

PLUMBIN'

— Developing solvents for unclogging the computational bottleneck in high-energy physics

Are Raklev

The problem

How do you test your fancy new theoretical model?

The problem

How do you test your fancy new theoretical model?

You compare it to the data

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What can you test in a physics model?

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What can you test in a physics model?

best-fit parameters

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What *parameters* ϑ in
my model fit the data?

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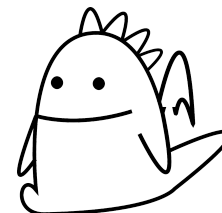
What can you test in a physics model?

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here be dragons!



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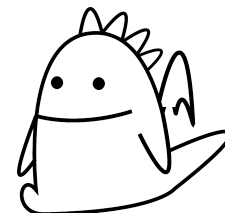
goodness-of-fit

best-fit parameters



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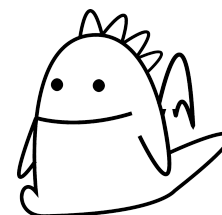
How probable is my
model given the data?
(How probable is my
model compared to
another model?)

best-fit parameters



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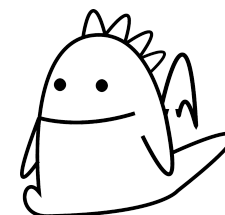
best-fit parameters



What *parameters ϑ* in my model fit the data?

here be dragons!

The focus here is always on *dis-proving* the model or the values of the parameters



The problem

How do you test your fancy new theoretical model?

You compare it to the data

WE WANT ALL THE DATA

How do you compare to data: the (global) likelihood

$$\mathcal{L} = \mathcal{L}_{\text{Collider}} \mathcal{L}_{\text{Higgs}} \mathcal{L}_{\text{Flavour}} \mathcal{L}_{\text{DM}} \mathcal{L}_{\text{Precision}} \dots$$



What can you test in a physics model?

goodness-of-fit



How probable is my model given the data?

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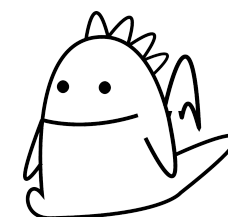
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What parameters ϑ in my model fit the data?

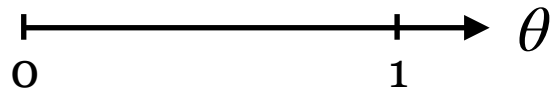
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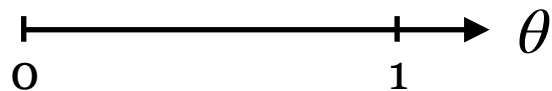
The problem with parameters

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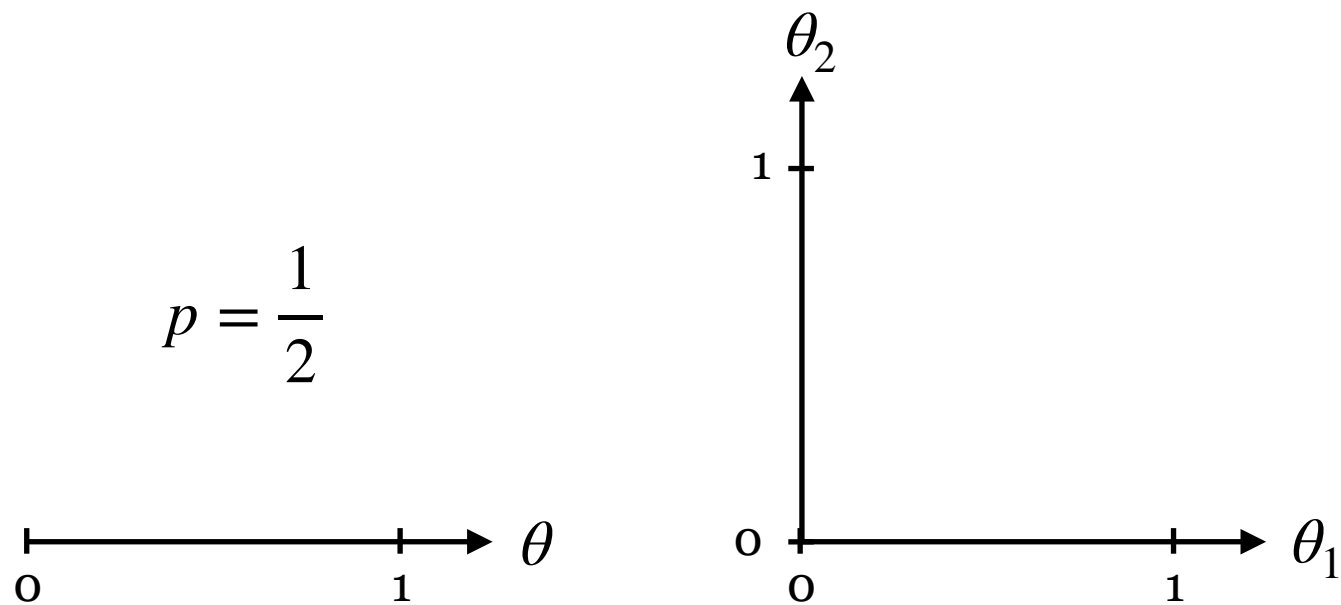


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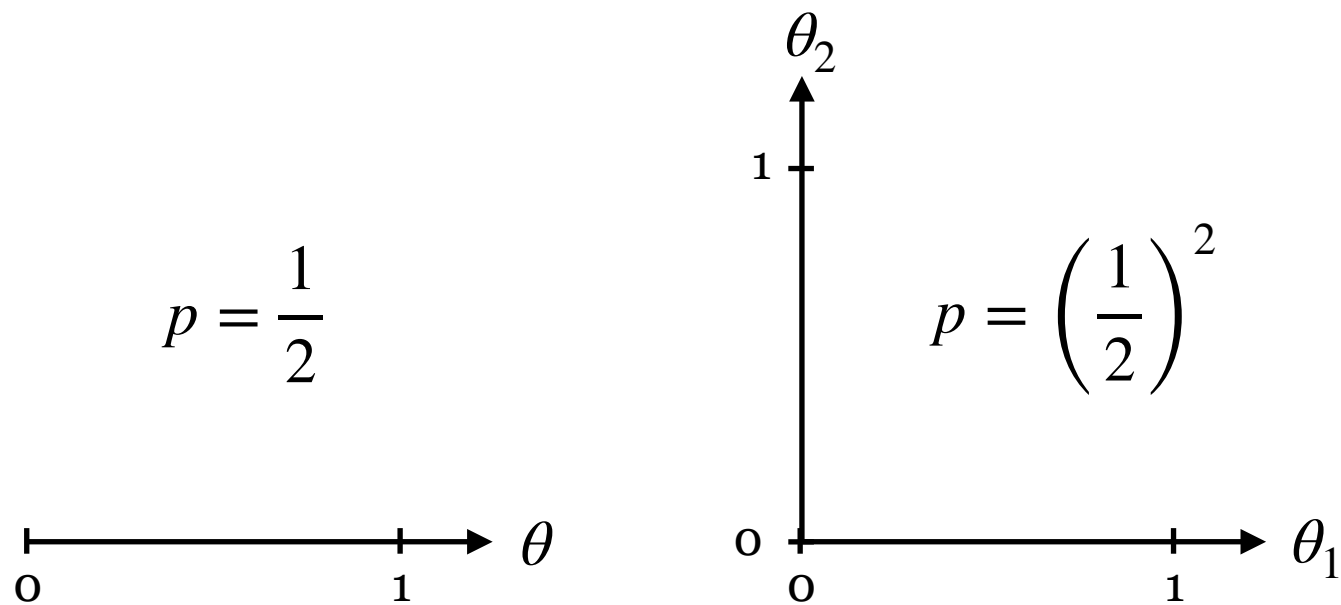
$$p = \frac{1}{2}$$



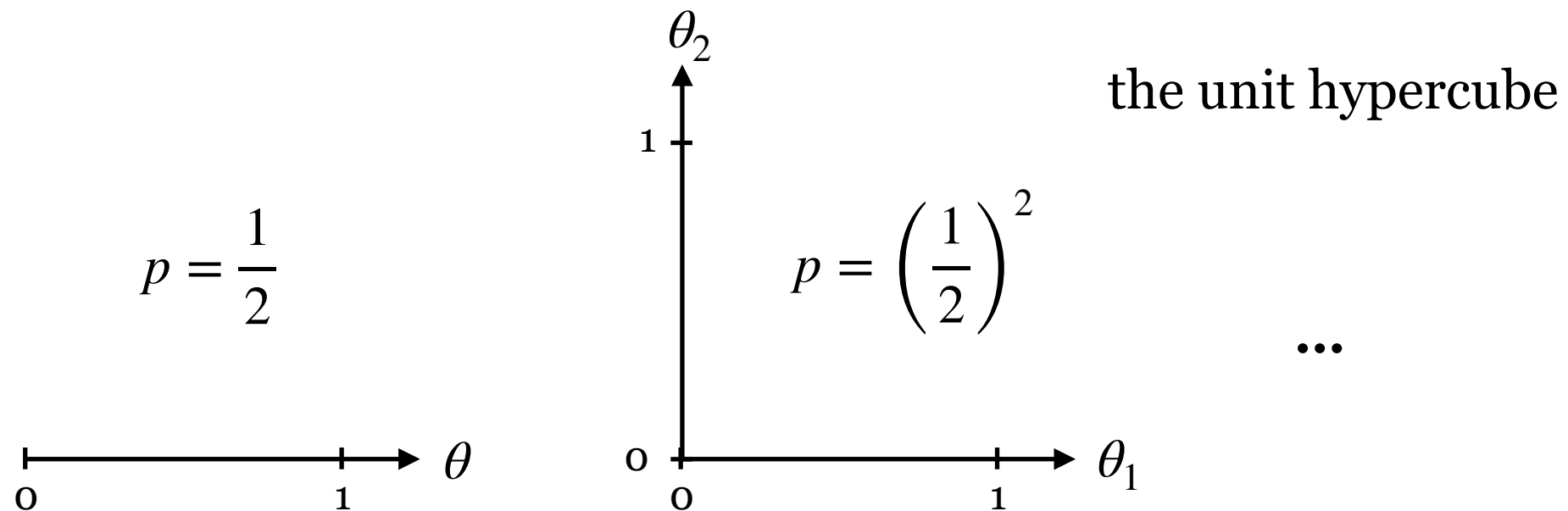
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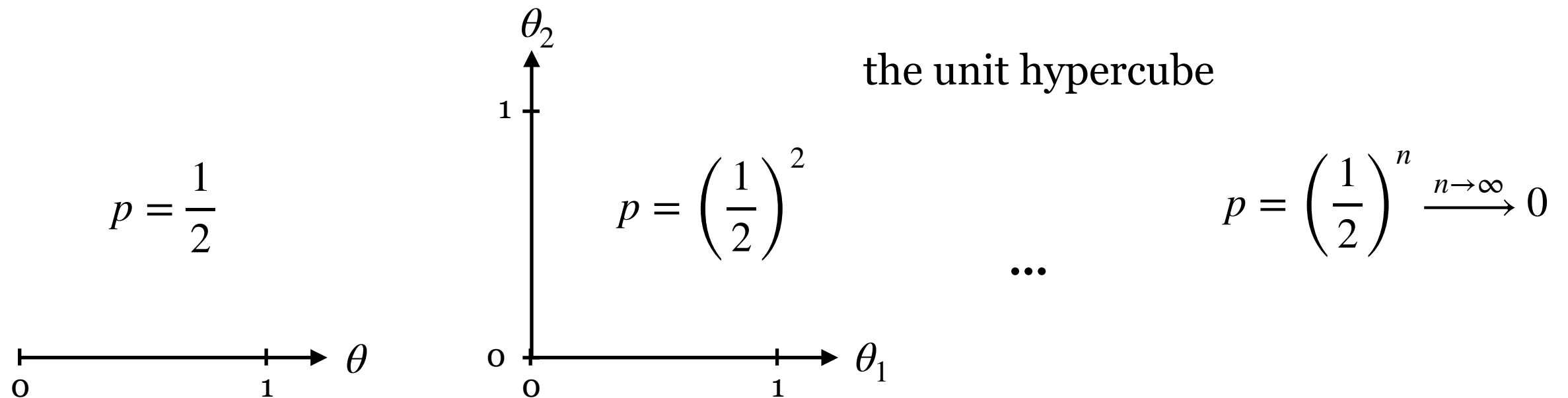
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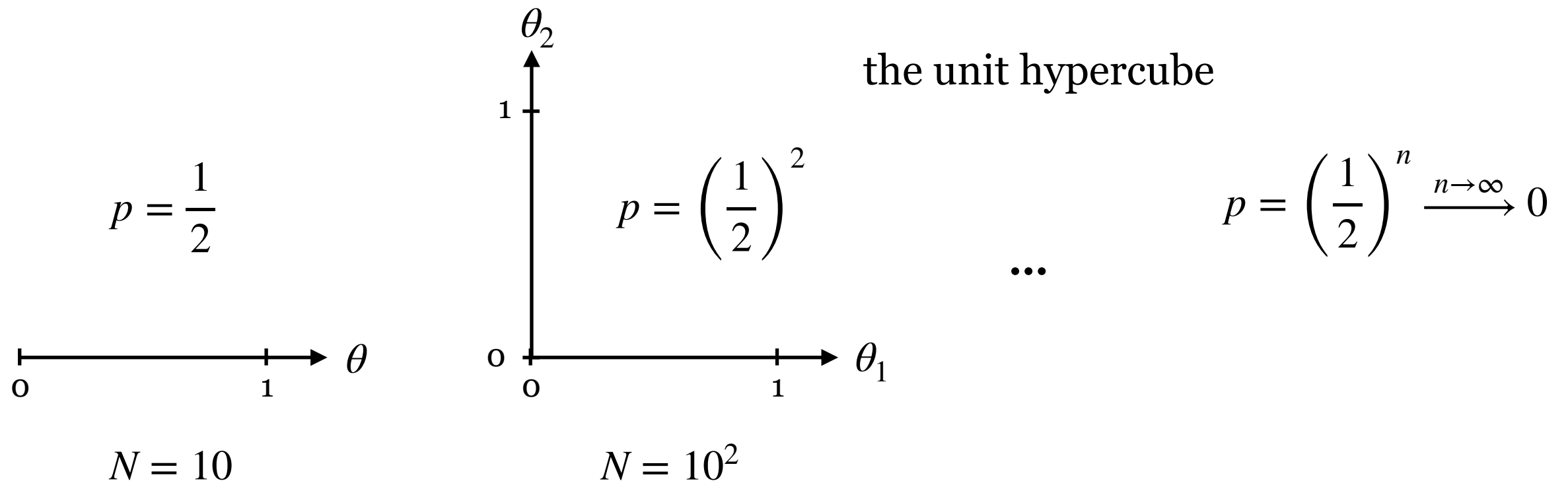
The problem with parameters



