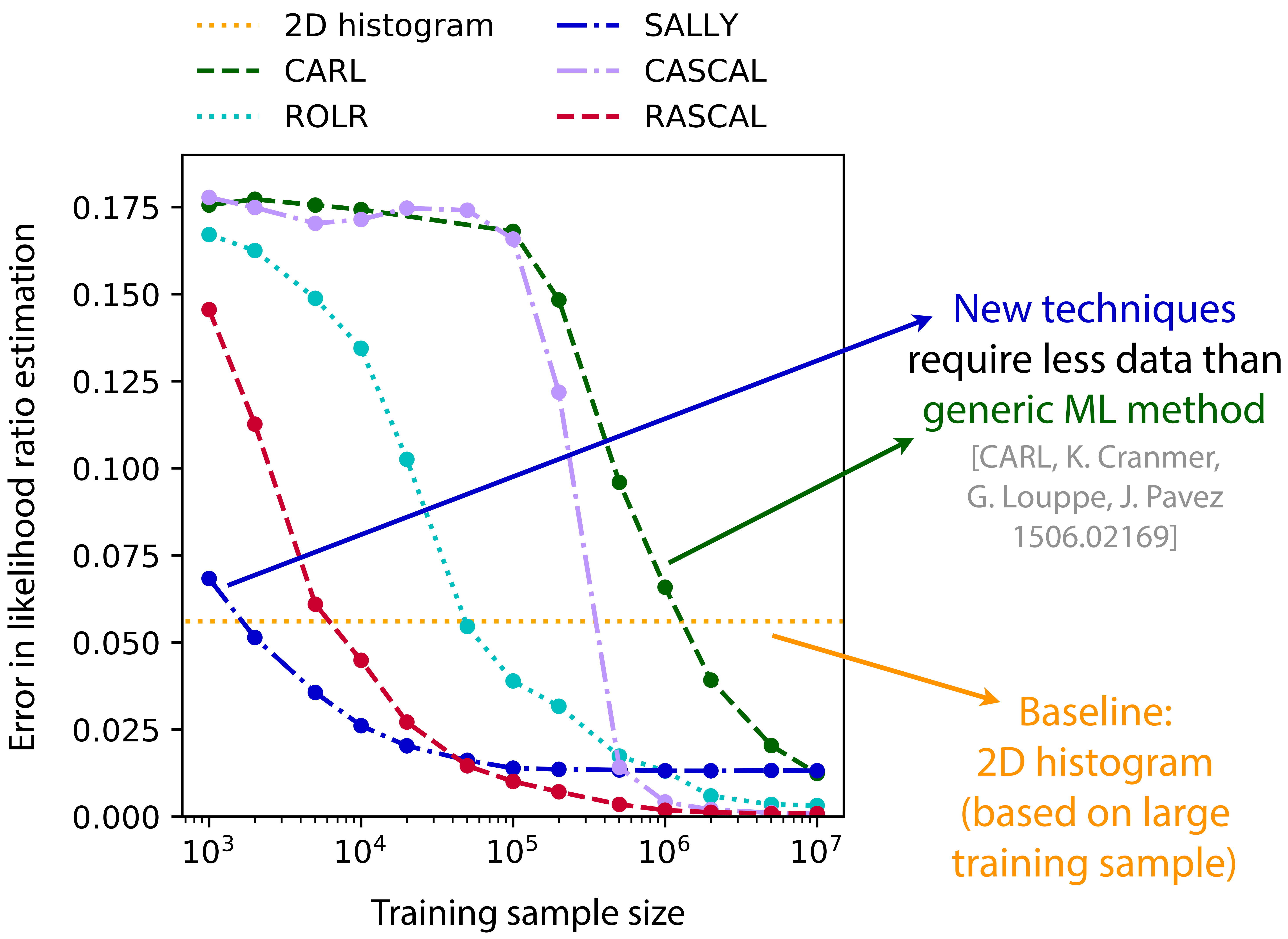


True log likelihood ratio
(usually don't have this)

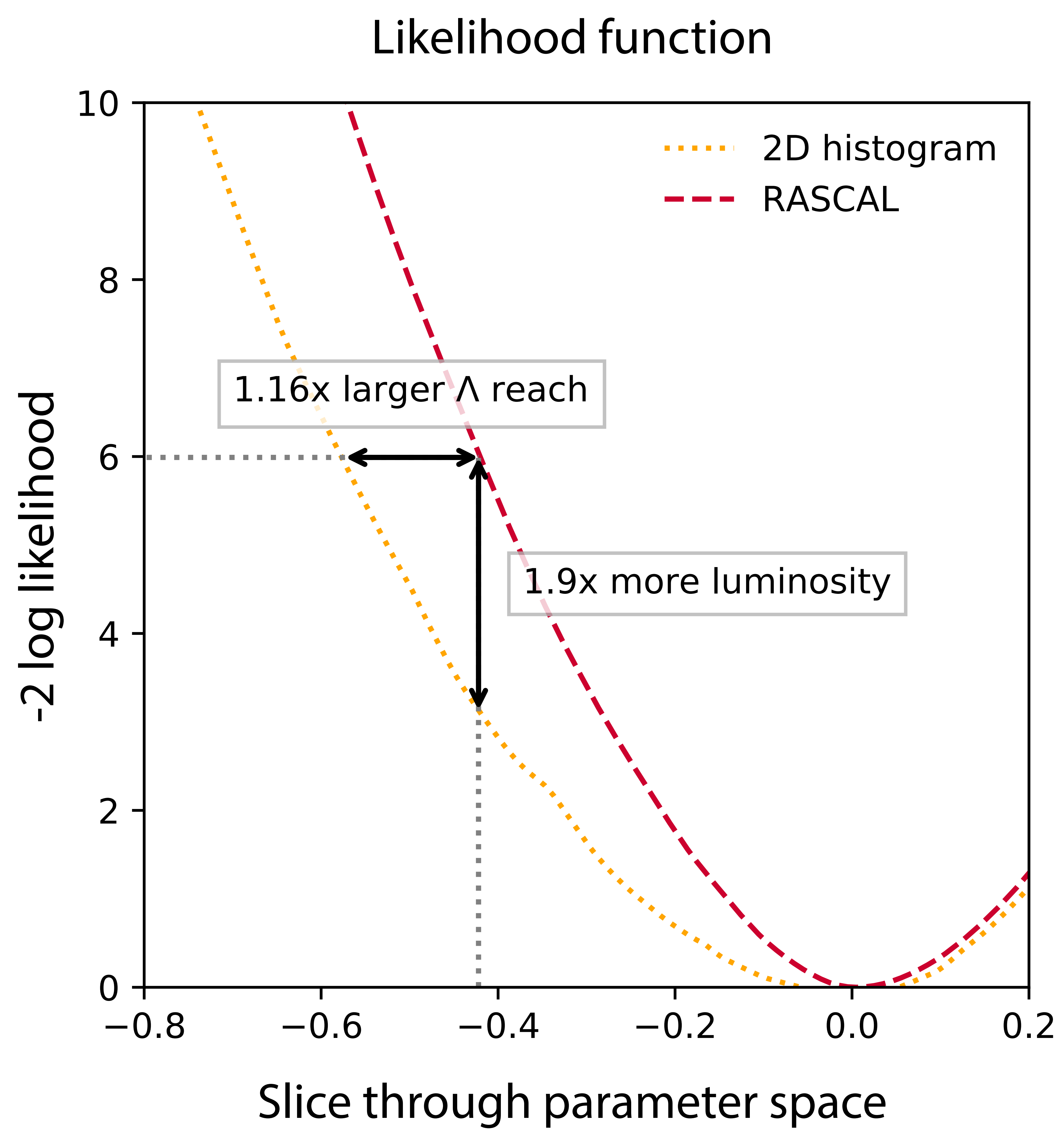
RASCAL
gives more precise likelihood
ratio estimates than the
2D histogram

