Global fit of BSM with CEPC using GAMBIT

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2020.07.31

Our Plan

✓ Build the CEPC likelihood in GAMBIT

- Using present experimental central values

✓ Postprocess the published CMSSM / NUMH1 / NUHM2 / MSSM global results

- Experimental constraints in latest GAMBIT
- CEPC proposed results

Working on this!
Besides the constraints, the calculation of observations are also improved.

✓ Analysis the results

‣ People: Peter Athron, Csaba Balazs, Andrew Fowlie, Wei Su, Yang Zhang from GAMBIT

Liangliang Su, Lei Wu from Nanjing Normal University

Global fits

What? Why? How?

Using slides from

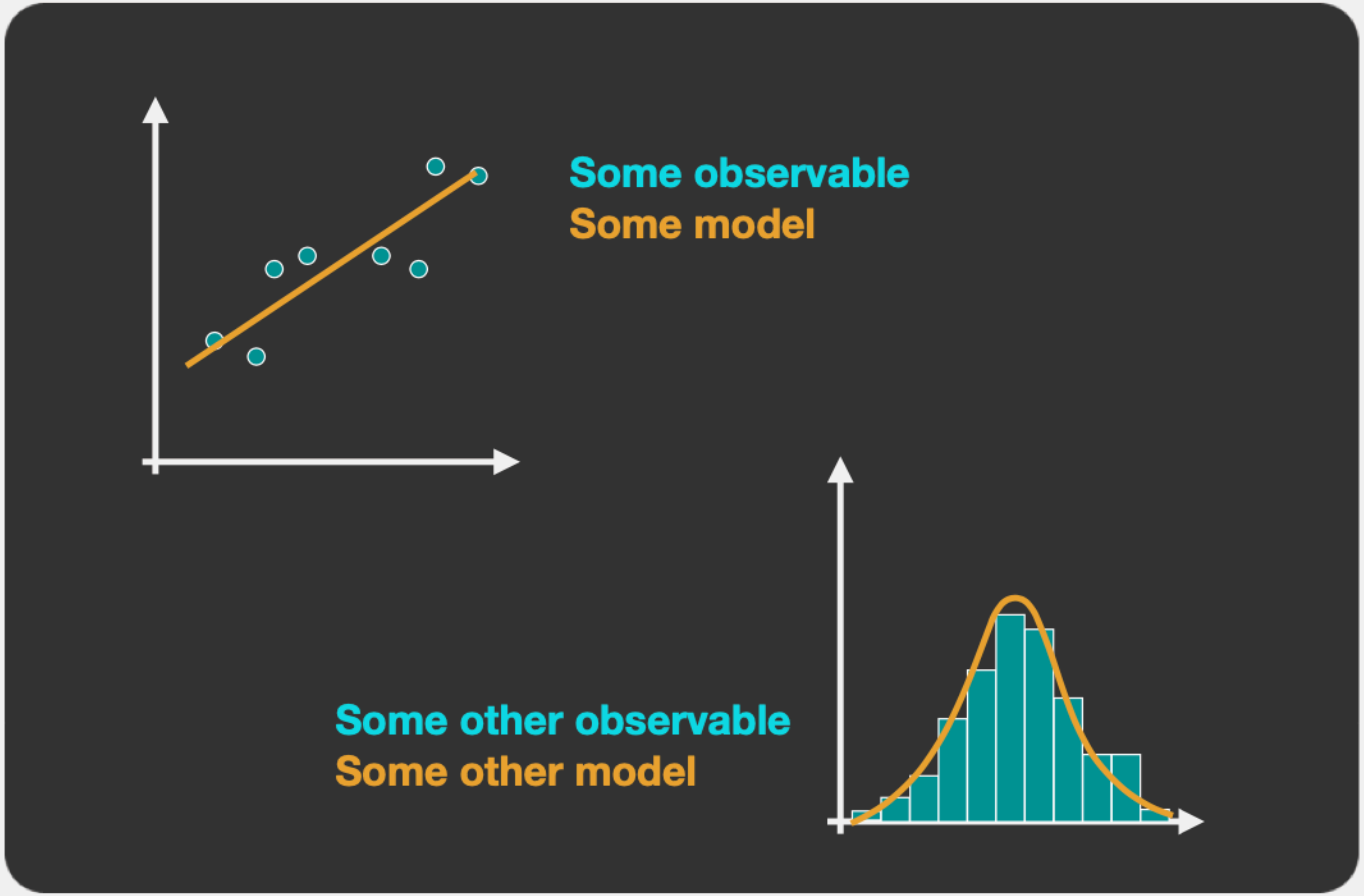
Investigating supersymmetry with GAMBIT

Anders Kvellestad, Imperial College London
on behalf of the GAMBIT Collaboration

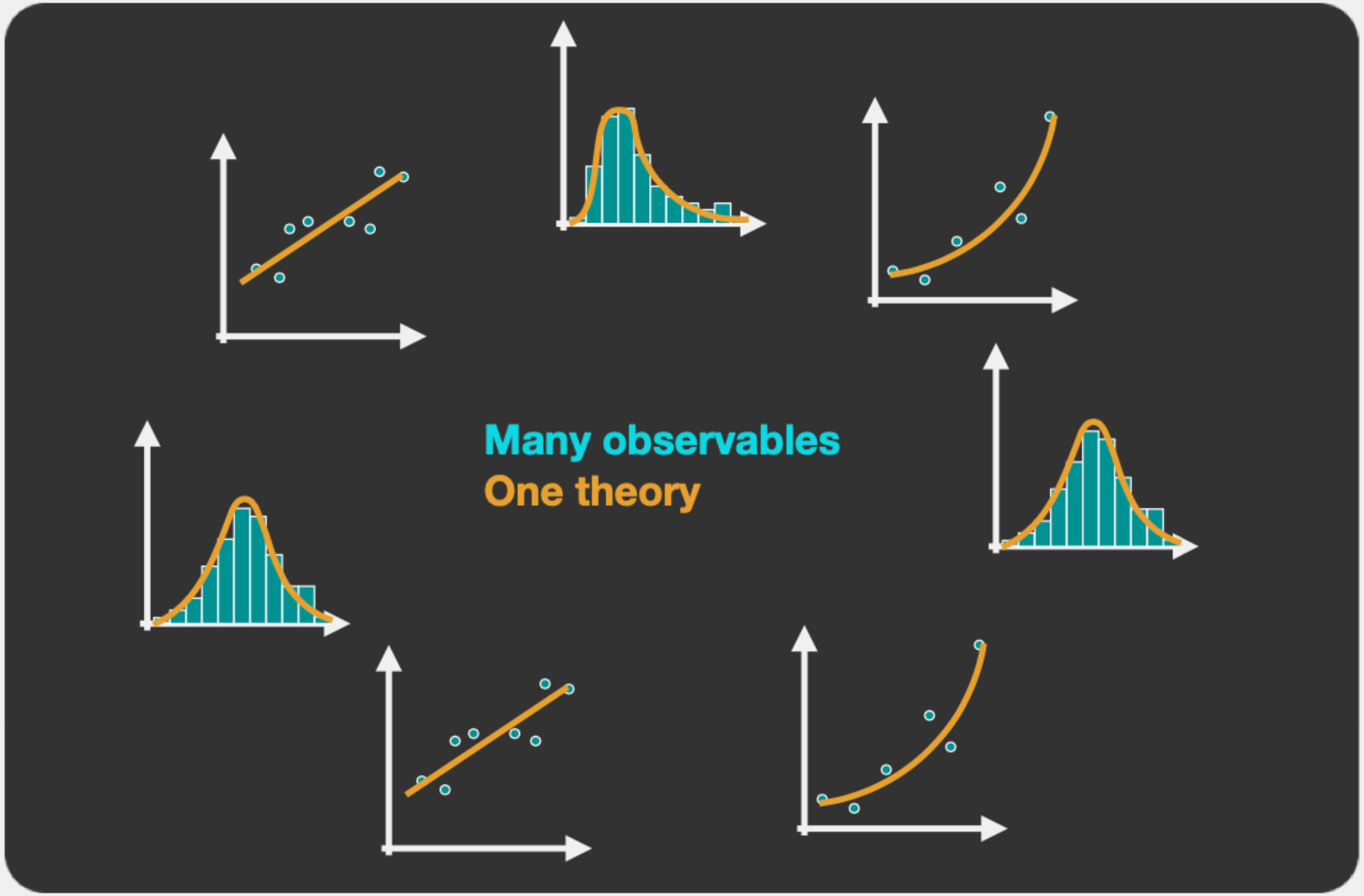
PRACEdays 2019, May 14 2019, Poznan

Imperial College London

Statistical fits