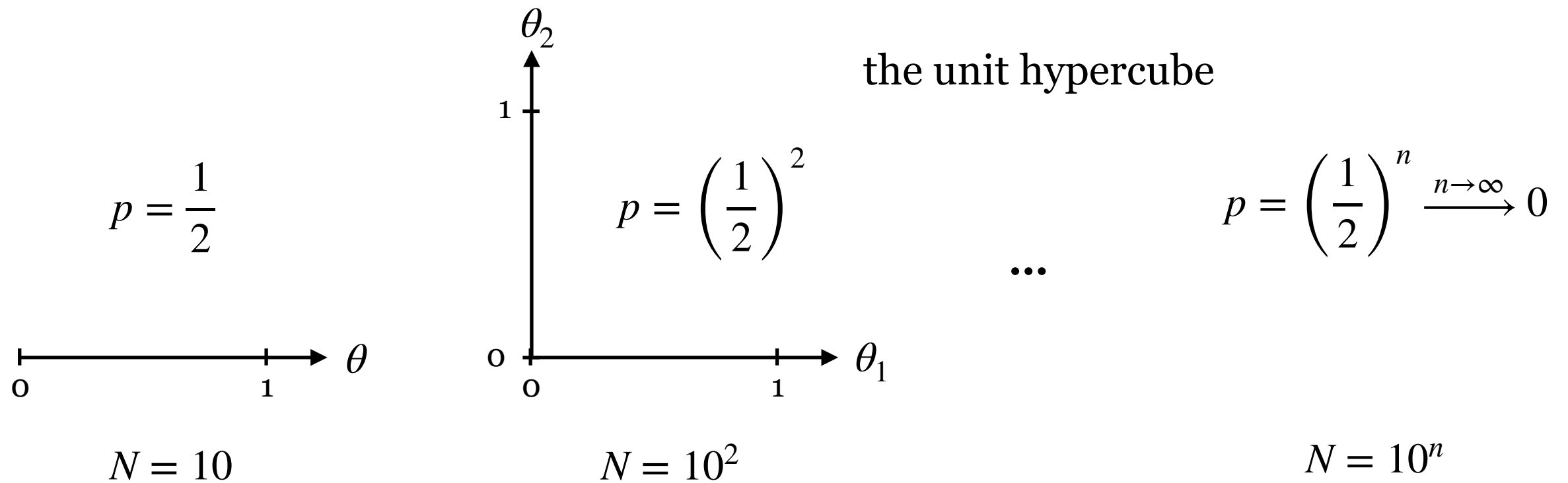
The problem with parameters



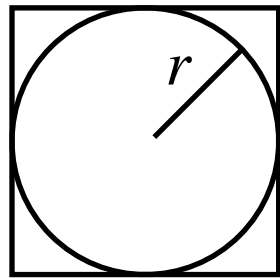
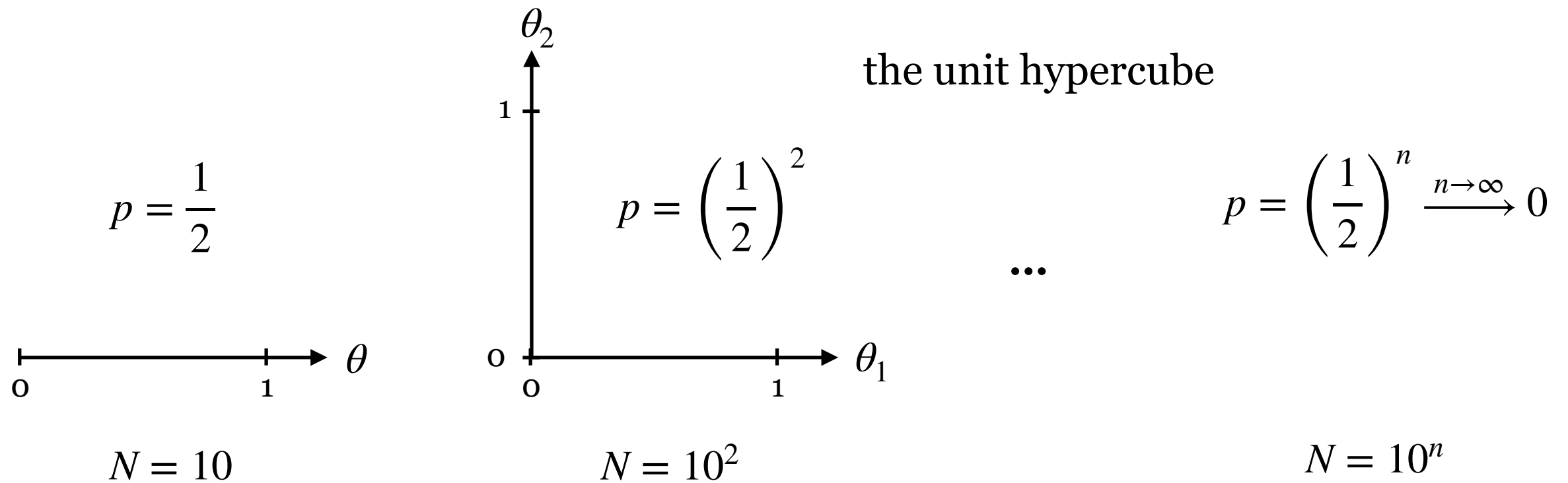
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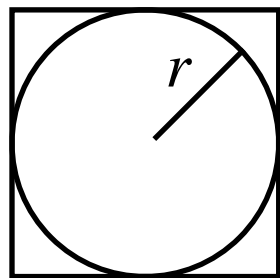
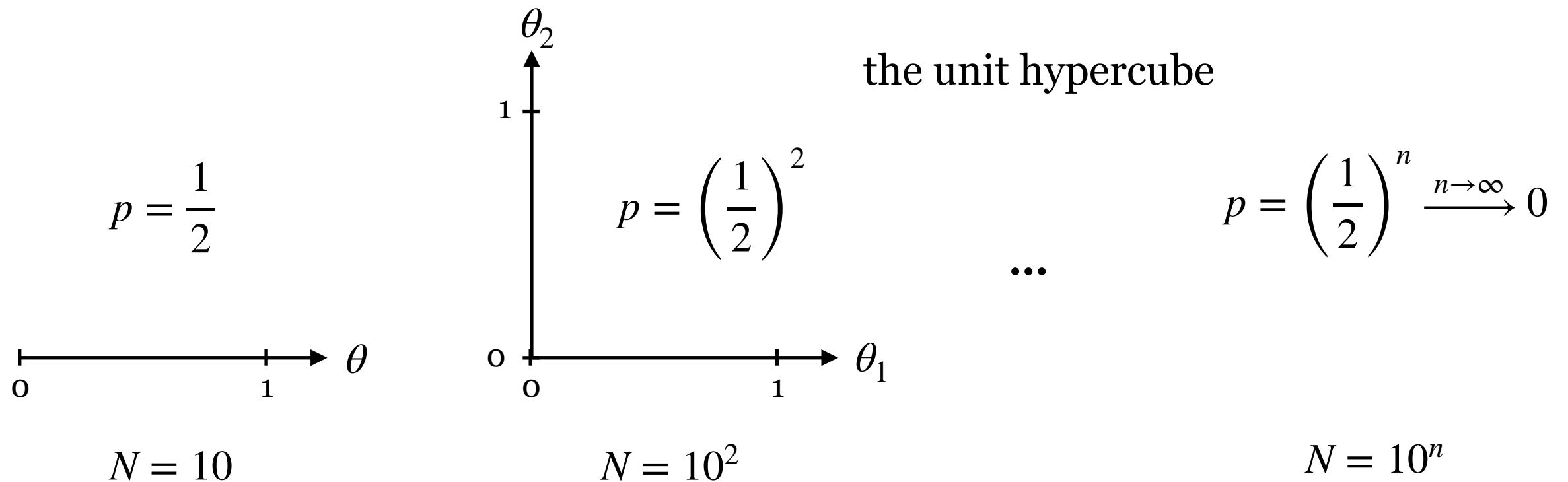
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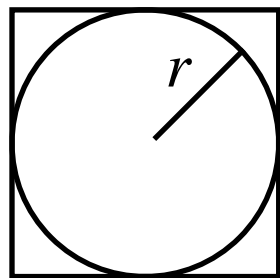
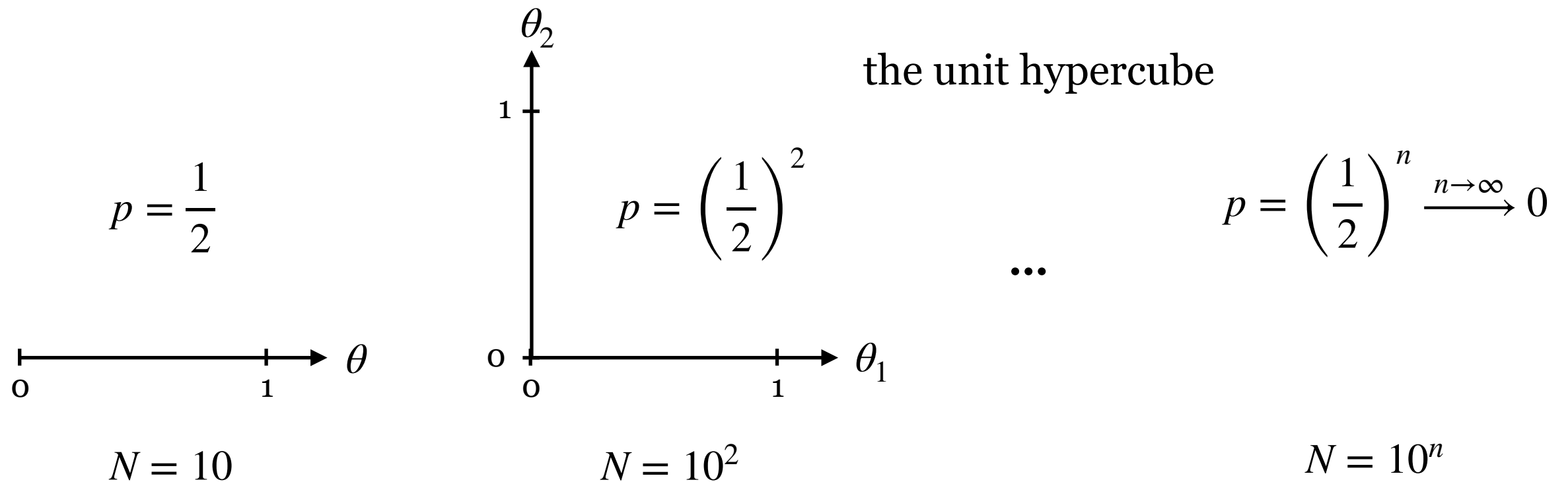