More precise likelihood ratio estimates with less training data



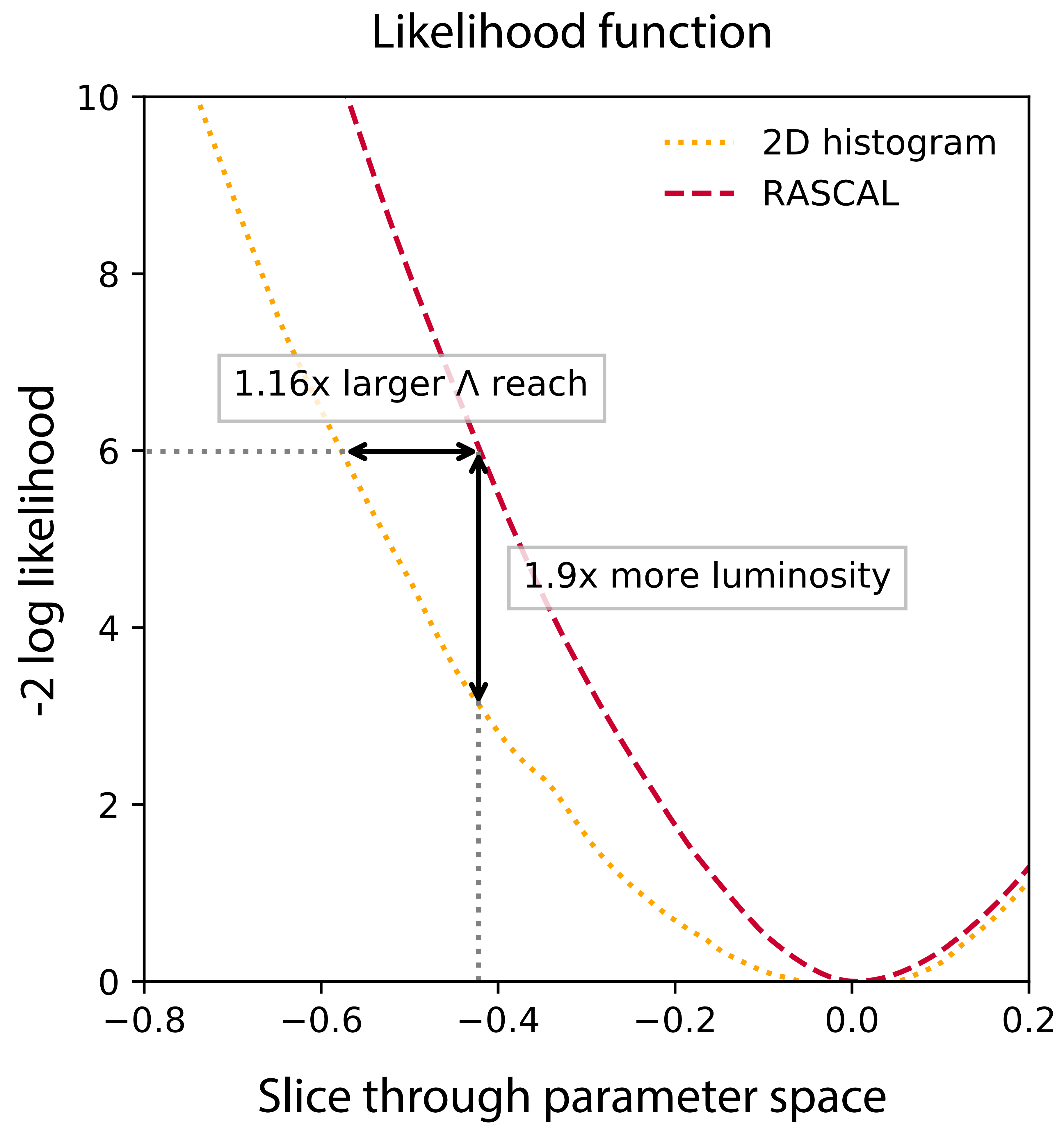


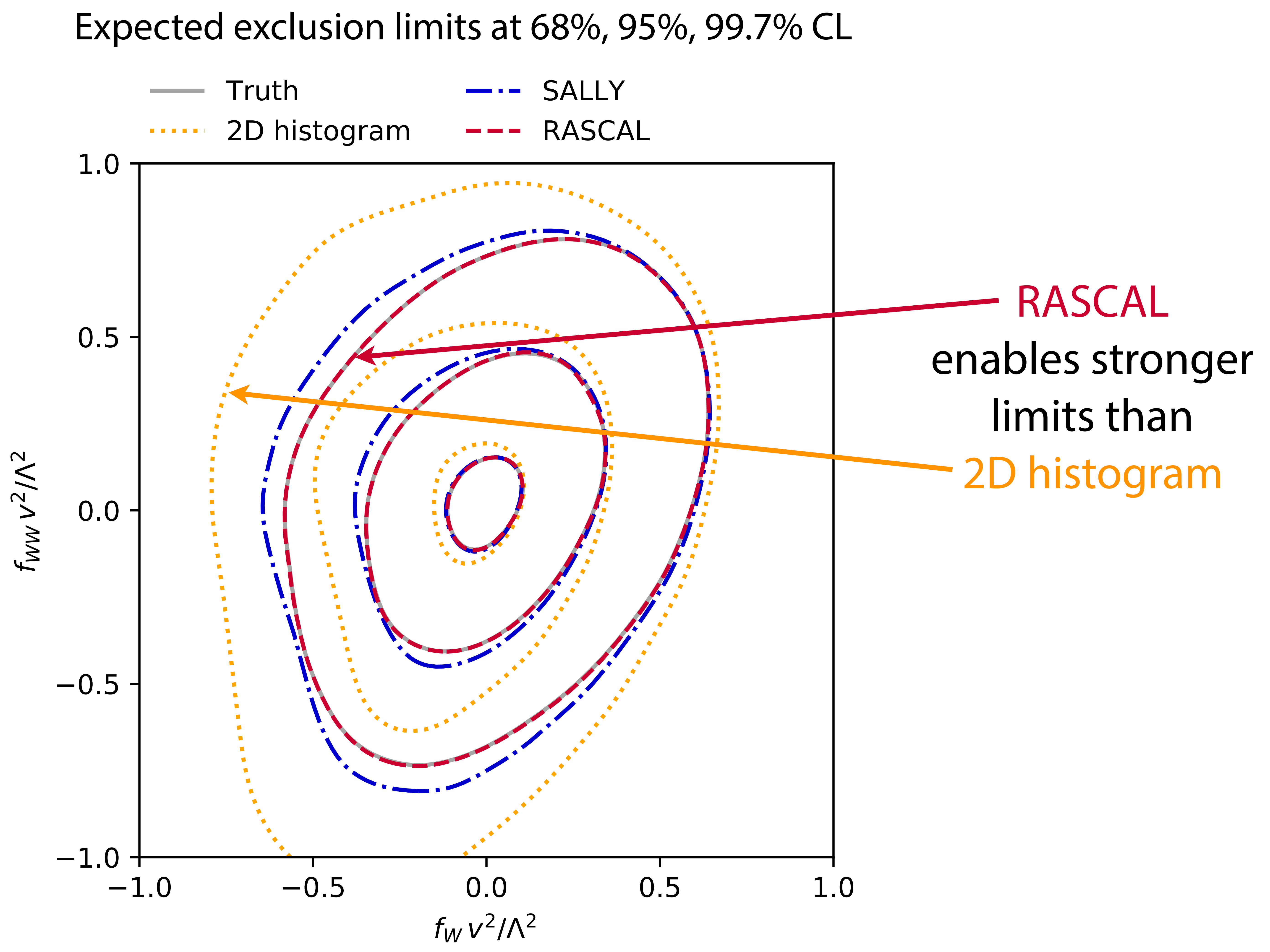
Better sensitivity to new physics



Results are based on 36 observed events, assuming SM

Better sensitivity to new physics





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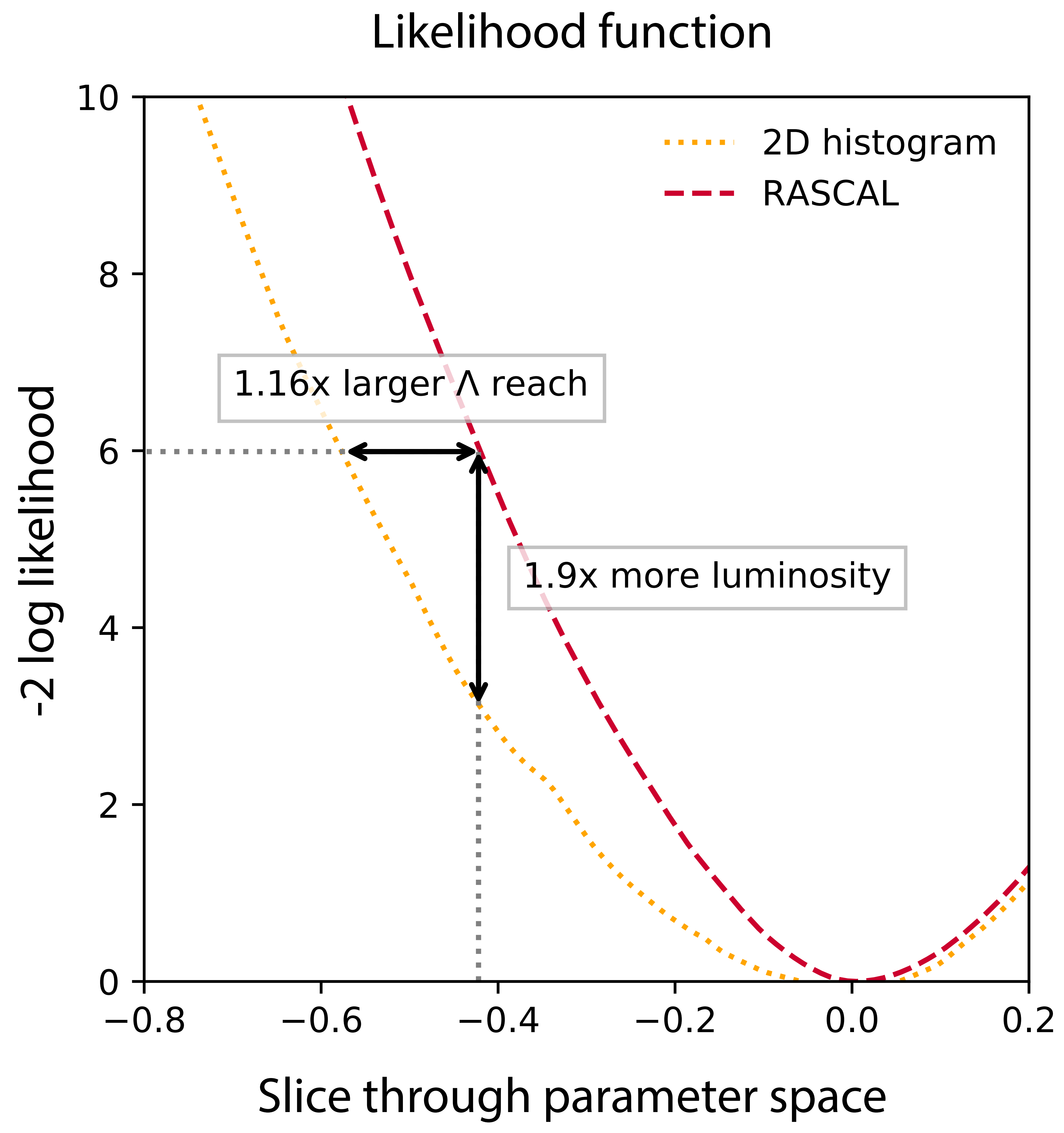