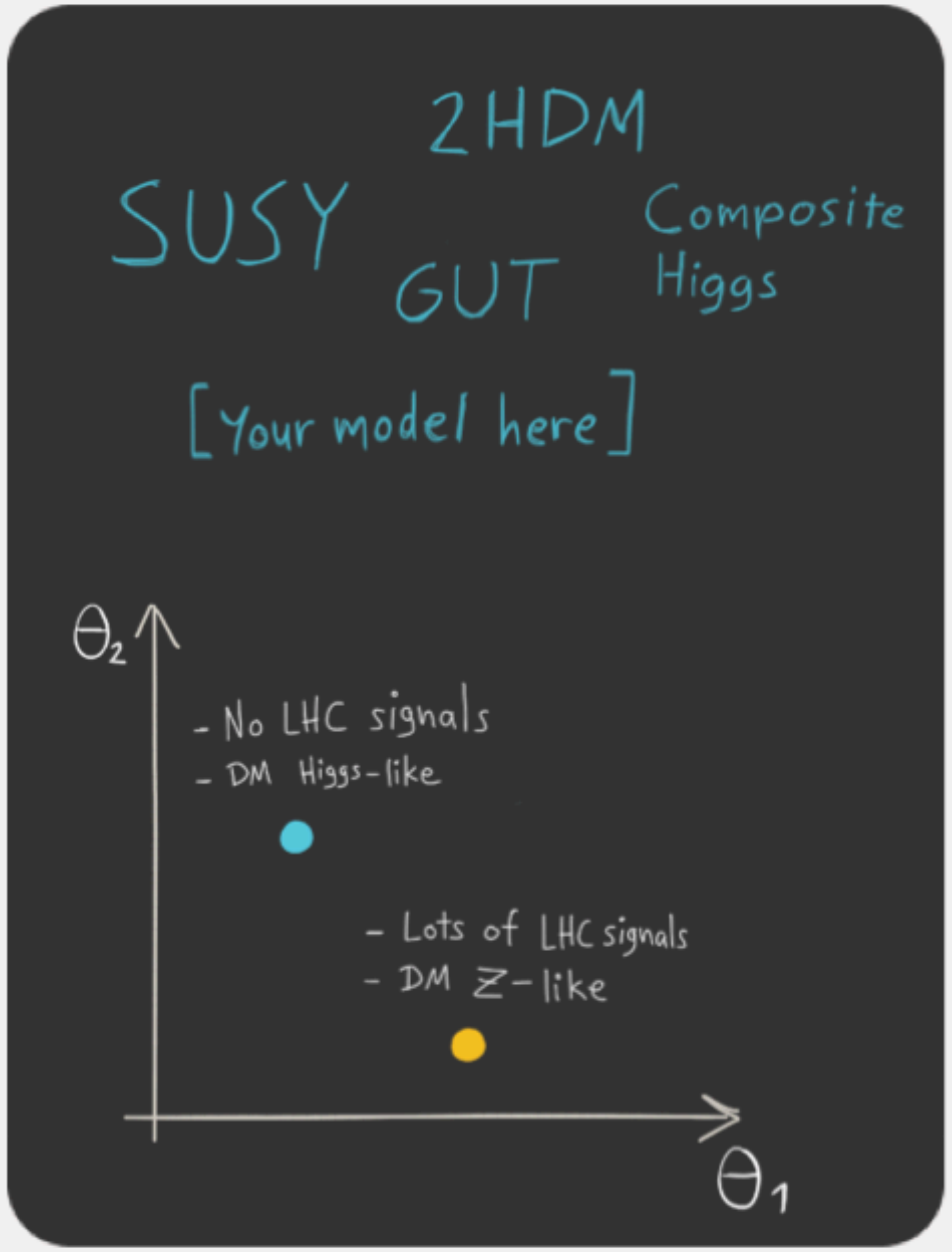


Global fits



Comparing new theories to data

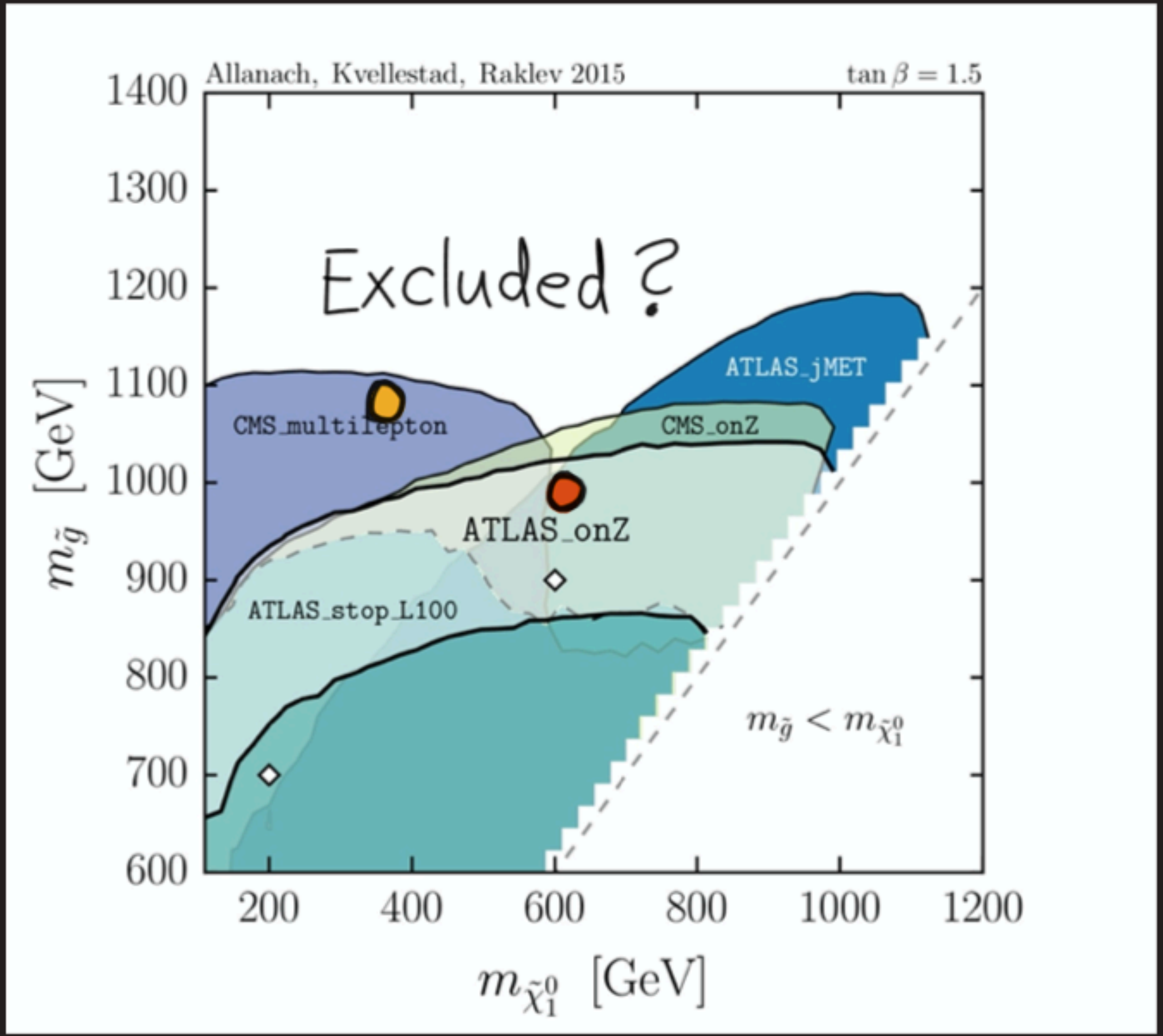
- Lots of theories for physics beyond the Standard Model
- For each theory, a parameter space of varying phenomenology
- Many different experiments can constrain each theory