The problem with parameters

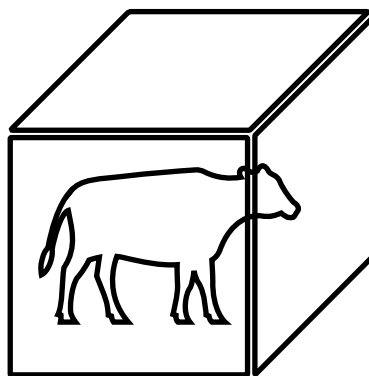


$$\frac{A_{\bigcirc}}{A_{\square}} = \frac{\pi r^2}{(2r)^2} = \frac{\pi}{4}$$

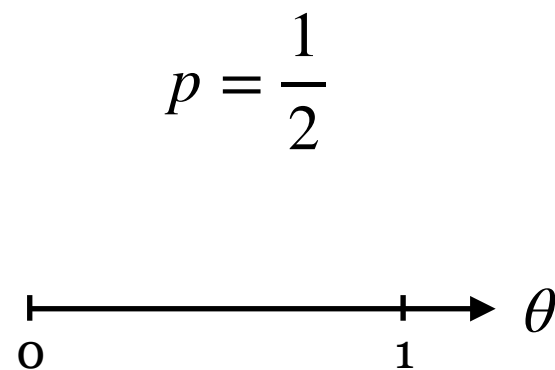
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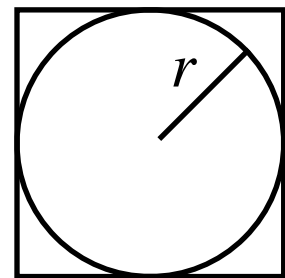
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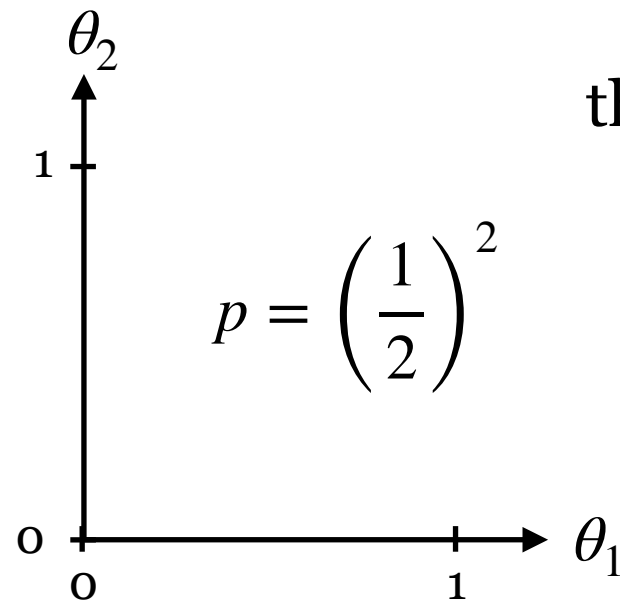
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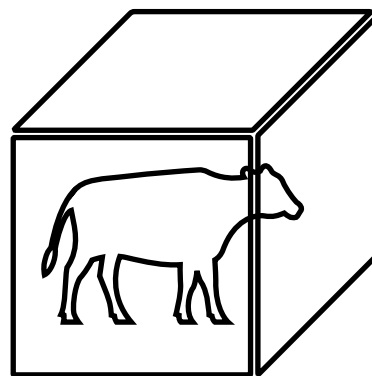
$$N = 10$$



$$\frac{A_{\bigcirc}}{A_{\square}} = \frac{\pi r^2}{(2r)^2} = \frac{\pi}{4}$$



$$N = 10^2$$



$$\frac{V_{\bigcirc}}{V_{\square}} = \frac{\frac{4}{3}\pi r^3}{(2r)^3} = \frac{\pi}{6}$$

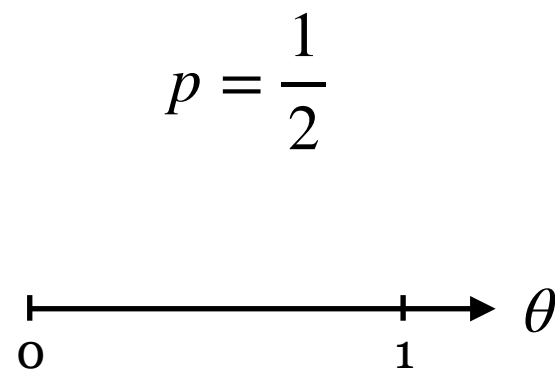
the unit hypercube

...

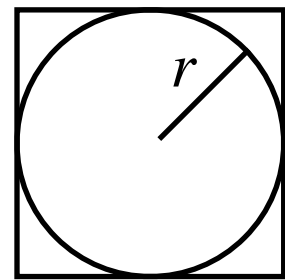
$$p = \left(\frac{1}{2}\right)^n \xrightarrow{n \rightarrow \infty} 0$$

$$N = 10^n$$

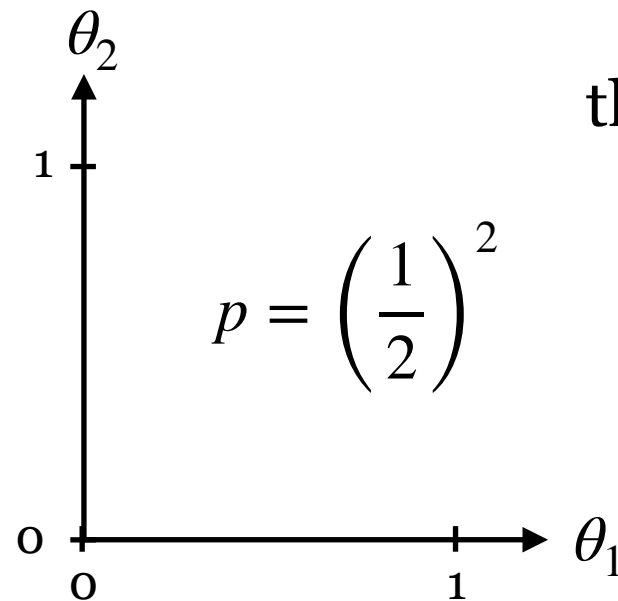
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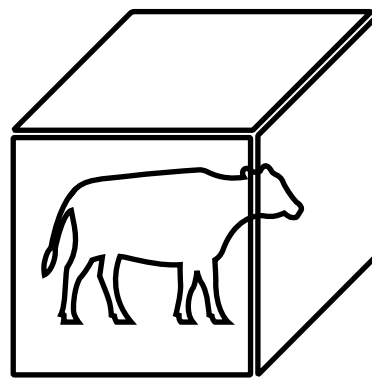
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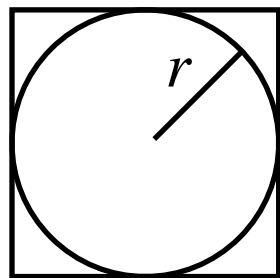
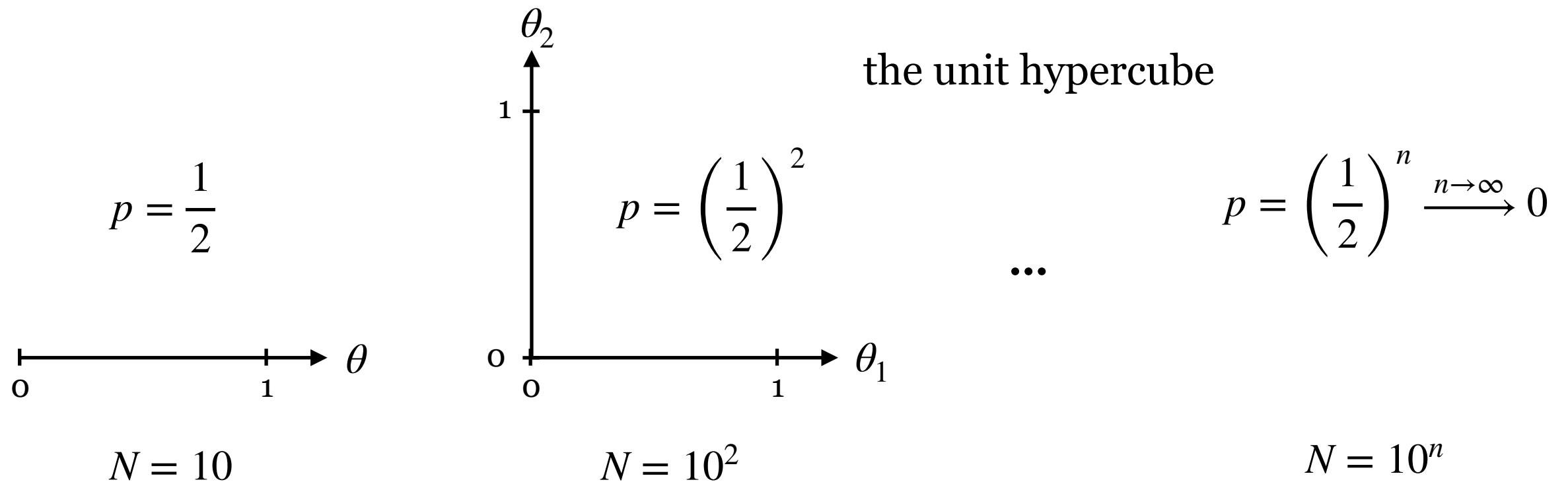
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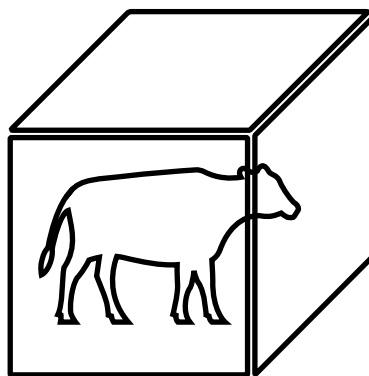
$$\frac{V_{\bigcirc^n}}{V_{\square^n}} = \frac{\frac{\pi^{n/2} r^n}{\Gamma(n/2 + 1)}}{(2r)^n} \xrightarrow{n \rightarrow \infty} 0$$

The problem with parameters

The curse of dimensionality



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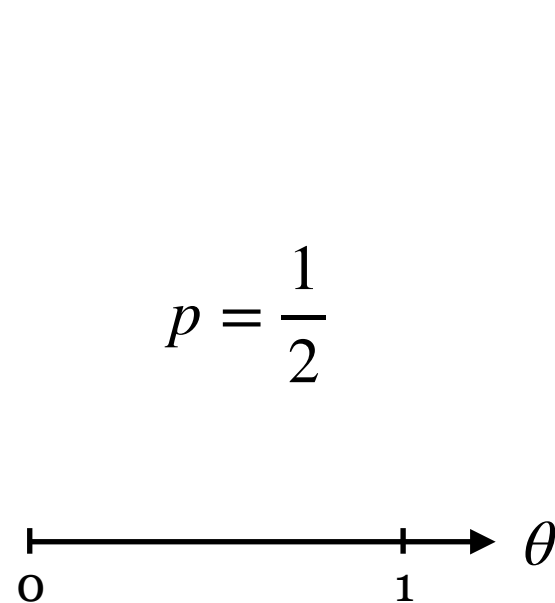


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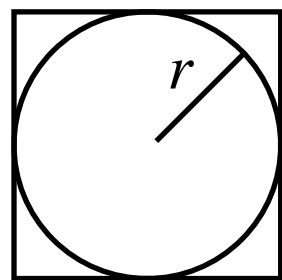
The problem with parameters

The curse of dimensionality

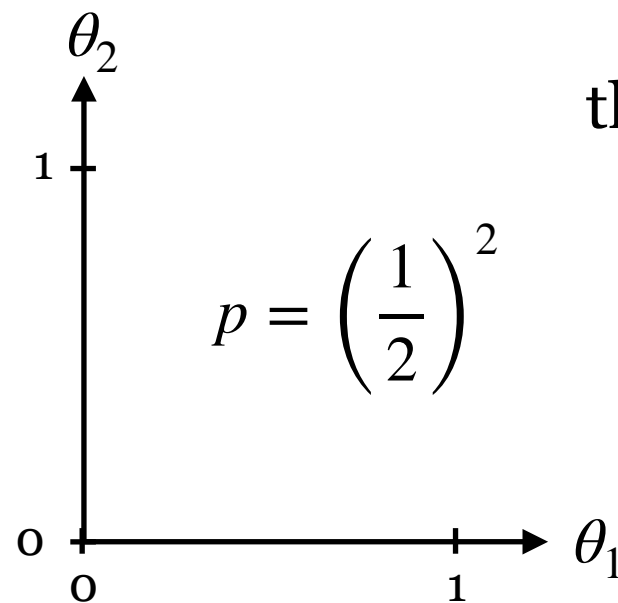


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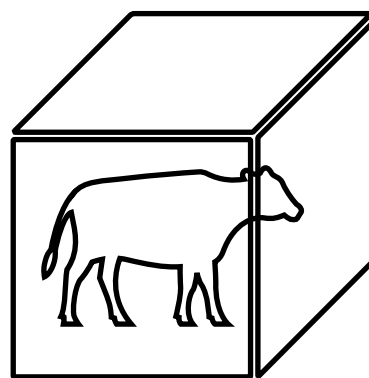


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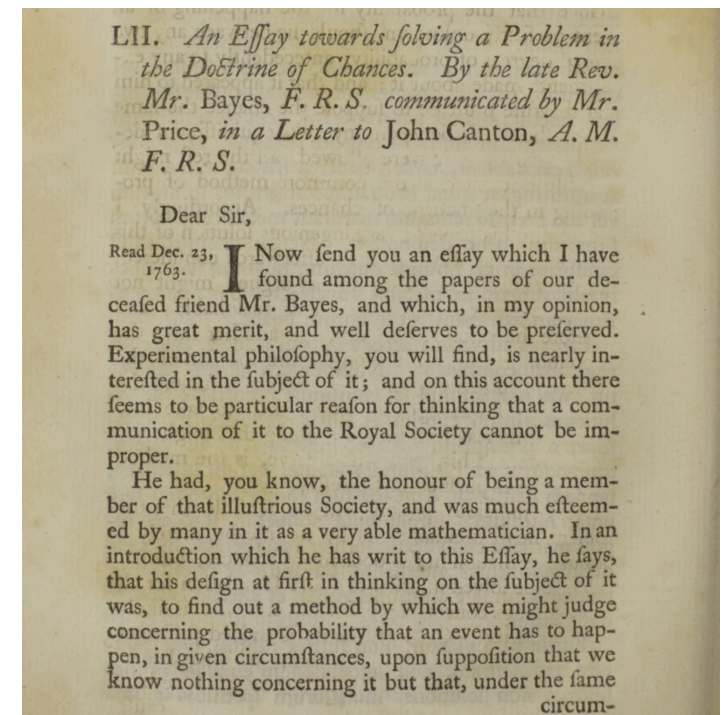
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you can't find your socks
in 11-dimensions