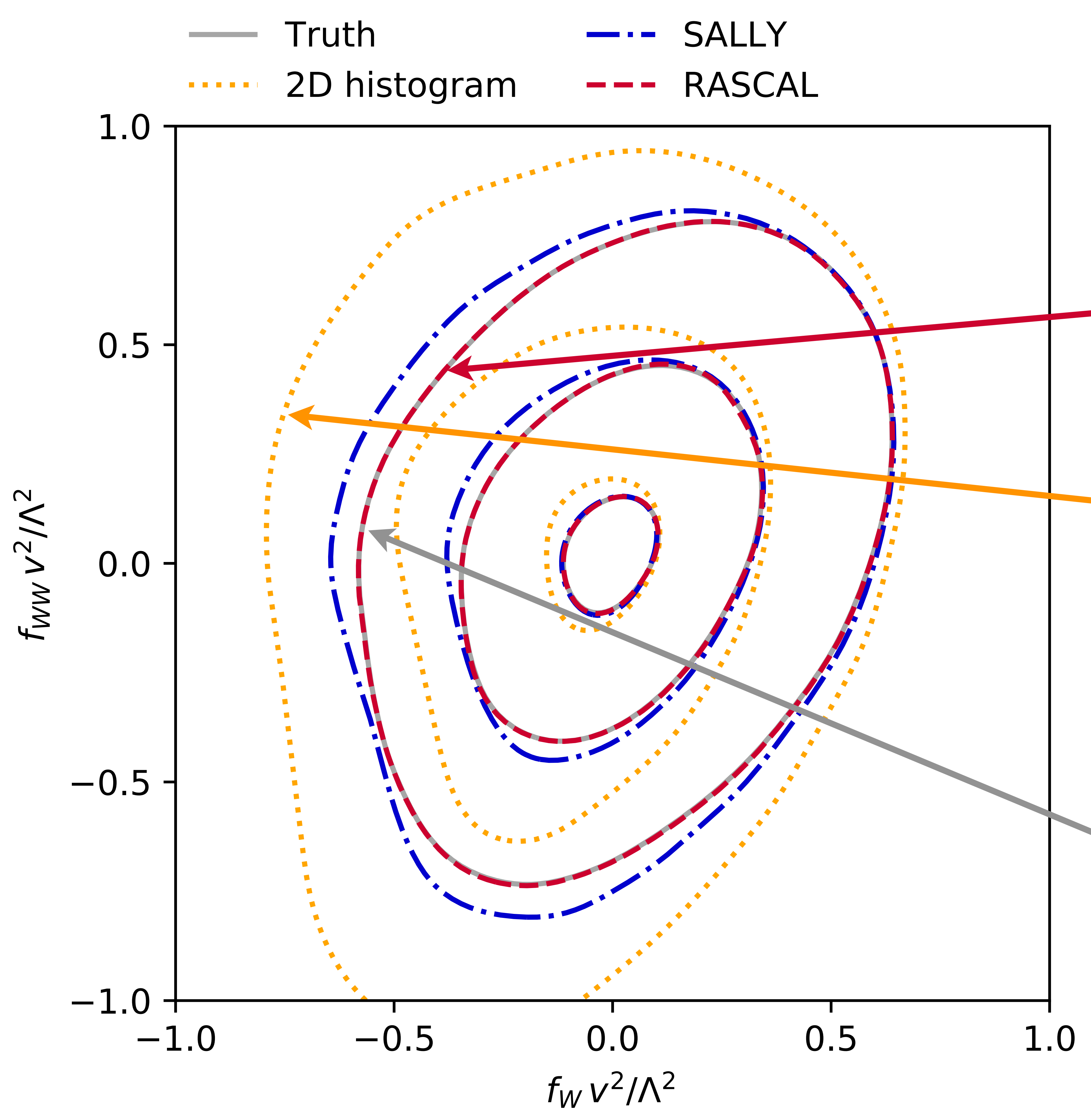




RASCAL enables stronger limits than 2D histogram

Limits from RASCAL indistinguishable from true likelihood
(usually we don't have that)

Results are based on 36 observed events, assuming SM

MadMiner

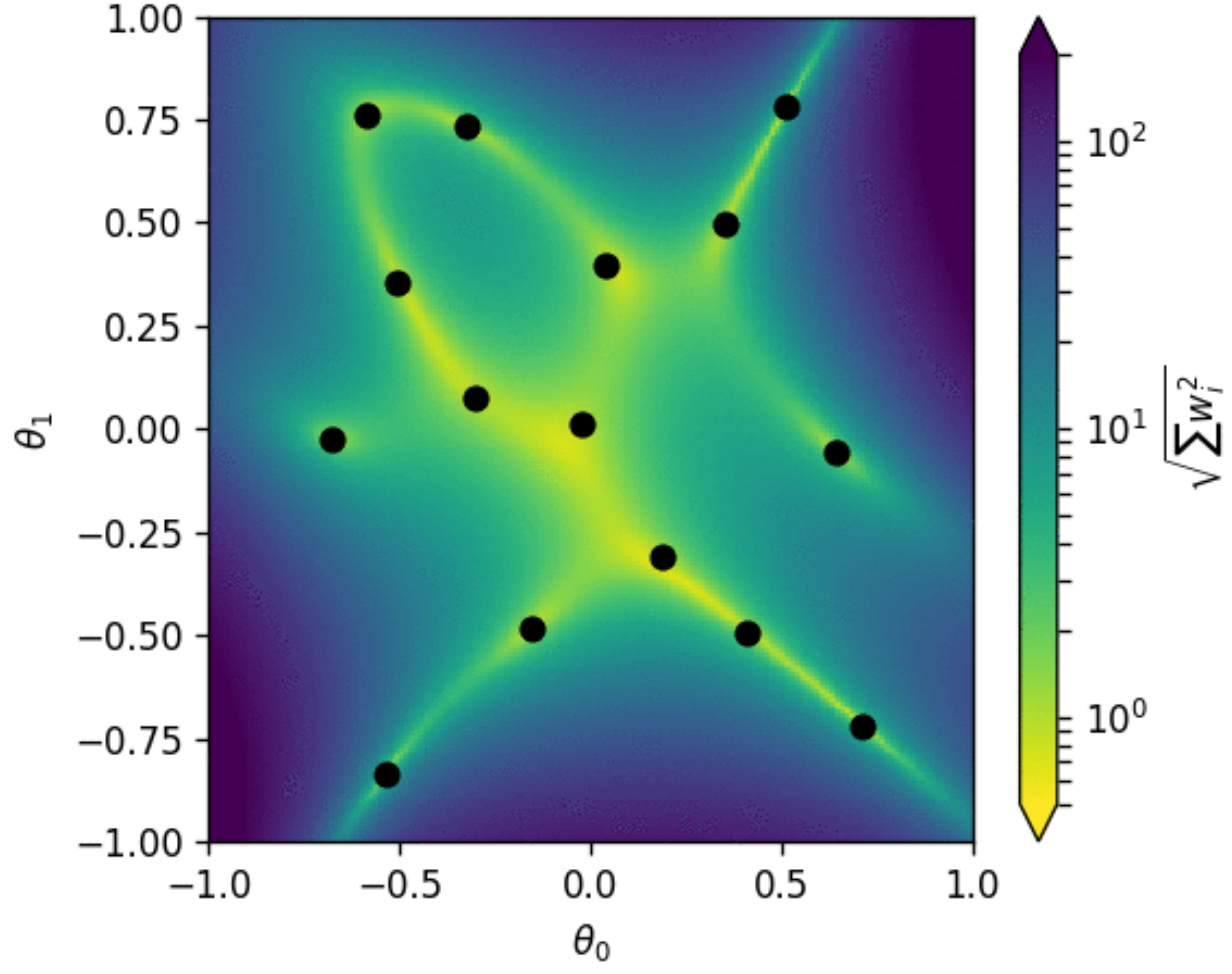
[JB, K. Cranmer, F. Kling in progress]

Can I use any of this?