Only a couple of parameters:

Compare preferred/excluded regions for different analyses

Allanach, Kvellestad, Raklev: 1504.02752



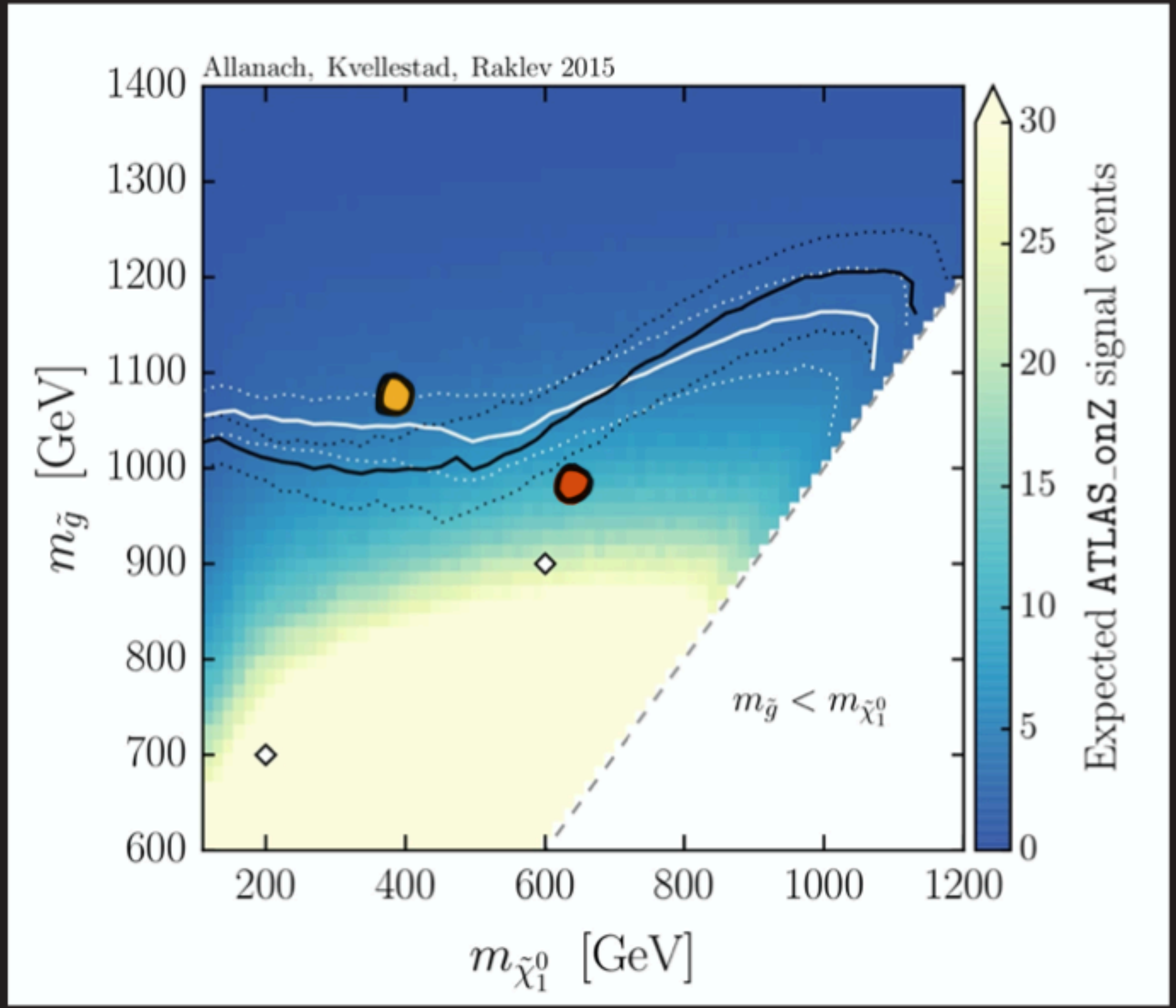
- + Simple to understand (at a qualitative level)
- ÷ Per-point interpretation is not straightforward
- ÷ Gets worse with increasing number of experimental analyses