Using likelihoods

Bayes' theorem

$$P(\theta | D) = \frac{P(D | \theta)P(\theta)}{P(D)}$$

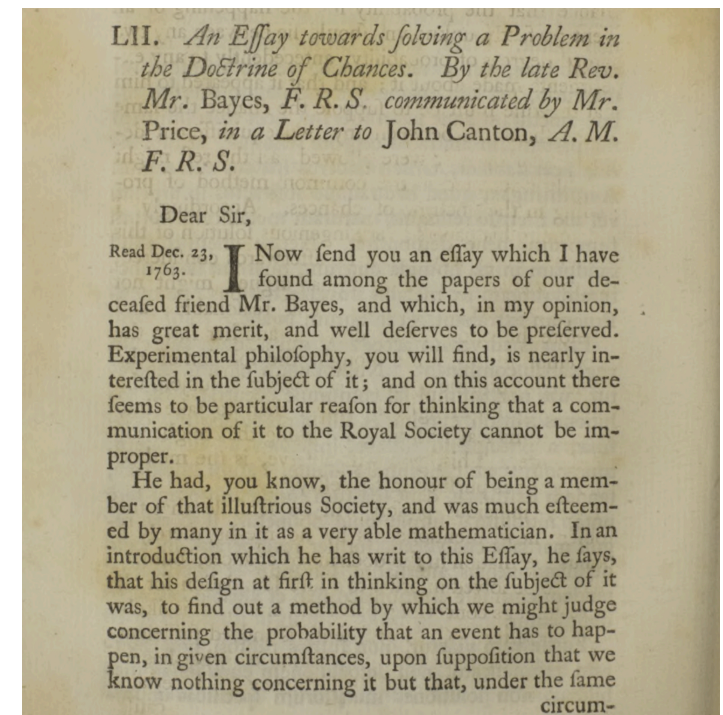


T. Bayes, *An Essay towards solving a Problem in the Doctrine of Chances*,
Philosophical Transactions of the Royal Society of London 53 (1763) 370–418

Using likelihoods

Bayes' theorem

$$P(\theta | D) = \frac{P(D | \theta)P(\theta)}{P(D)} \quad \leftarrow \begin{array}{l} \text{the prior} \\ \pi(\theta) = P(\theta) \end{array}$$



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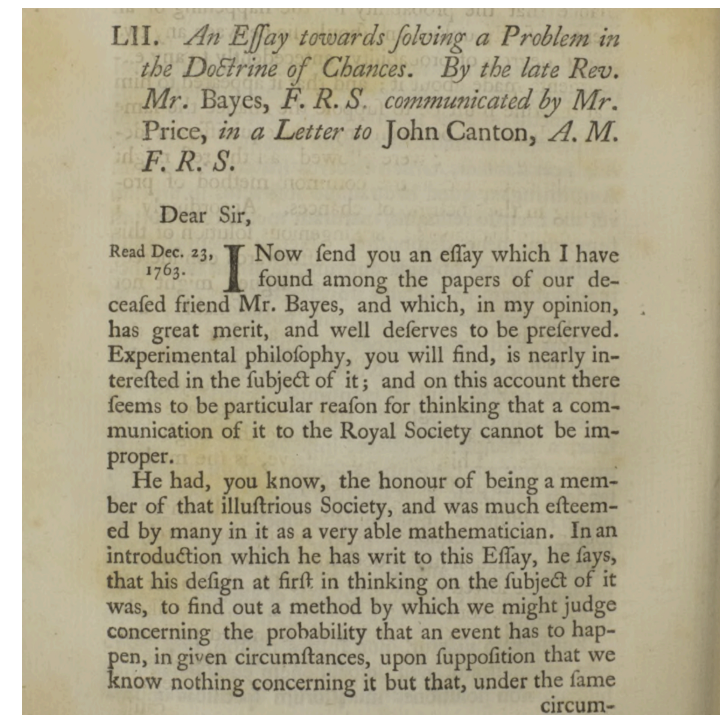
Using likelihoods

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← the prior
 $\pi(\theta) = P(\theta)$

↑
the
posterior
 $\mathcal{P}(\theta) = P(\theta | D)$



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Using likelihoods

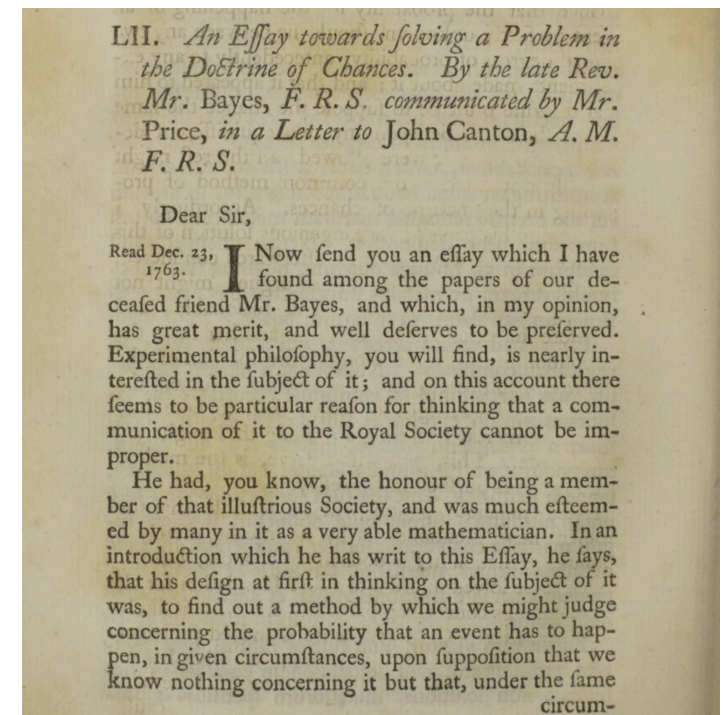
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the posterior $\mathcal{P}(\theta) = P(\theta | D)$

the prior $\pi(\theta) = P(\theta)$

the evidence $\mathcal{E} = P(D)$



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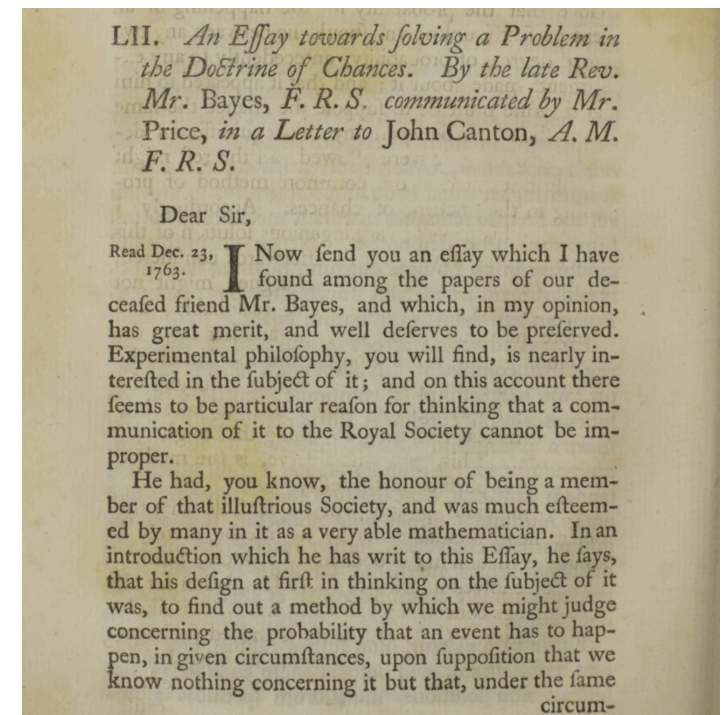
the posterior $\mathcal{P}(\theta) = P(\theta | D)$

the prior $\pi(\theta) = P(\theta)$

the evidence $\mathcal{Z} = P(D)$

The likelihood

$$\mathcal{L}(\theta) = P(D | \theta)$$



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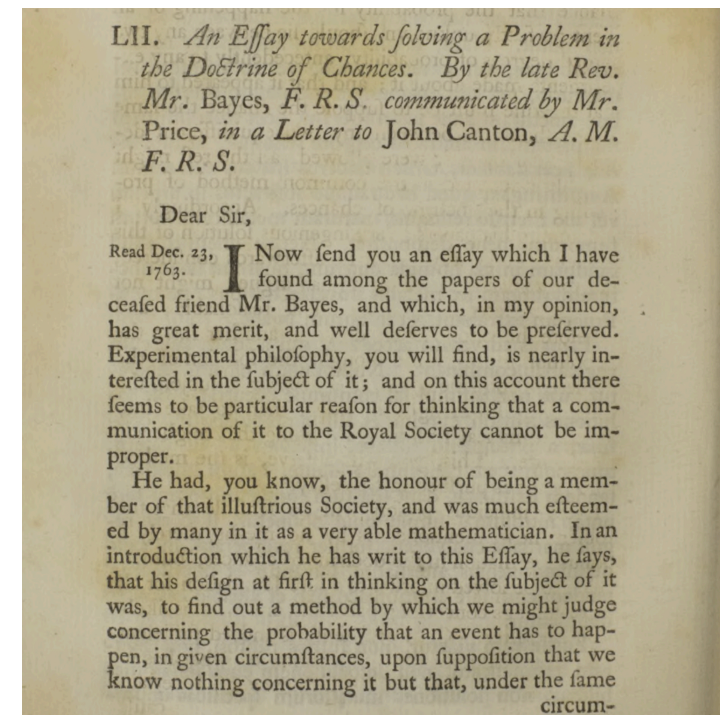
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The likelihood can be maximised wrt. to the parameters to find the *best-fit* region.



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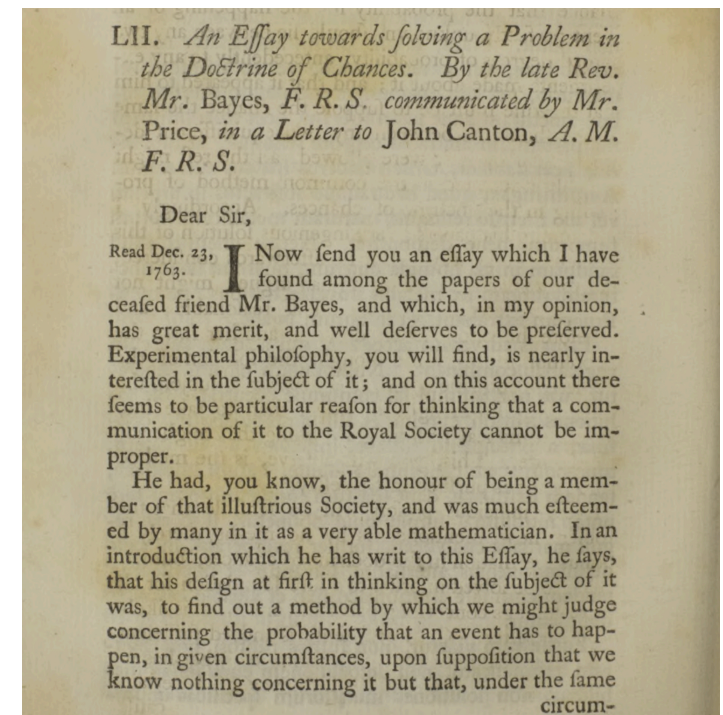
The likelihood

$$\mathcal{L}(\theta) = P(D | \theta)$$

The likelihood can be maximised wrt. to the parameters to find the *best-fit* region.