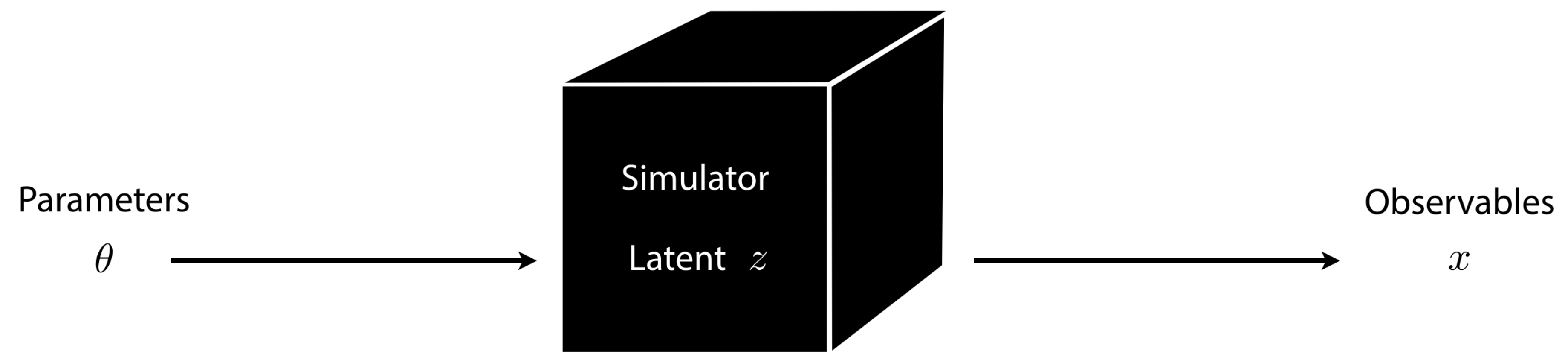
Yes! To make that as painless as possible, we're working on the python package MadMiner:

- "Mining gold" from MadGraph + Pythia + detector simulation
- Morphing: reconstruct full dependence on model parameters from few MC runs
- Likelihood ratio estimation with RASCAL and friends
- Calculate Fisher information (truth or reco level)

Come visit us soon at github.com/johannbrehmer/madminer!

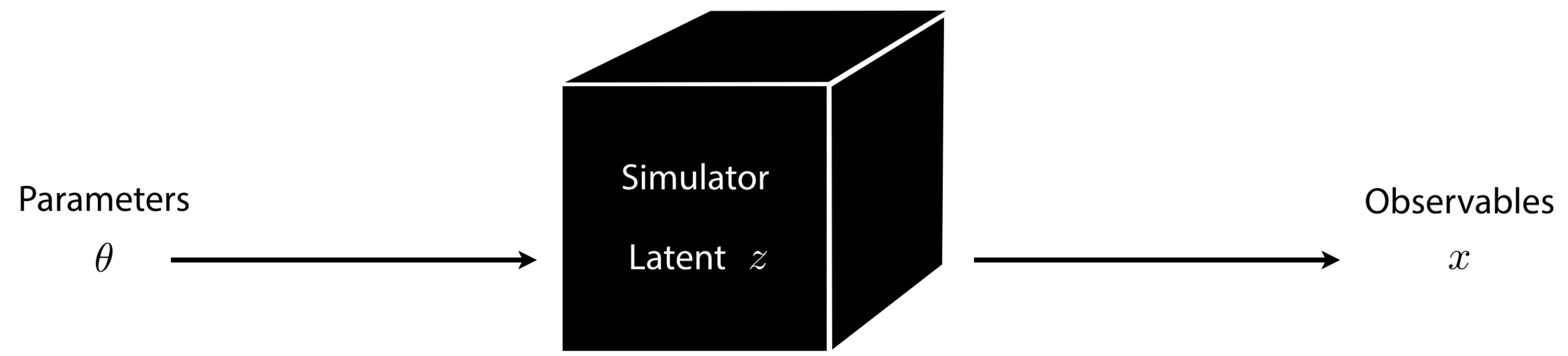


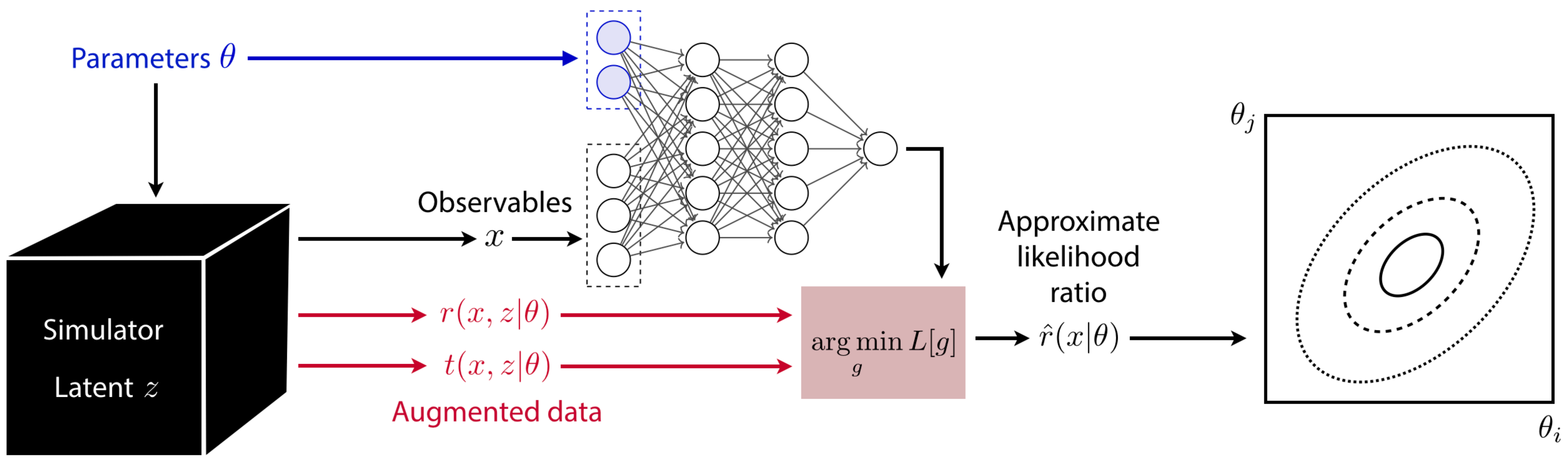
A new approach to simulator-based inference



- Many LHC analyses (and much of modern science) are based on simulations, "likelihood-free"