Many different searches:

Combine searches in a total likelihood function

- Clear per-point interpretation
- ...but what if there are many parameters?

Allanach, Kvellestad, Raklev: 1504.02752



Many parameters and many constraints:

Theory $\rightarrow f(x;\theta)$

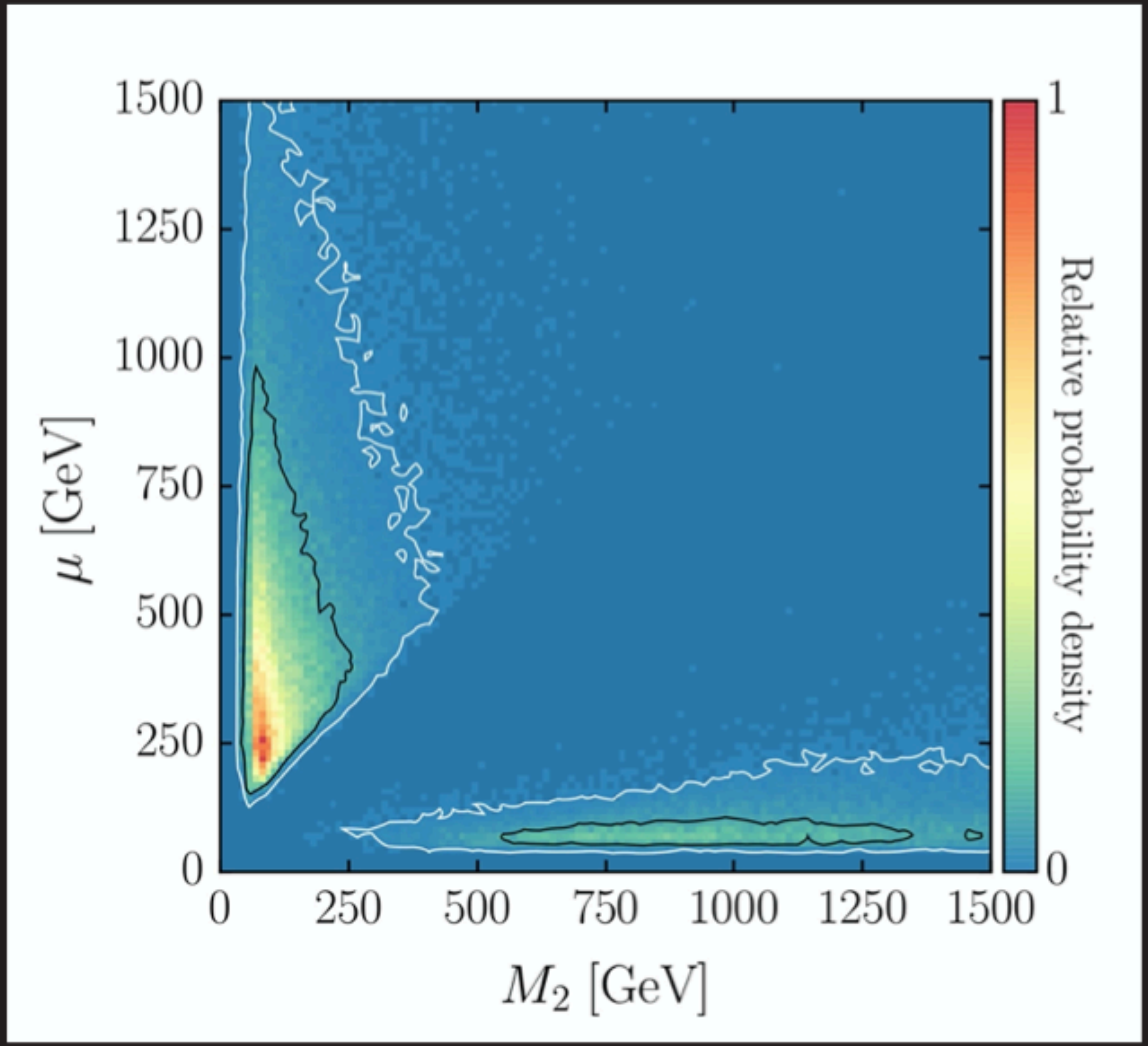
Experiment $\rightarrow \mathcal{L}(\theta) = f(x_{data};\theta)$