In practice one uses the *test statistic* q to set confidence regions on some of the parameters ϑ ignoring others ν

$$q(\theta) = -2 \ln \frac{\mathcal{L}(\theta, \hat{\nu})}{\mathcal{L}(\hat{\theta}, \hat{\nu})}$$



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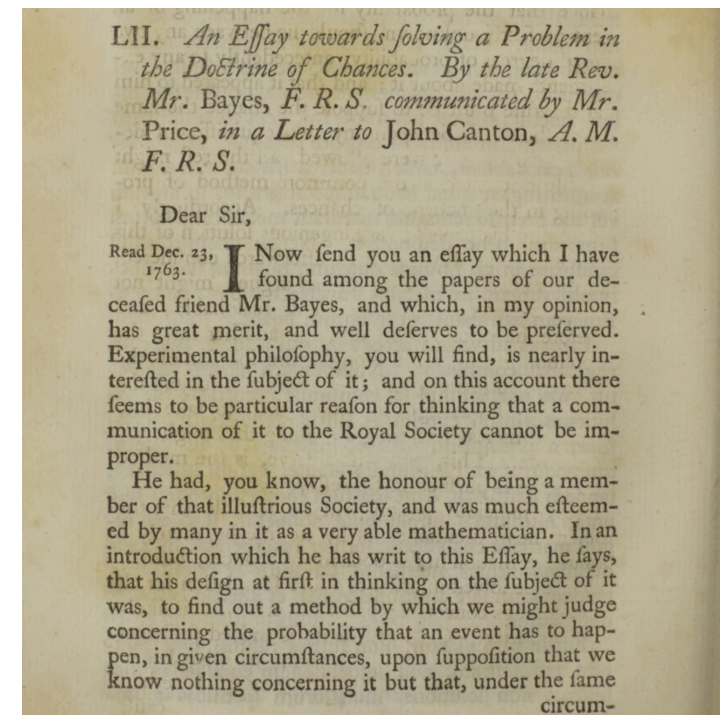
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The likelihood

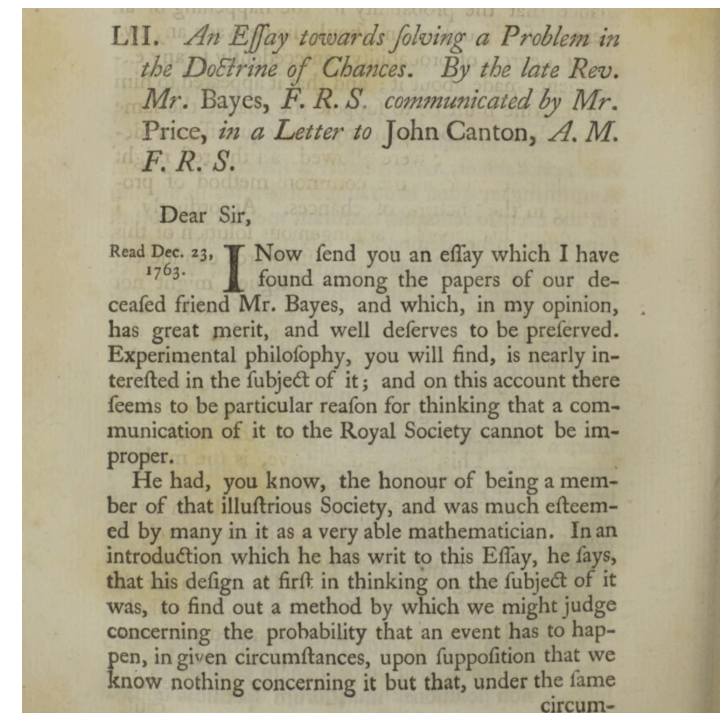
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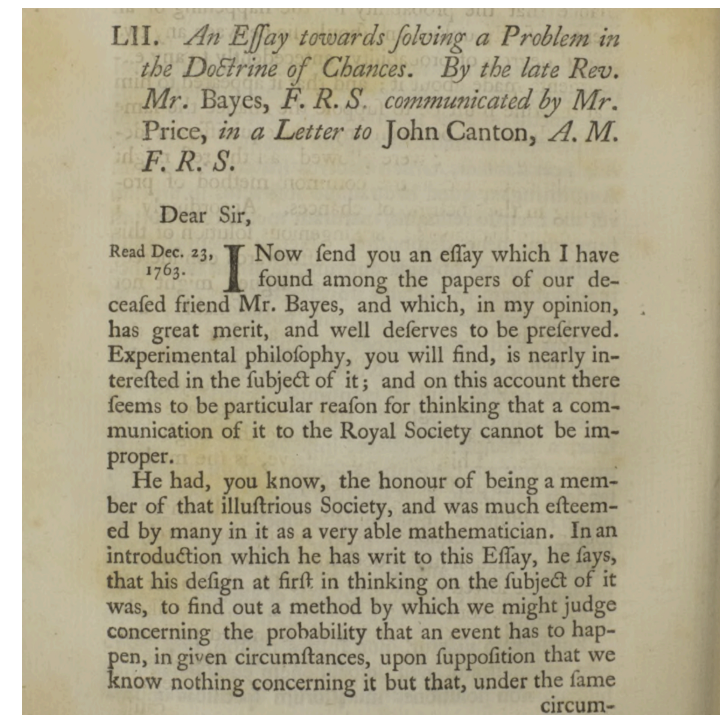
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Wilks' theorem: q is χ^2 distributed

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 ← the maximum



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The LHC likelihood

The central equation of particle physics

$$S = \mathcal{L} \sigma \epsilon$$

The LHC likelihood

The central equation of particle physics

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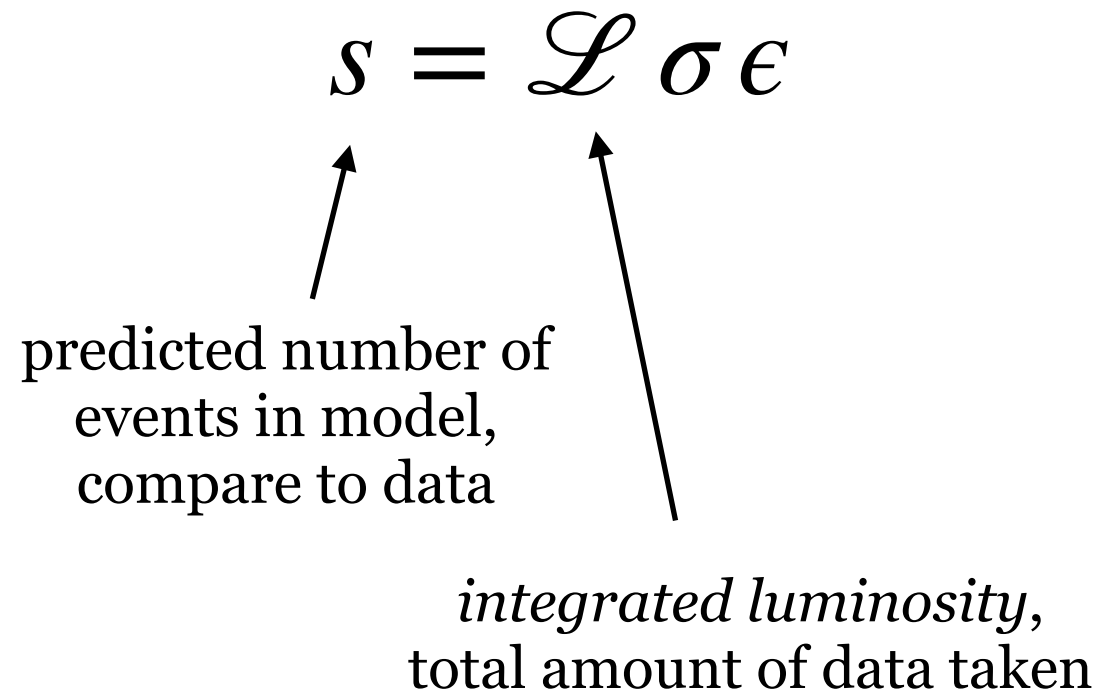
predicted number of
events in model,
compare to data

The LHC likelihood

The central equation of particle physics

$$S = \mathcal{L} \sigma \epsilon$$

predicted number of
events in model,
compare to data

A diagram showing the equation $S = \mathcal{L} \sigma \epsilon$. Two arrows point from descriptive text below to the variables S and \mathcal{L} in the equation. The first arrow points from the text 'predicted number of events in model, compare to data' to the variable S . The second arrow points from the text 'integrated luminosity, total amount of data taken' to the variable \mathcal{L} .

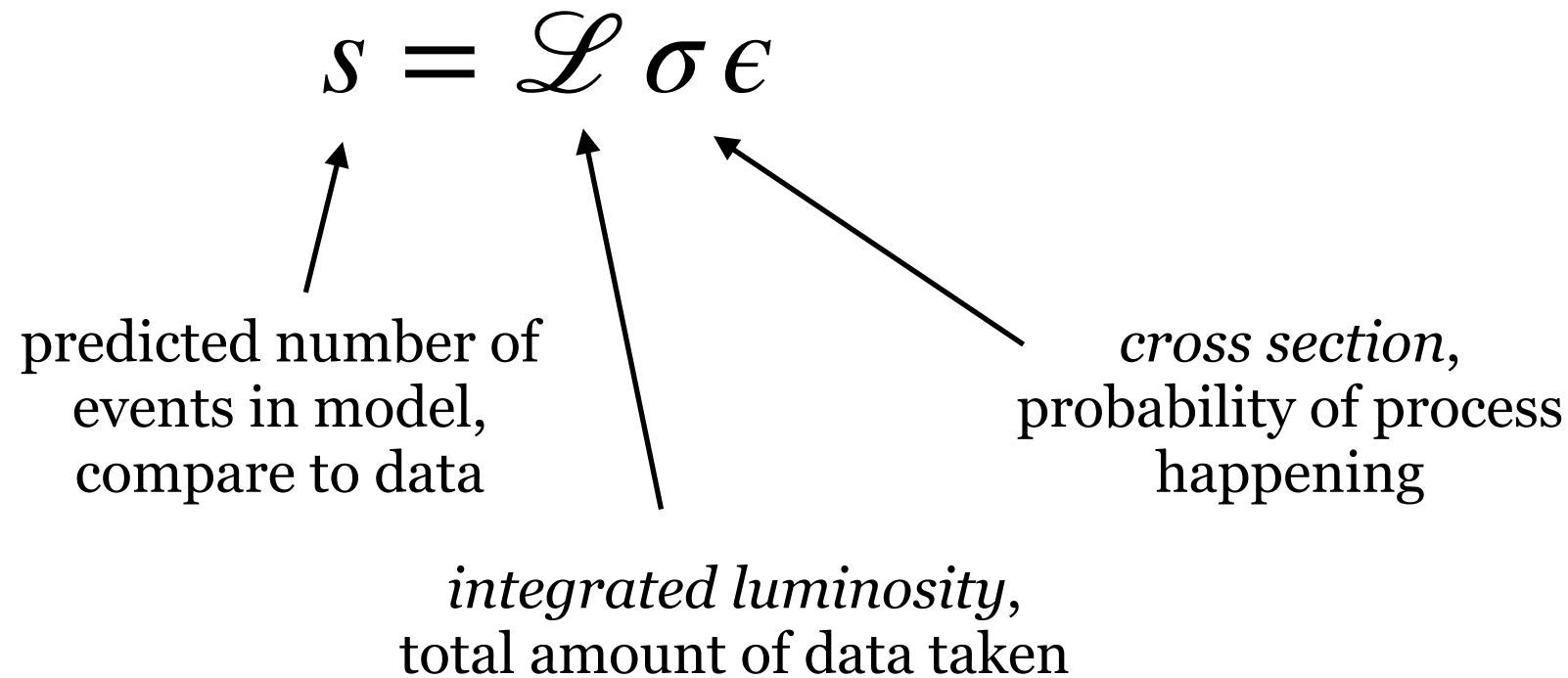
integrated luminosity,
total amount of data taken

The LHC likelihood

The central equation of particle physics

$$S = \mathcal{L} \sigma \epsilon$$

predicted number of
events in model,
compare to data



The diagram illustrates the central equation of particle physics, $S = \mathcal{L} \sigma \epsilon$. Three arrows point from descriptive text to the variables in the equation: one from 'predicted number of events in model, compare to data' to S , one from 'integrated luminosity, total amount of data taken' to \mathcal{L} , and one from 'cross section, probability of process happening' to σ . The variable ϵ is not explicitly described.

integrated luminosity,
total amount of data taken

cross section,
probability of process
happening

The LHC likelihood

The central equation of particle physics

$$S = \mathcal{L} \sigma \epsilon$$

Diagram illustrating the central equation of particle physics, $S = \mathcal{L} \sigma \epsilon$, with arrows indicating the meaning of each term:

- S : predicted number of events in model, compare to data
- \mathcal{L} : integrated luminosity, total amount of data taken
- σ : cross section, probability of process happening
- ϵ : efficiency of experiment to identify single event

The LHC likelihood

The central equation of particle physics

$$S = \mathcal{L} \sigma \epsilon$$

← *efficiency of experiment to identify single event*

← *cross section, probability of process happening*

← *integrated luminosity, total amount of data taken*

← predicted number of events in model, compare to data

The LHC likelihood

$$\mathcal{L}(n | s, b) = \frac{e^{-(s+b)}(s + b)^n}{n!}$$

The LHC likelihood

The central equation of particle physics

$$s = \mathcal{L} \sigma \epsilon$$

← *efficiency of experiment to identify single event*

← *cross section, probability of process happening*

← *integrated luminosity, total amount of data taken*

← predicted number of events in model, compare to data

not the same \mathcal{L} !