A new approach to simulator-based inference

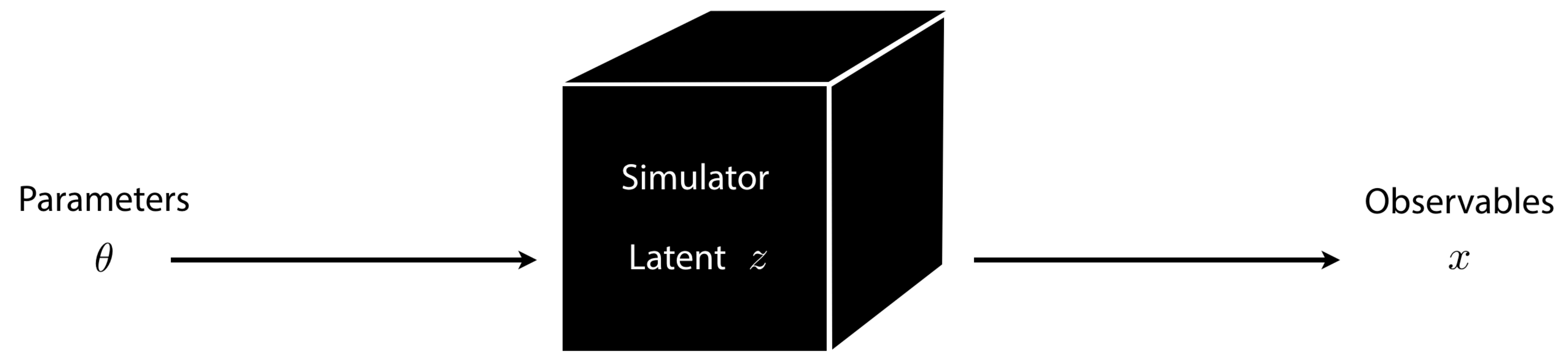


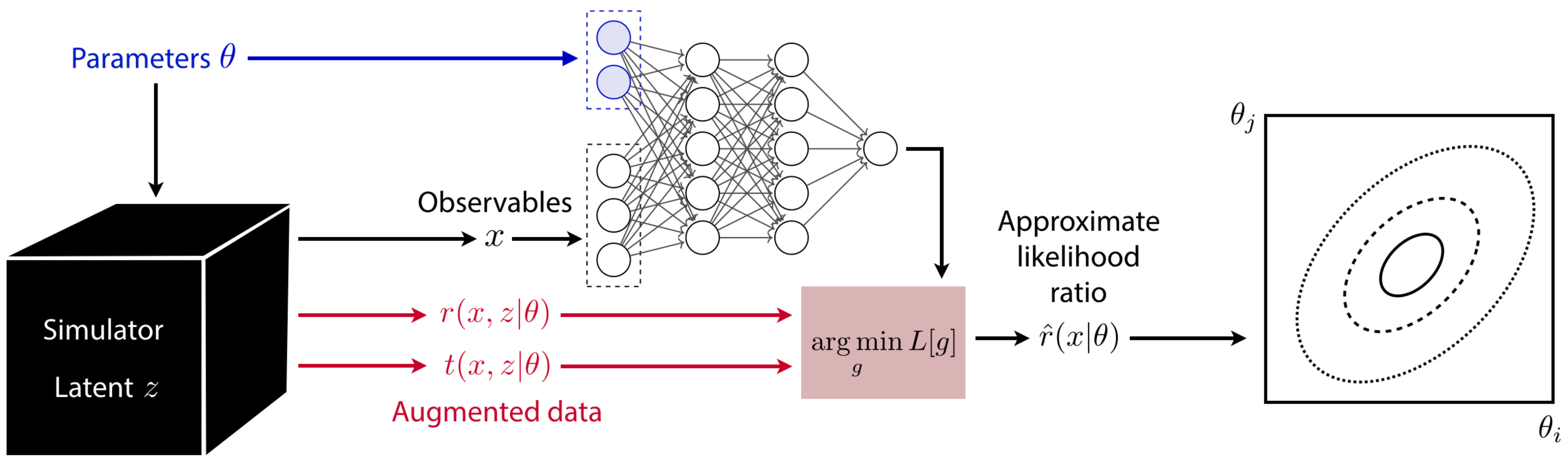


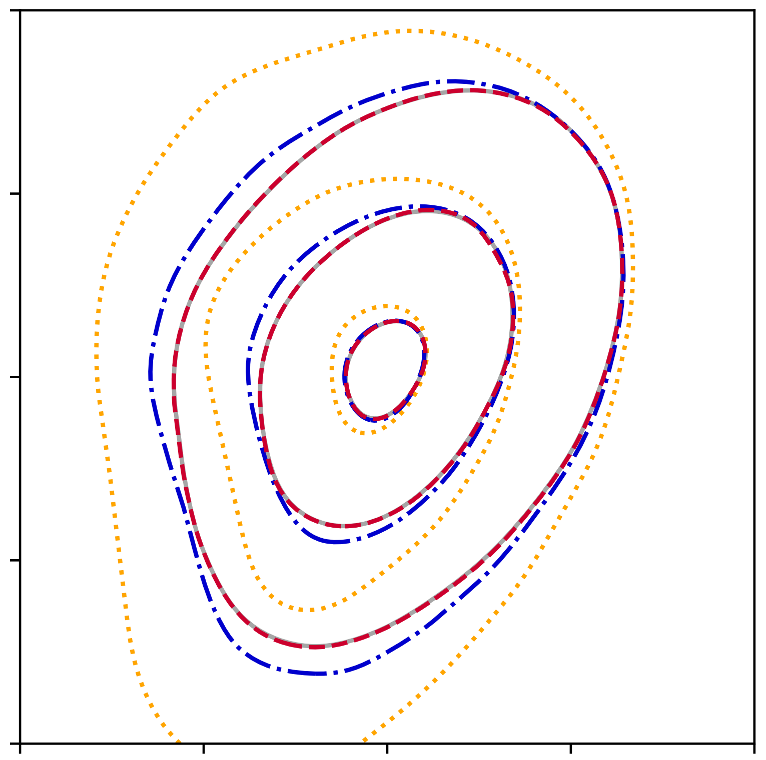
- Many LHC analyses (and much of modern science) are based on simulations, “likelihood-free”

- New multivariate inference techniques: Leverage more information from simulator + power of machine learning

A new approach to simulator-based inference







- Many LHC analyses (and much of modern science) are based on simulations, "likelihood-free"
- New multivariate inference techniques: Leverage more information from simulator + power of machine learning
- First application to LHC physics: Stronger EFT constraints with less simulations

References

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Juan Pavez

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MS, **JB**, GL, JP, KC: Likelihood-free inference with an improved cross-entropy estimator [1808.00973]

JB, KC, FK: MadMiner In preparation

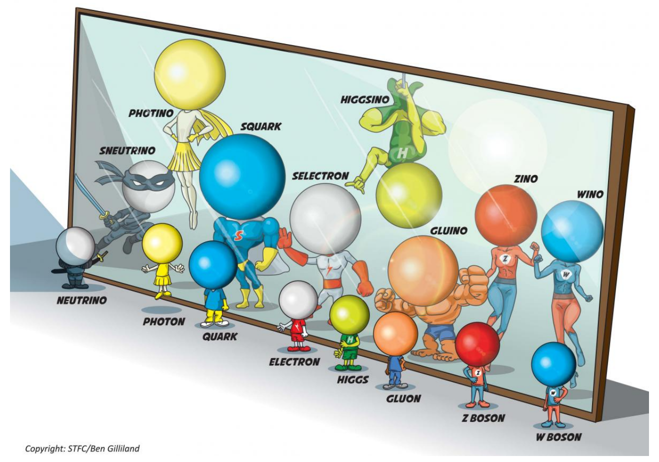
+ new projects with Sally Dawson, Irina Espejo, Sam Homiller, Marvin Meng, Duccio Pappadopulo, Josh Rudermann…

Thanks to Kyle and Gilles for inspiring many slides!

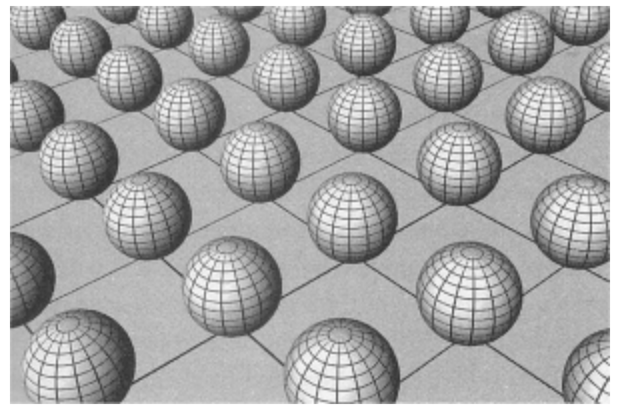
Bonus material

Effective field theory

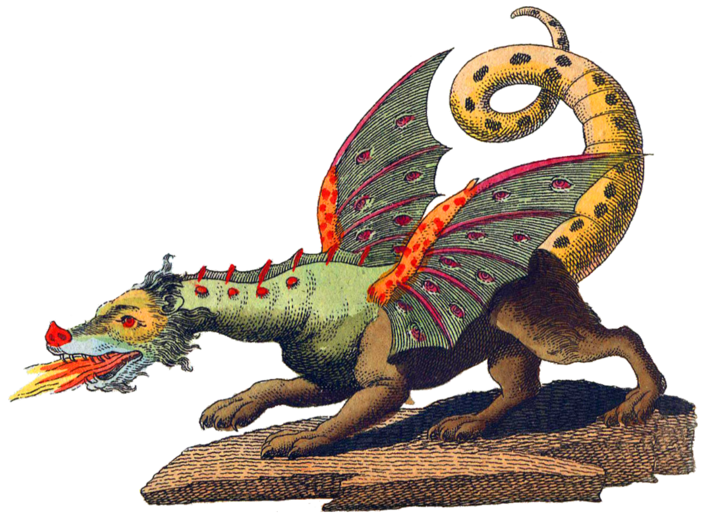
Energy



Supersymmetry?



Extra dimensions?



Dragons?

Composite Higgs?