Perform a statistical fit to all available data — a global fit

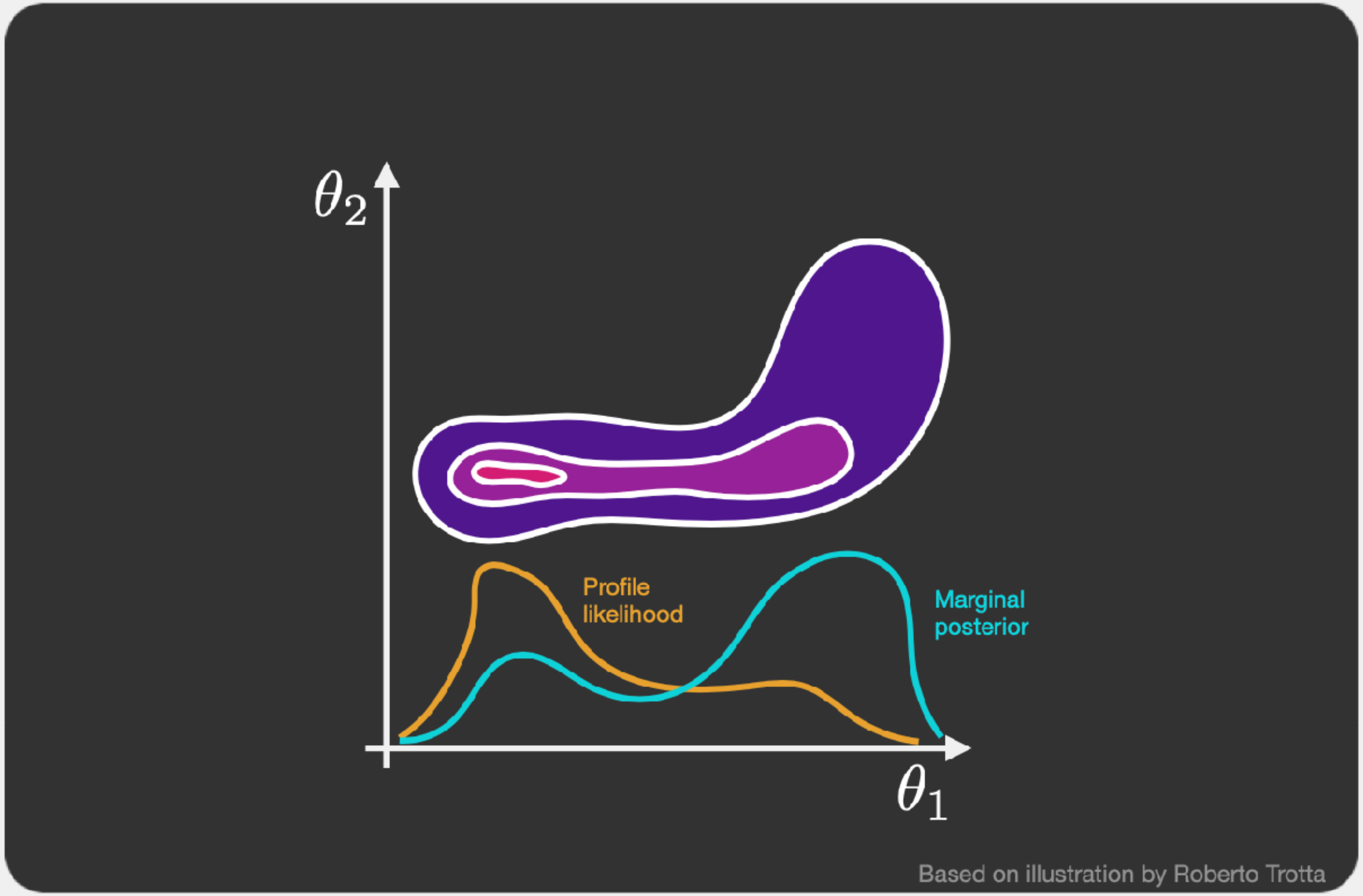
$$\mathcal{L} = \mathcal{L}_{Collider}\,\mathcal{L}_{Higgs}\,\mathcal{L}_{DM}\,\mathcal{L}_{EWPO}\,\mathcal{L}_{Flavor}\ldots$$

- Explore likelihood across entire parameter space (smart sampling)
- Interpretation: frequentist/Bayesian
- Project down to 1 or 2 parameters (profile/marginalise)

Bomark, Kvellestad, Lola, Osland, Raklev: 1410.0921



Different questions, different answers



The basic steps of a global fit

- Choose your **model and parameterisation**

- Construct the **combined likelihood function** including observables from collider physics, dark matter, flavor physics, +++

$$\mathcal{L} = \mathcal{L}_{\mathrm{collider}}\mathcal{L}_{\mathrm{DM}}\mathcal{L}_{\mathrm{flavor}}\mathcal{L}_{\mathrm{EWPO}}\cdots$$

- Use **sophisticated scanning techniques** to explore the likelihood function across the parameter space of the theory

- Test **parameter regions** in a statistically sensible way — not just single points *(parameter estimation)*

- Test **different theories the same way** *(model comparison)*

It's difficult...

$$[\text{large number of observables}]$$
$$\times$$
$$[\text{long calculation time per observable per parameter point}]$$
$$\times$$
$$[\text{huge number of points required to explore parameter space}]$$
$$\approx$$
$$\infty$$

GAMBIT

The Global And Modular BSM Inference Tool

- A **general** framework for BSM global fits
- Fully **open source**
- **Modular design:** can be extended with
  — new models
  — new likelihoods
  — new theory calculators
  — new scanning algorithms
- Use external codes (**backends**) as **runtime plugins**
  — Supported languages:
  C, C++, Fortran, Python and Mathematica
- **Two-level parallellization** with MPI and OpenMP
- **Hierarchical** model database
- **Flexible output streams** (ASCII, HDF5, …)
- Many **scanners** and **backends** already included

gambit.hepforge.org