The LHC likelihood

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The LHC likelihood

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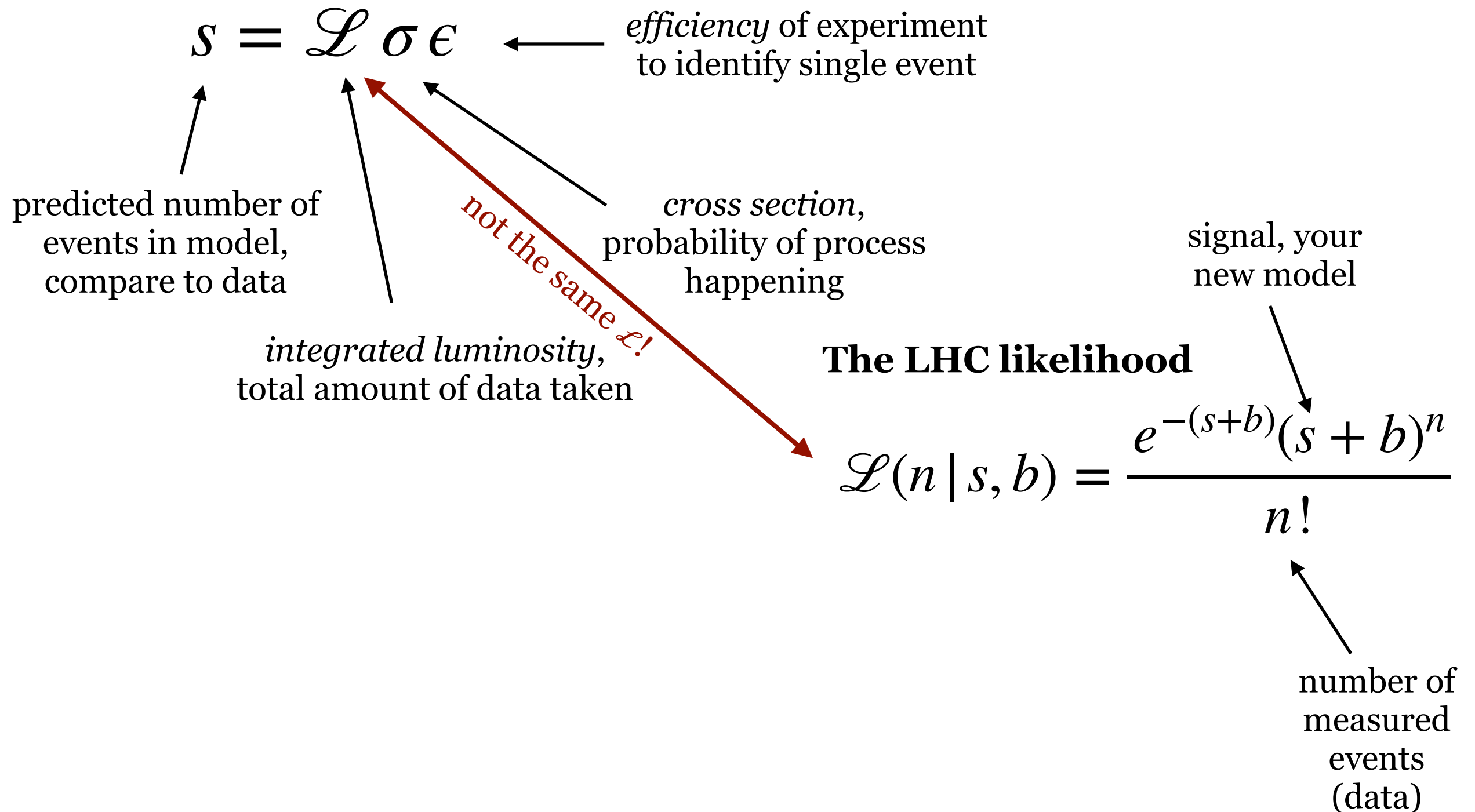
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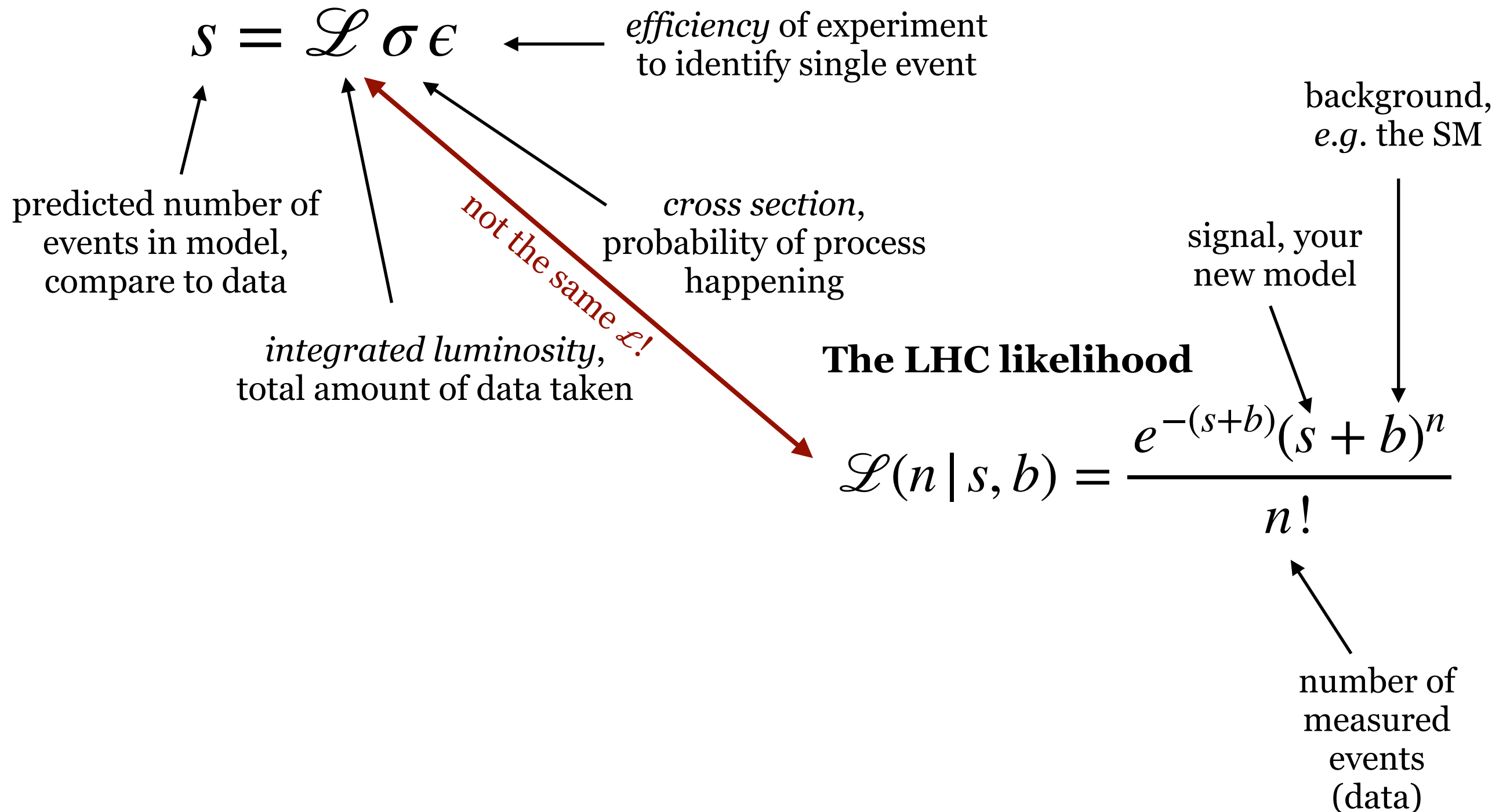
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The LHC likelihood

LHC likelihood including uncertainties

$$\mathcal{L}(n | s, b) = \int_0^\infty \frac{e^{-\xi(s+b)} [\xi(s+b)]^n}{n!} P(\xi) d\xi$$

$$P(\xi) = \frac{1}{2\pi\sigma_\xi} \frac{1}{\xi} \exp \left[-\frac{1}{2} \left(\frac{\ln \xi}{\sigma_\xi} \right)^2 \right]$$

$$\sigma_\xi = \frac{(\sigma_s^2 + \sigma_b^2)}{(s+b)^2}$$

$$\mathcal{L}(n | s, b) = \frac{e^{-(s+b)} (s+b)^n}{n!}$$

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Cross sections

The parton level cross section in QFT

$$\hat{\sigma} = \alpha^2 \hat{\sigma}_{\text{LO}} + \alpha^4 \hat{\sigma}_{\text{NLO}} + \alpha^6 \hat{\sigma}_{\text{NNLO}} + \dots$$

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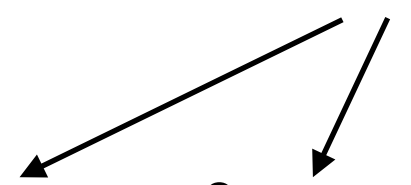
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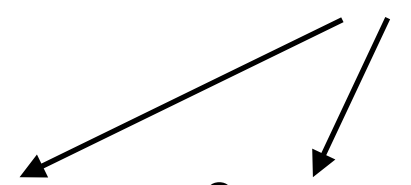
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Significant uncertainty from coupling constant α_s value, PDFs and higher order contributions.

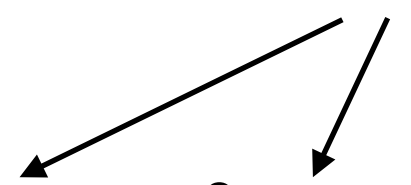
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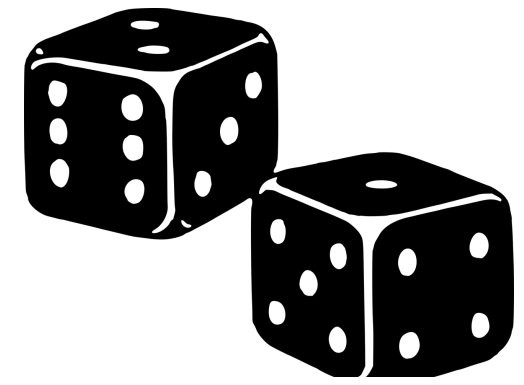
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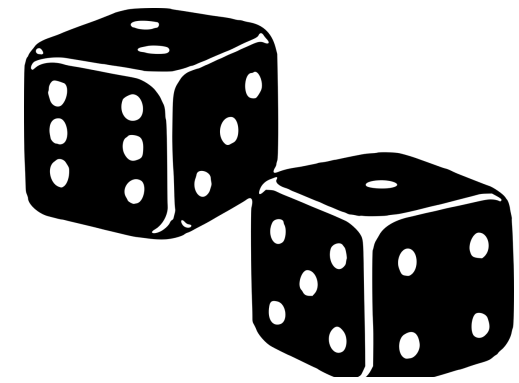
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This depends on unknown scales μ_F and μ_R which can be taken to represent the uncertainty from higher order corrections.

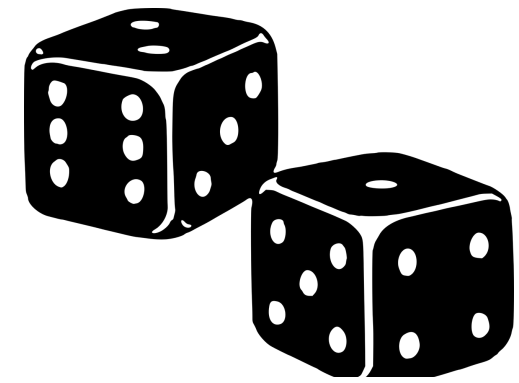


Event simulation



Event simulation

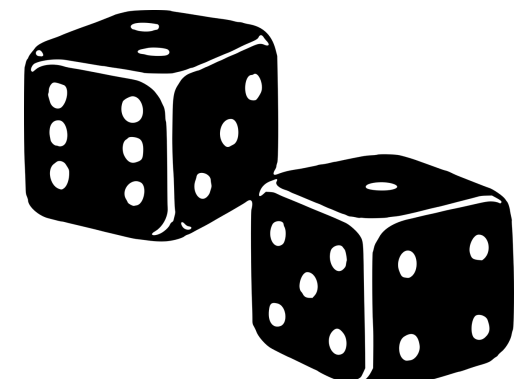
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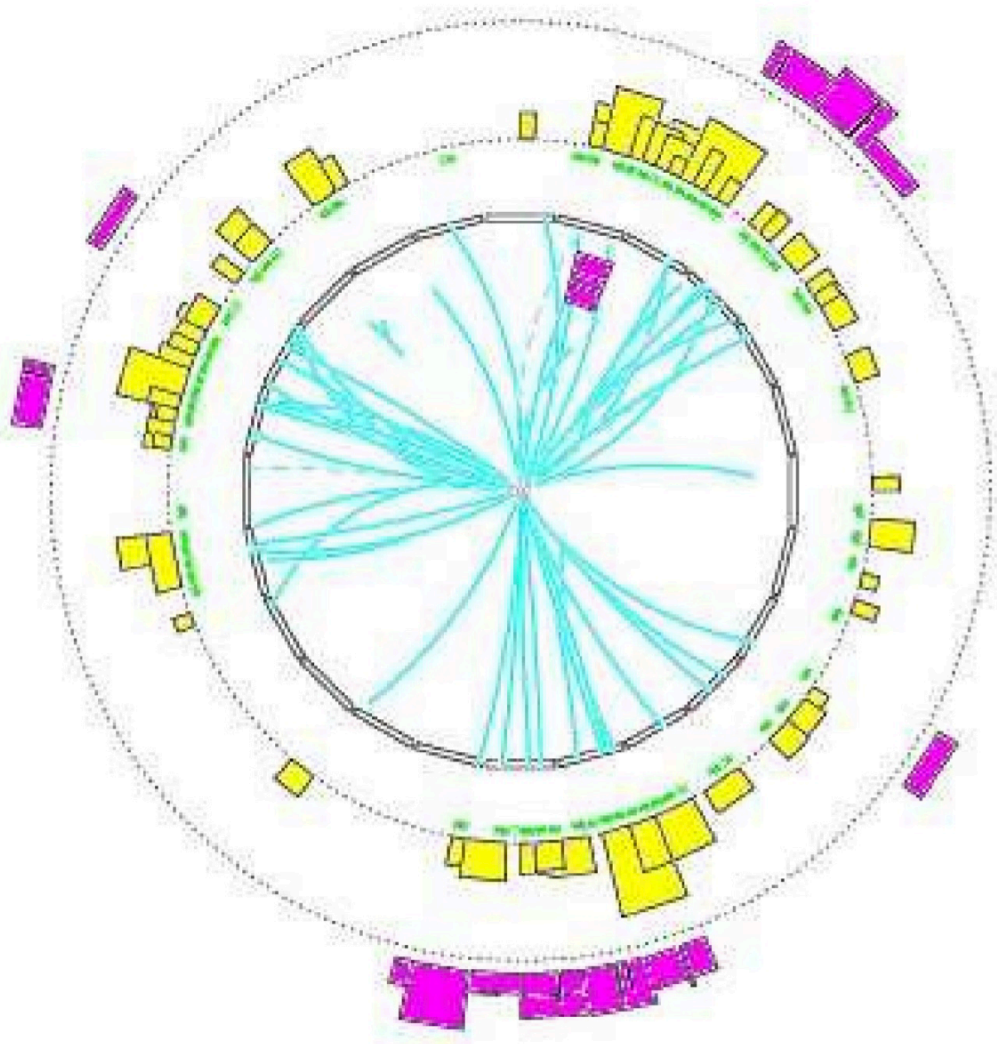
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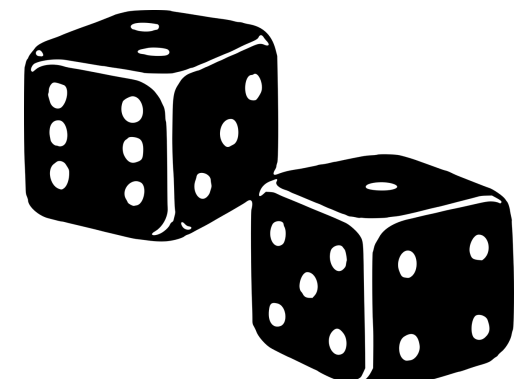