…

Λ

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

…

Variational calculus

$$L[\hat{g}(x)] = \int \mathrm{d}x\,\mathrm{d}z\; p(x,z|\theta)\;|g(x,z) - \hat{g}(x)|^2$$

$$= \int \mathrm{d}x\;\underbrace{\left[\hat{g}^2(x)\int \mathrm{d}z\; p(x,z|\theta) - 2\hat{g}(x)\int \mathrm{d}z\; p(x,z|\theta)\,g(x,z) + \int \mathrm{d}z\; p(x,z|\theta)\,g^2(x,z)\right]}_{F(x)}$$

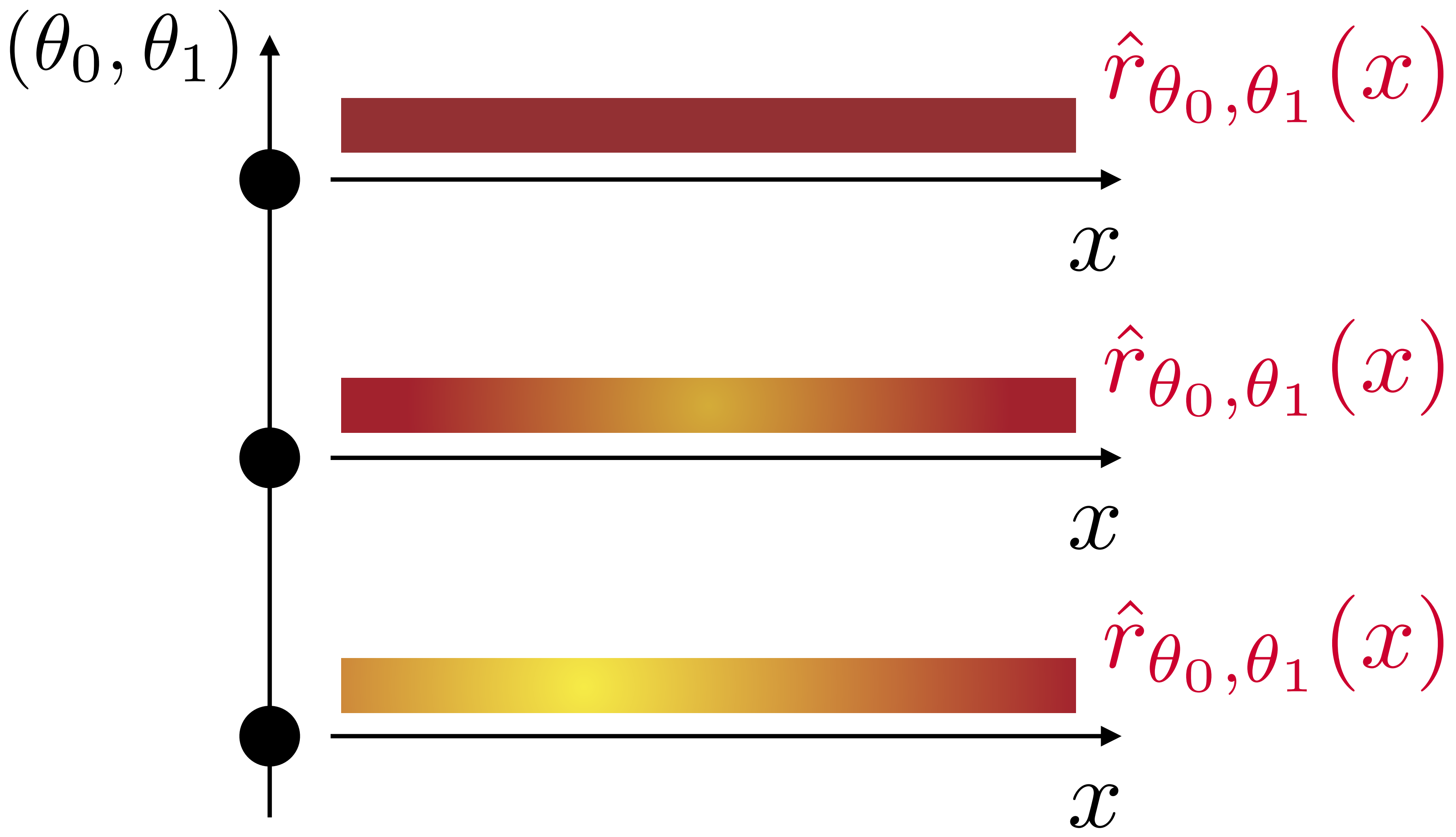
$$0 = \left.\frac{\delta F}{\delta \hat{g}}\right|_{g^*} = 2\hat{g}\underbrace{\int \mathrm{d}z\; p(x,z|\theta)}_{=p(x|\theta)} - 2\int \mathrm{d}z\; p(x,z|\theta)\,g(x,z)$$

