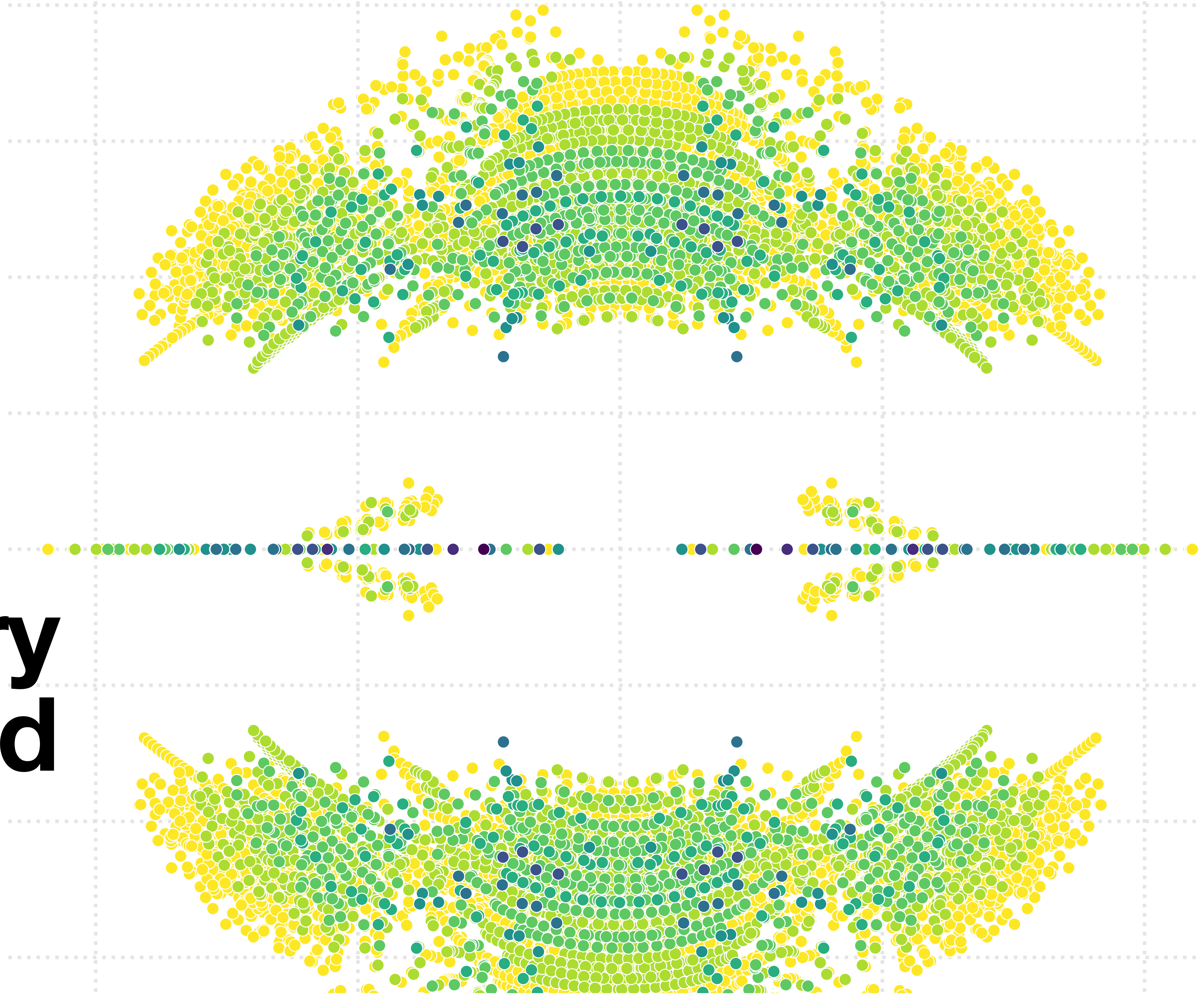

Connecting string theory with particle physics and cosmology via AI

Sven Krippendorf, 13.11.2025
Quantum100xAI, University of Münster

UNIVERSITY OF CAMBRIDGE

“Give me string models that realise an EFT at low-energies consistent with all experiments and observations.”

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… we have been asking this question for over 40 years!

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… we have been asking this question for over 40 years!

We haven’t gotten the answers we are after. So when and how do we deliver?

This talk: AI is THE game changer

many of the speakers here have been saying this since ~2017.