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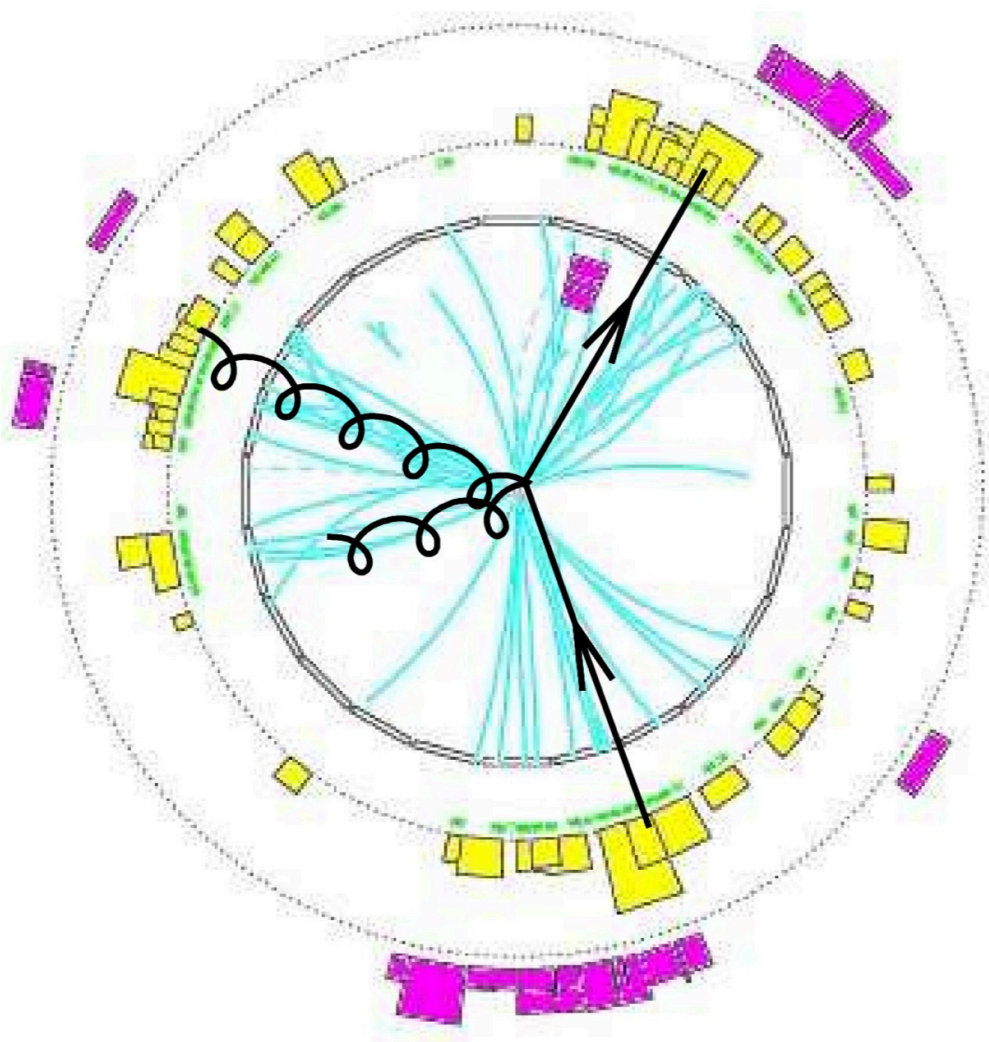


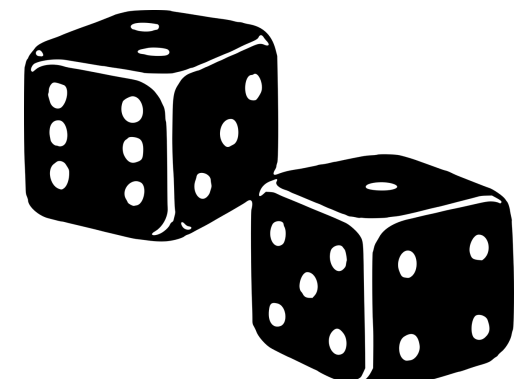


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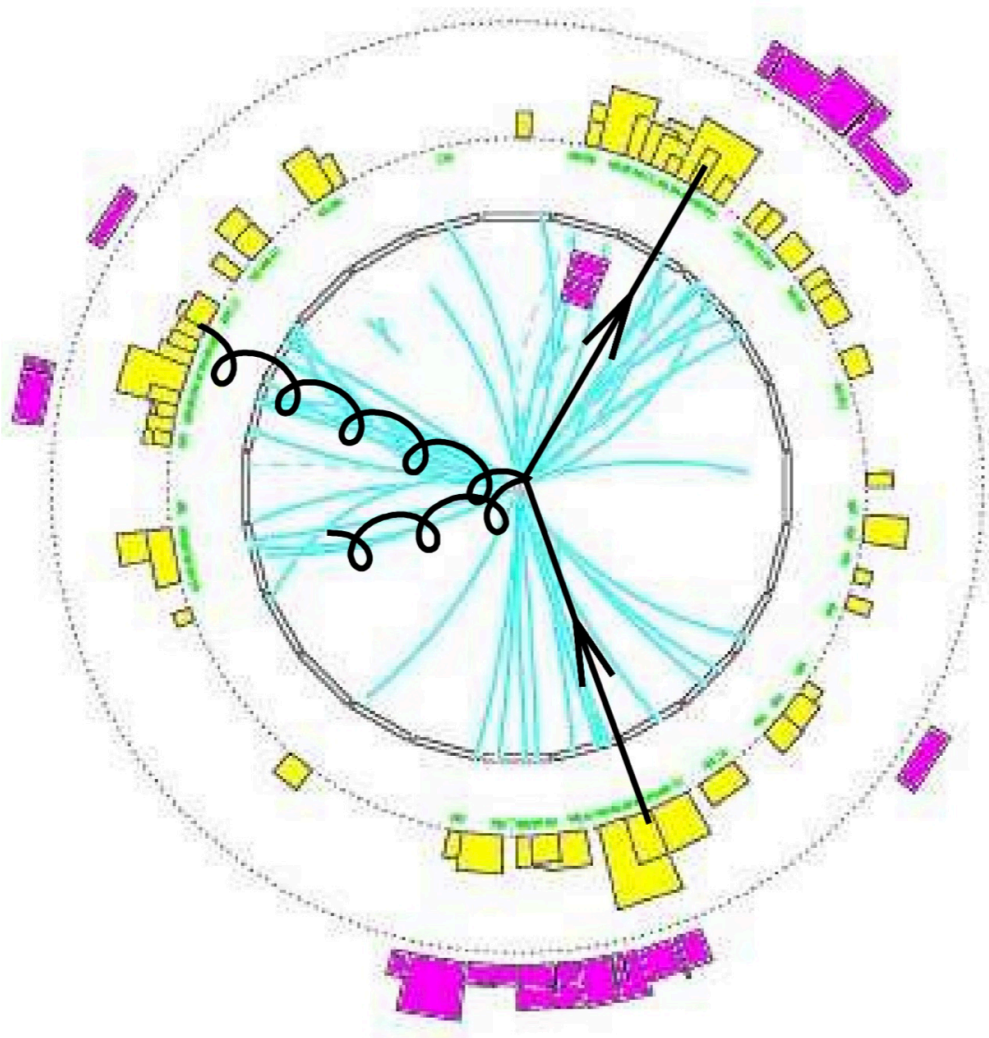




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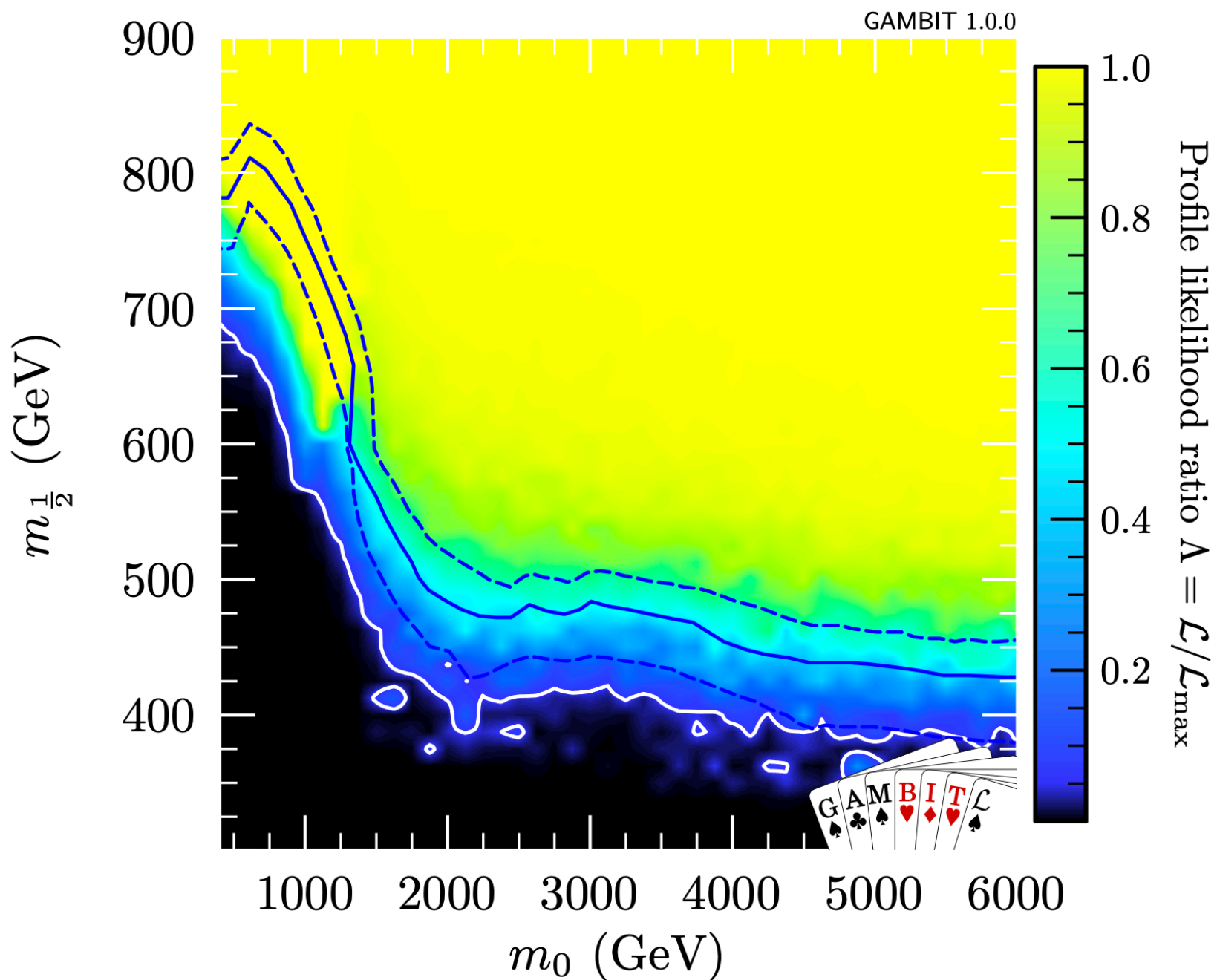
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One of the most expensive parts is the reconstruction of hadronic jets, where the cost for n final state particles is $\mathcal{O}(n \ln n)$.