$$g^*(x) = \frac{1}{p(x|\theta)}\int \mathrm{d}z\; p(x,z|\theta)\,g(x,z)$$

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



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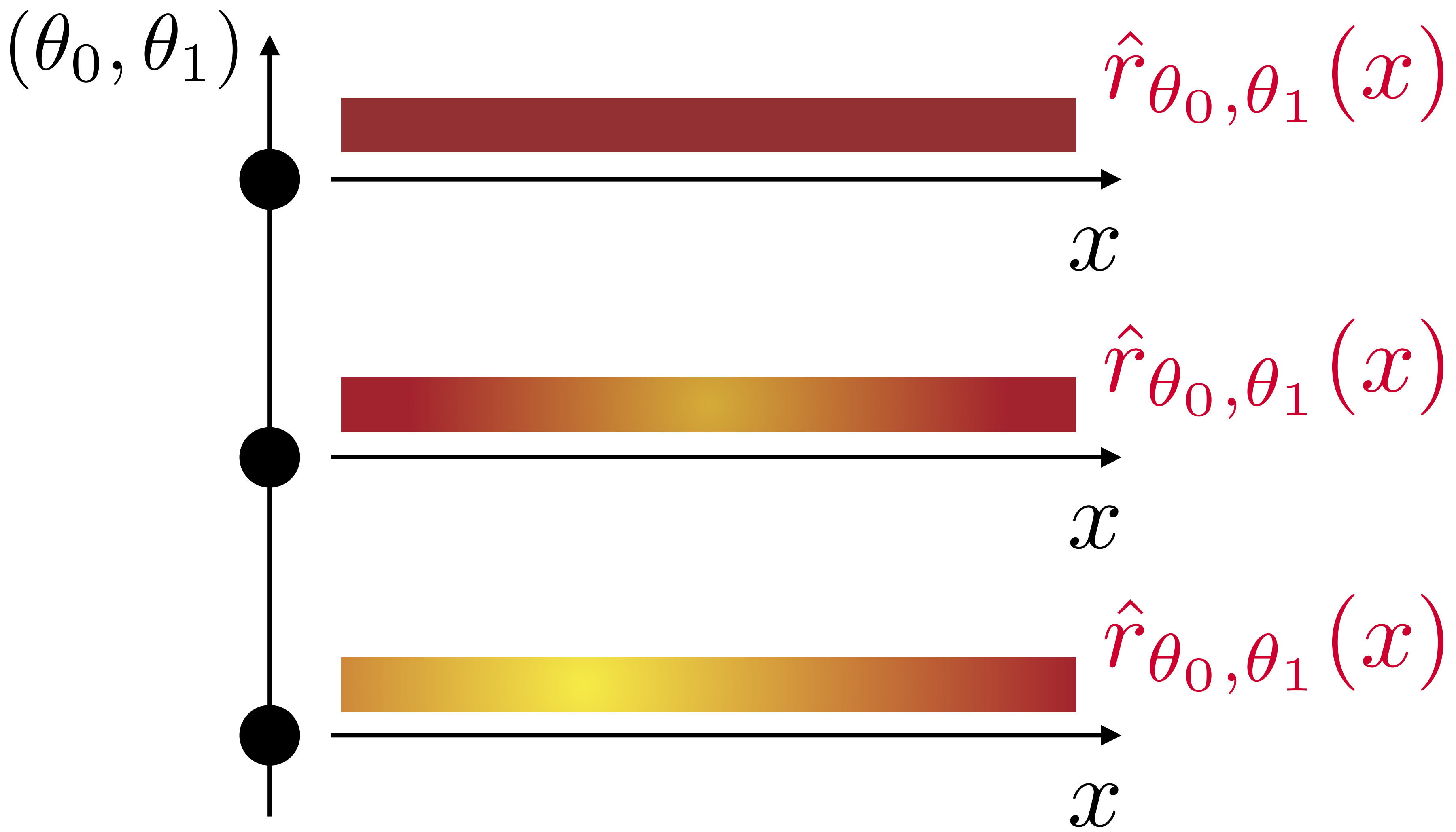
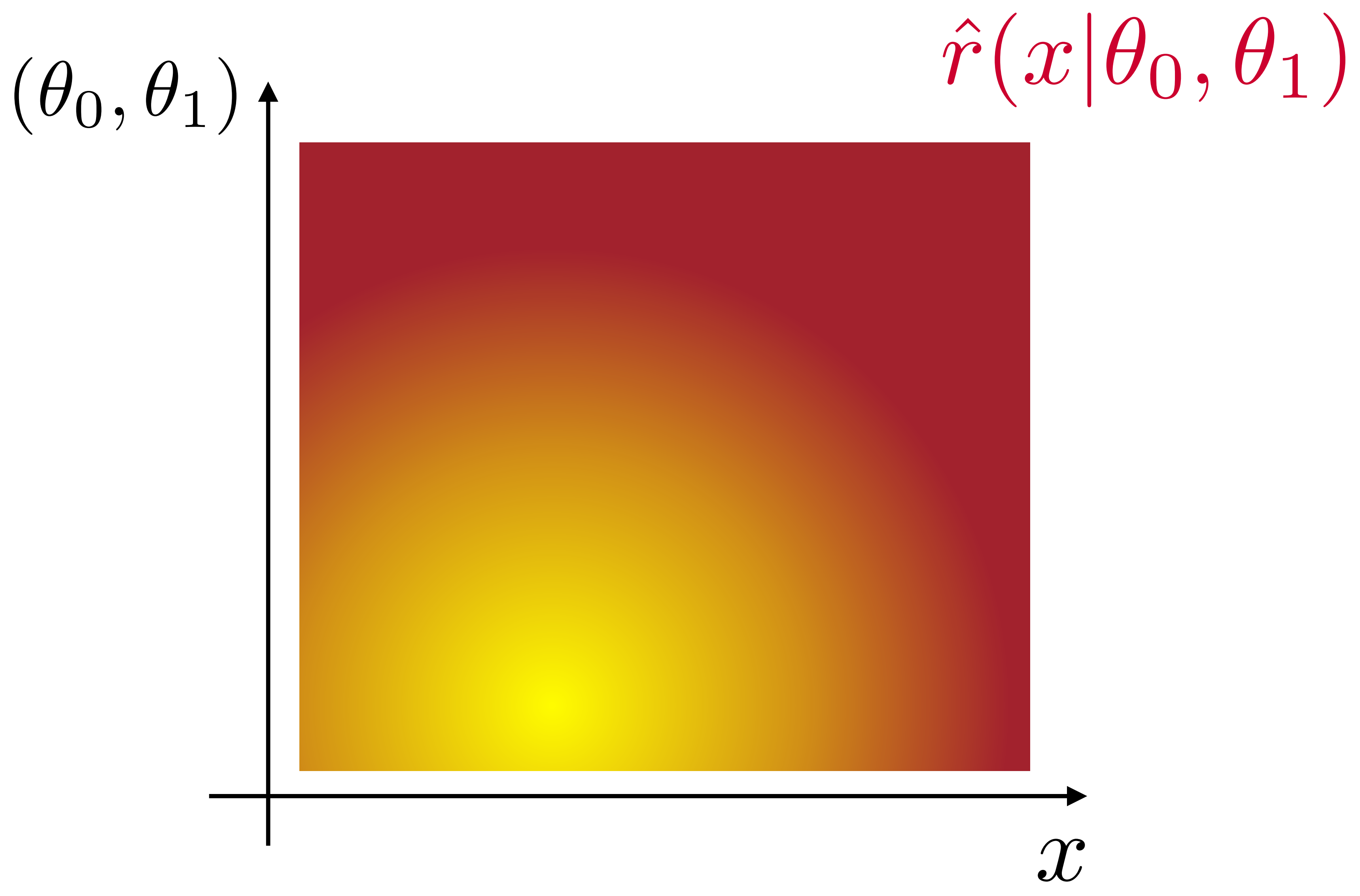
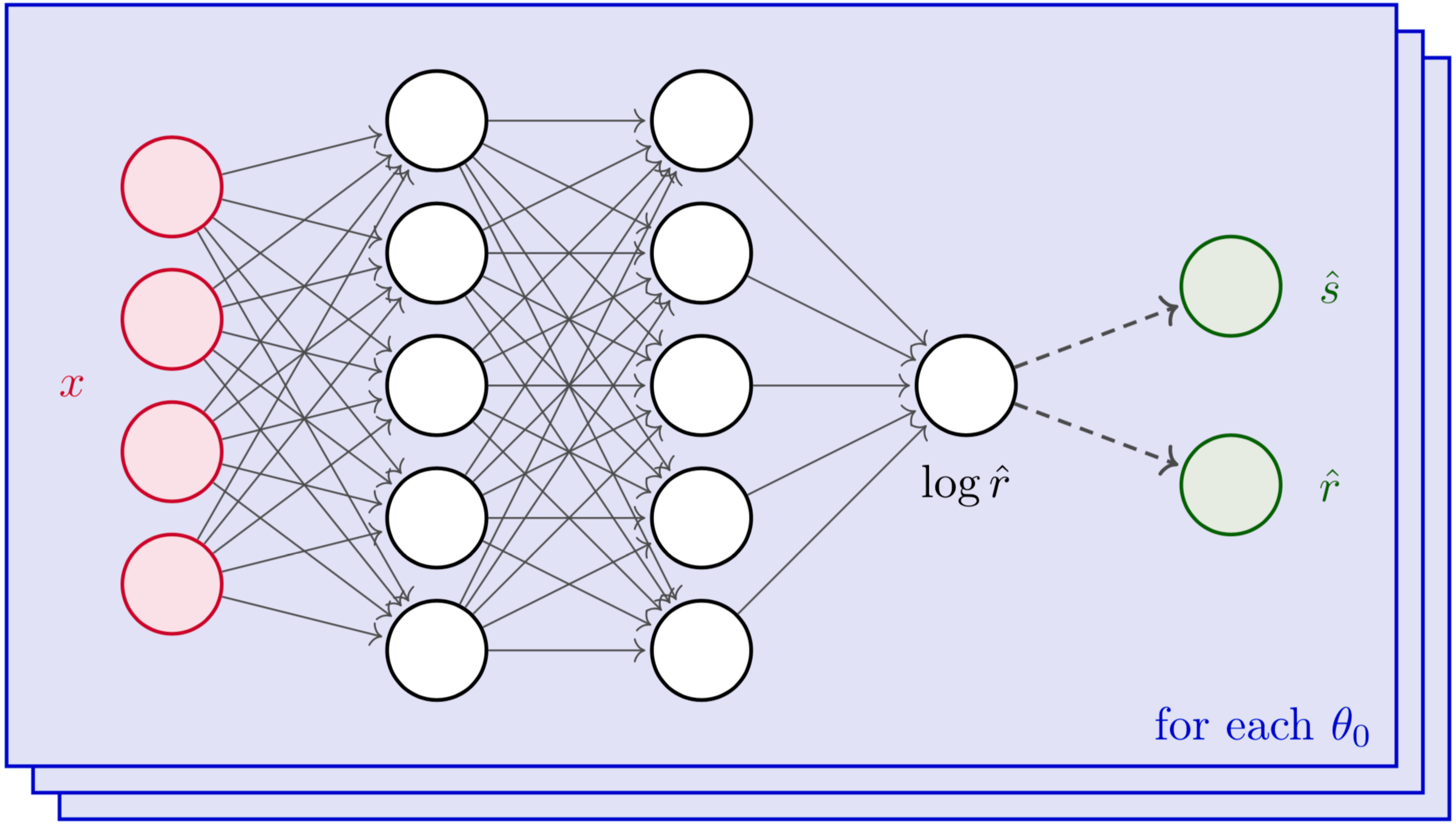


B) Parameterized: [P. Baldi et al. 1506.02169]

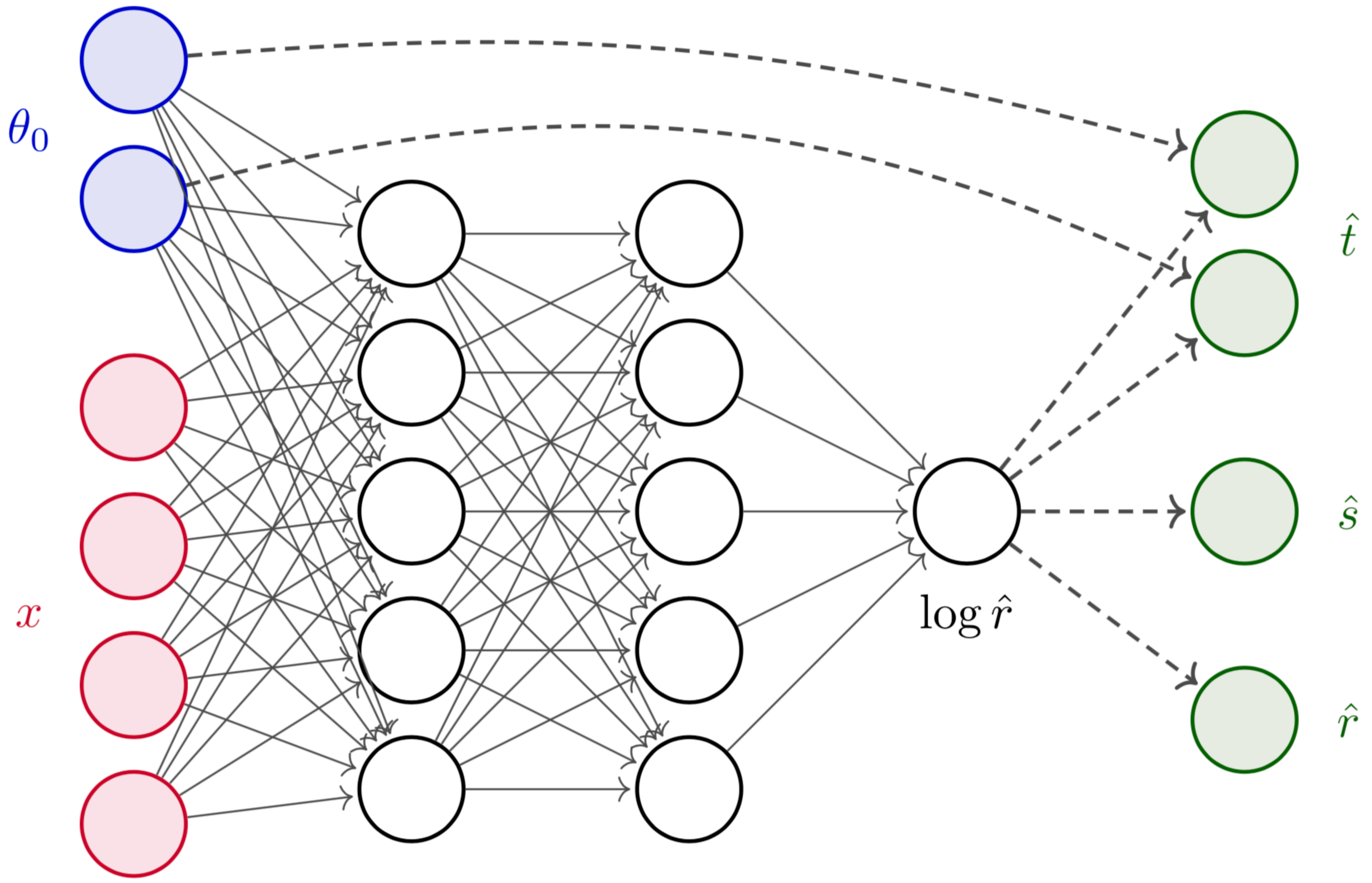
- create one estimator $\hat{r}(x|\theta_0, \theta_1)$ that is a function of θ_0 and θ_1
- no further interpolation necessary
- "borrows information" from close points