(however, in practise $\mathcal{O}(n^2)$ for $n < 10^4$)

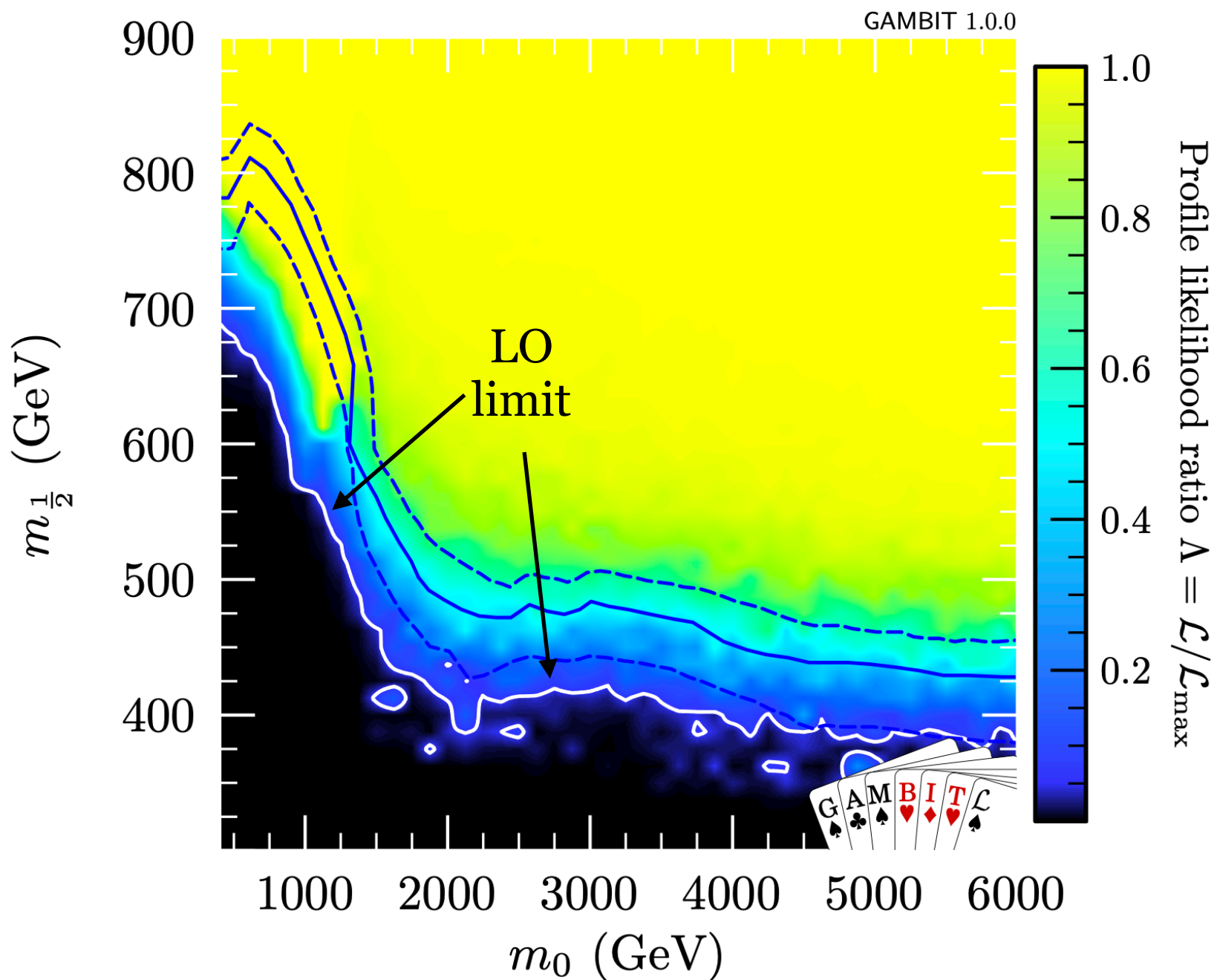
Putting it all together



An example of what happens in a simple supersymmetric model (mSUGRA/CMSSM) with four parameters: m_0 , $m_{1/2}$, A_0 , $\tan \beta$.

The GAMBIT Collaboration (P. Athron *et al.*), *ColliderBit: a GAMBIT module for the calculation of high-energy collider observables and likelihoods*, Eur. Phys. J. C77 (2017) 11, 795, e-Print: 1705.07919 [hep-ph]

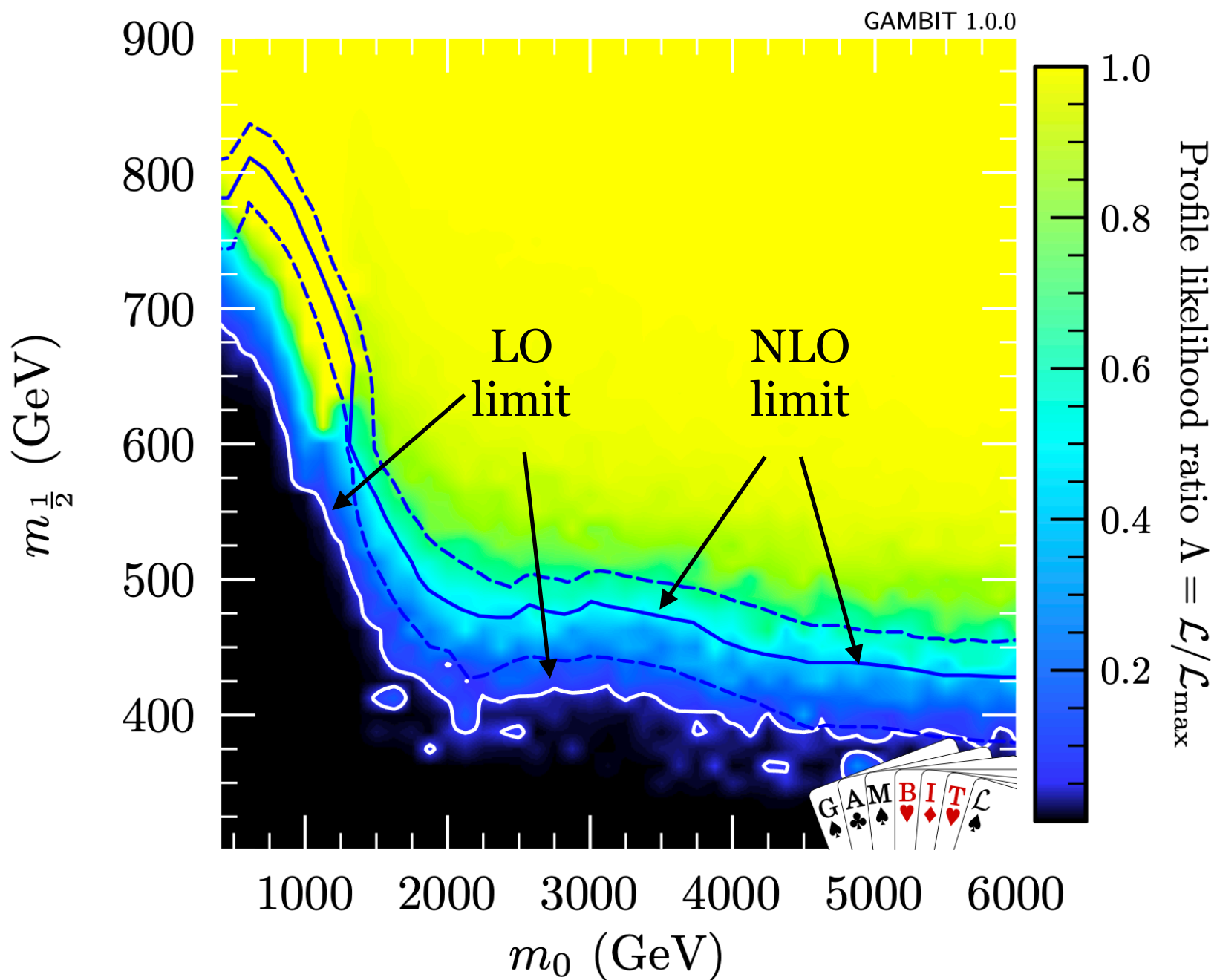
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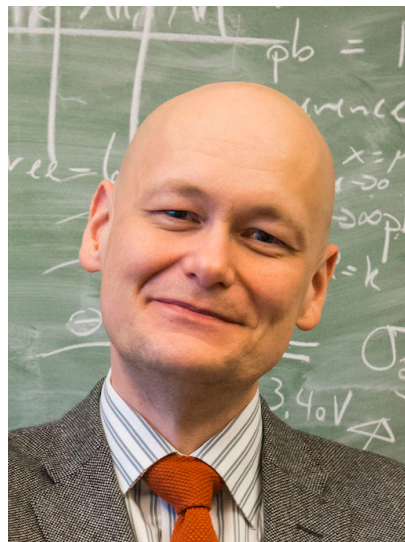
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The PLUMBIN' Team



Are Raklev



**Riccardo
De Bin**



**Anders
Kvellestad**

Co-PIs



**Lasse
Braseth**



**Timo
Lohrmann**



**Tore
Klungland**

PhD-students

**Andrea Jensen
Marthinussen**

**Carl Martin
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**Erik Alexander
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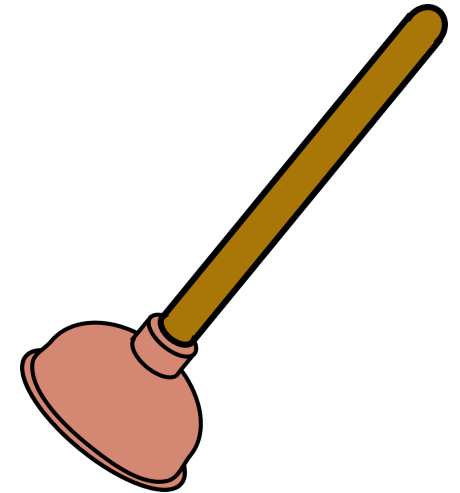
Master-students

What's in a name?

- We are PLUMBIN'?!?

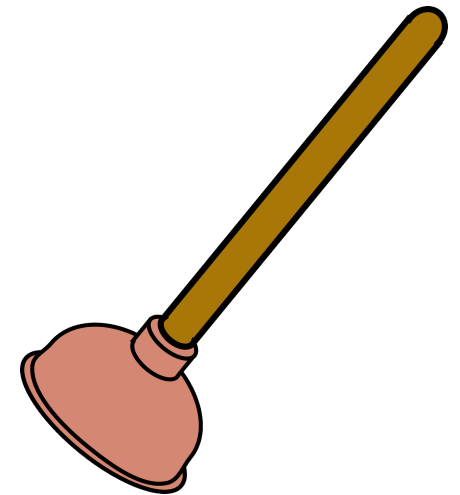
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 - Physics Learning Using Machines and Bayesian INference



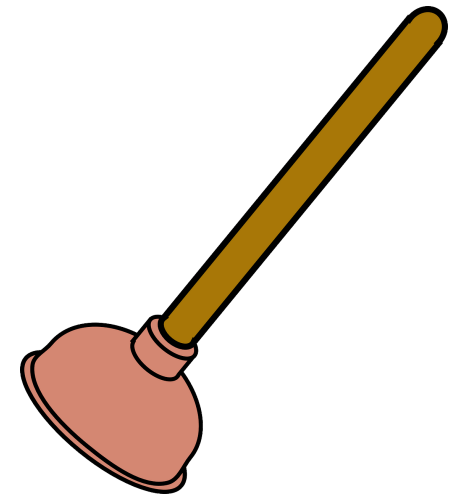
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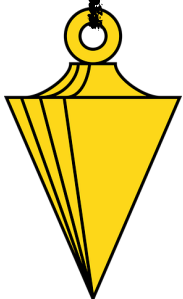
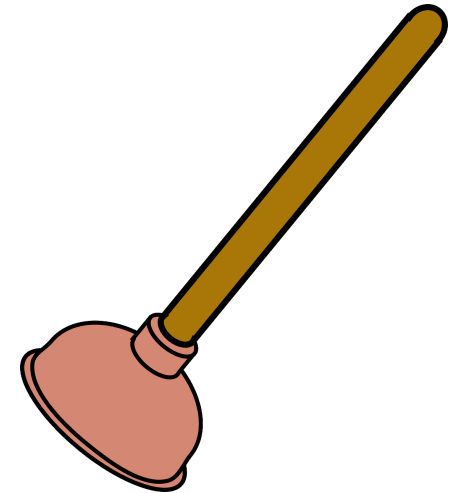
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Financing

- **Funder:** Research Council of Norway (RCN) & UiO joint FRIPRO “Fellesløftet” funding 2021
- **Project duration:** 01.08.2022 to 31.07.2028
- **One five year researcher** position (Anders Kvellestad)
- **Three PhD-positions:**
 - 2022-2026: Tore Klungland (DP)
 - 2024-2027: NN (DM)
 - 2025-2028: NN (DP)
- **Two two-year postdoc positions**
 - 2023-2025: NN (DP)
 - 2024-2026: NN (DM)
- Money for **travel** and **HPC** computing (sigma2 resources)
- Relevant **master thesis projects**.

Our goals

- Create an open-source machine-learning based regression tool for fast numerical evaluation of quantum field theory calculations.
- Develop a framework and tool for reliable probabilistic modelling of uncertainties from higher-order quantum field theory contributions.
- Develop a continual learning framework to speed up global scans, *e.g.* by fast evaluation of the joint likelihood from past data.
- Develop a fast pseudo-likelihood approach for reliable extraction of *best-fit* confidence regions.
- Find corrections to existing test-statistics to make *goodness-of-fit* evaluation in global fits computationally feasible.
- Perform a number of global fits of new physics models utilising these developments.

Preliminary conclusions

- Lots of exciting physics/statistics/computational problems to solve!
- I'm not allowed to apply for more RCN projects ❤️ (until 2028)
- Potential master student projects with Anders, Lasse, Tore and myself as supervisors.
- Future PhD & postdoc positions here and at DM.