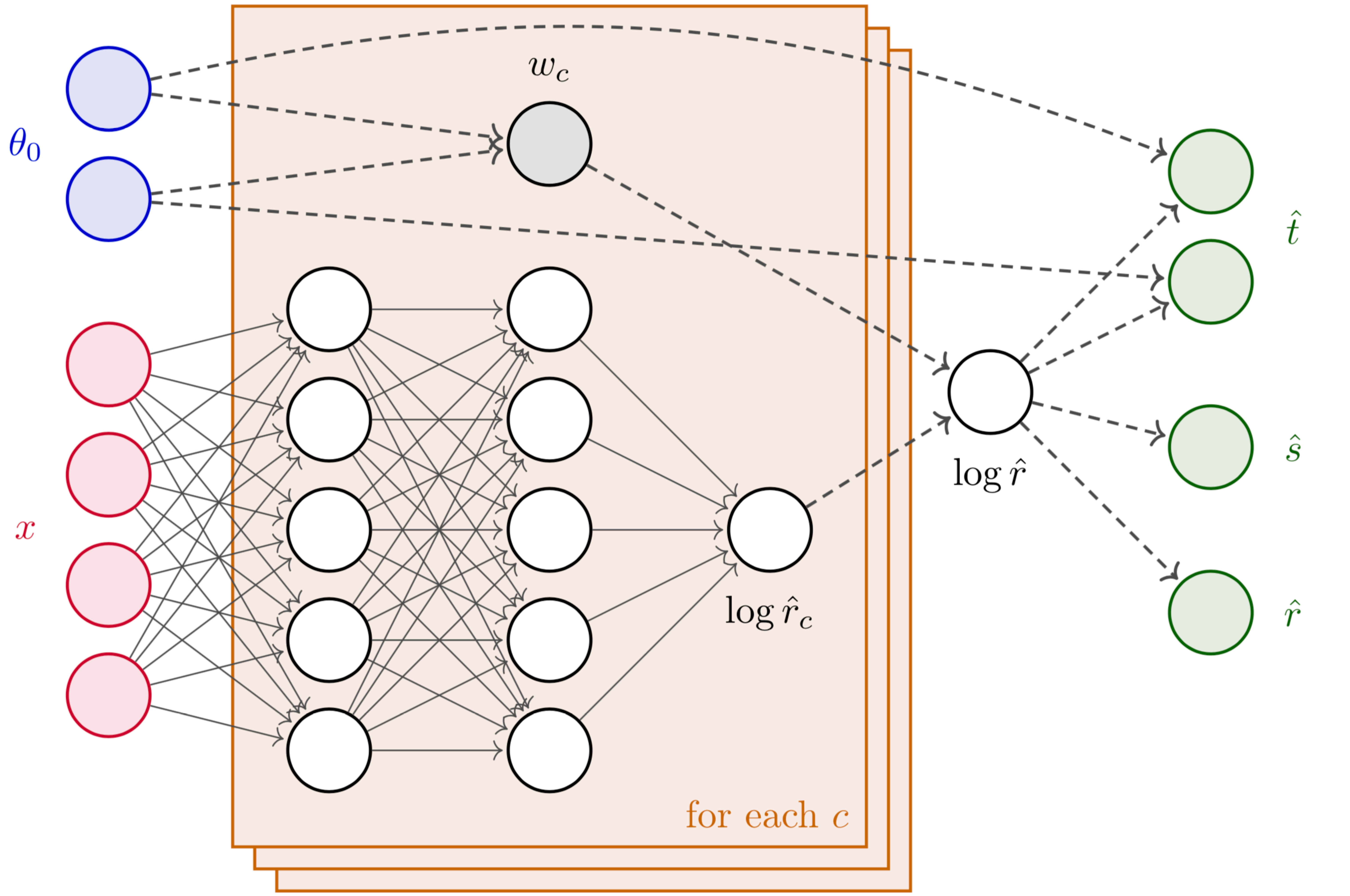
Point by point



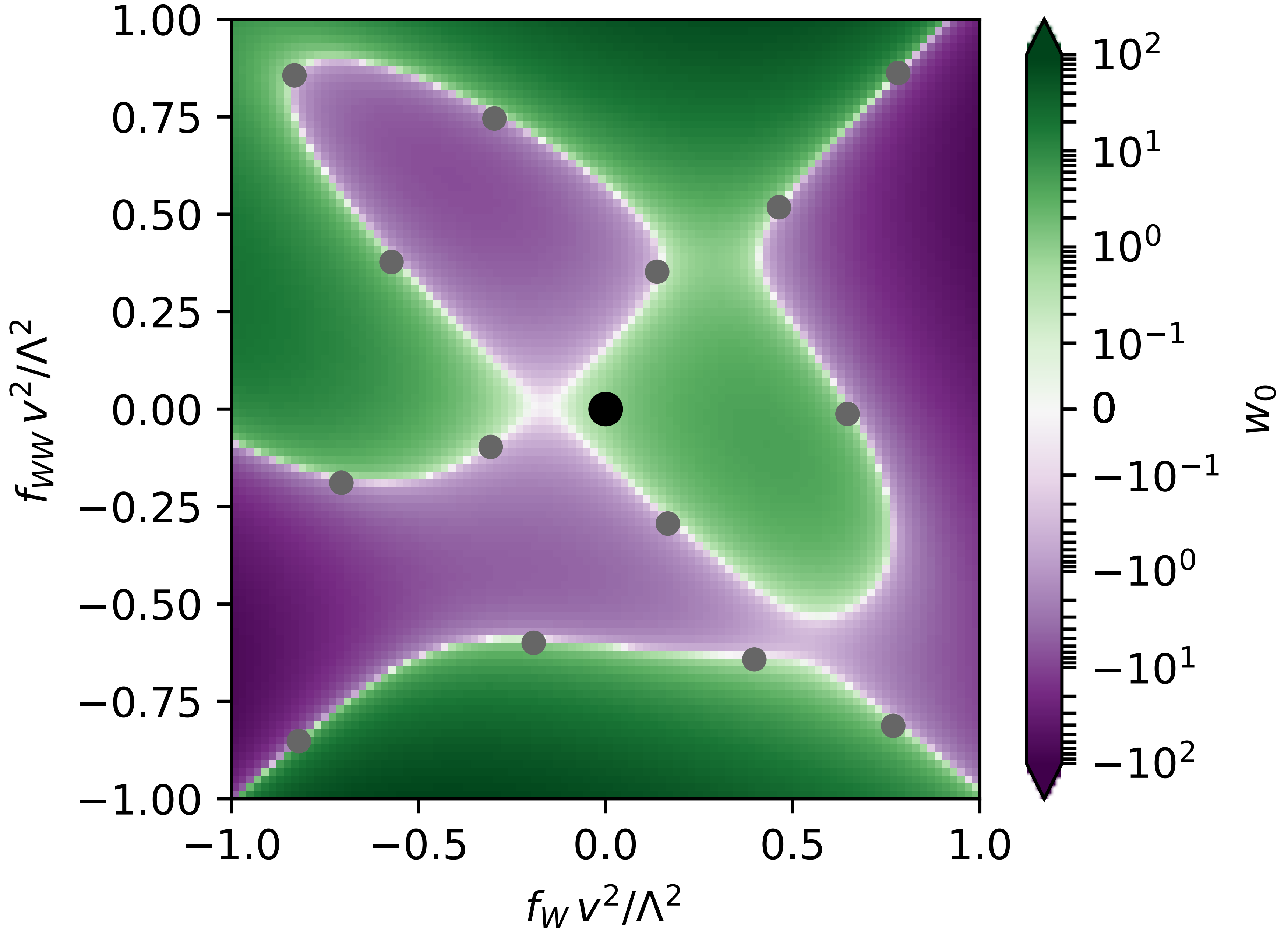
(Agnostic) parameterized estimators



Morphing-aware parameterized estimators



$$\hat{r}(x|\theta_0, \theta_1) = \sum_c w_c(\theta_0)\, \hat{r}_c(x)$$



Detector effects