AI is THE game changer for theoretical physics

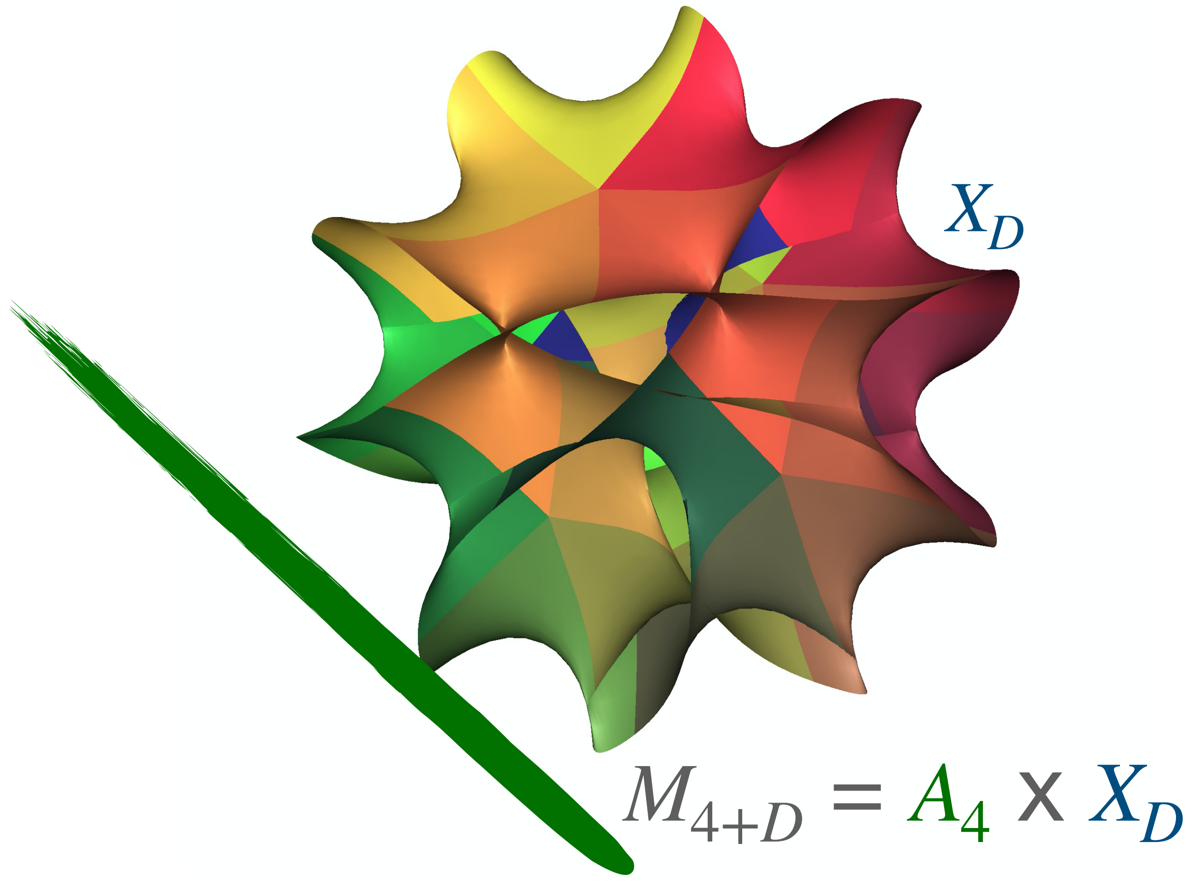
Examples and Directions — Content for today’s talk

- Neural networks as efficient function approximators: Calabi-Yau metrics [solving Einsteins equations in higher dimensions]
- Differential programming for efficient tools: Sampling flux vacua
- Generative models as a core tool for exploration: Towards generating string theory models consistent with low-energy observations
- Comments on the future with LLM agents to overcome resource limitations

Part 1: NNs as efficient function approximators and where we care…

Which BSM physics does string theory predict?

Problem: understand “all” aspects of EFT for a single geometry



The metric of extra-dimensions is key to determine some couplings in the EFT (after dimensional reduction from 10d to 4d):

$$S = \int_{M_{4+D}} d^{4+D}x \sqrt{-\det g_{4+D}}\; R(g_{4+D})$$

combined metric

Anderson, Gerdes, Gray, Krippendorf, Raghuram, Ruehle: 2012.04656
Gerdes, Krippendorf: 2211.12520; many other works …

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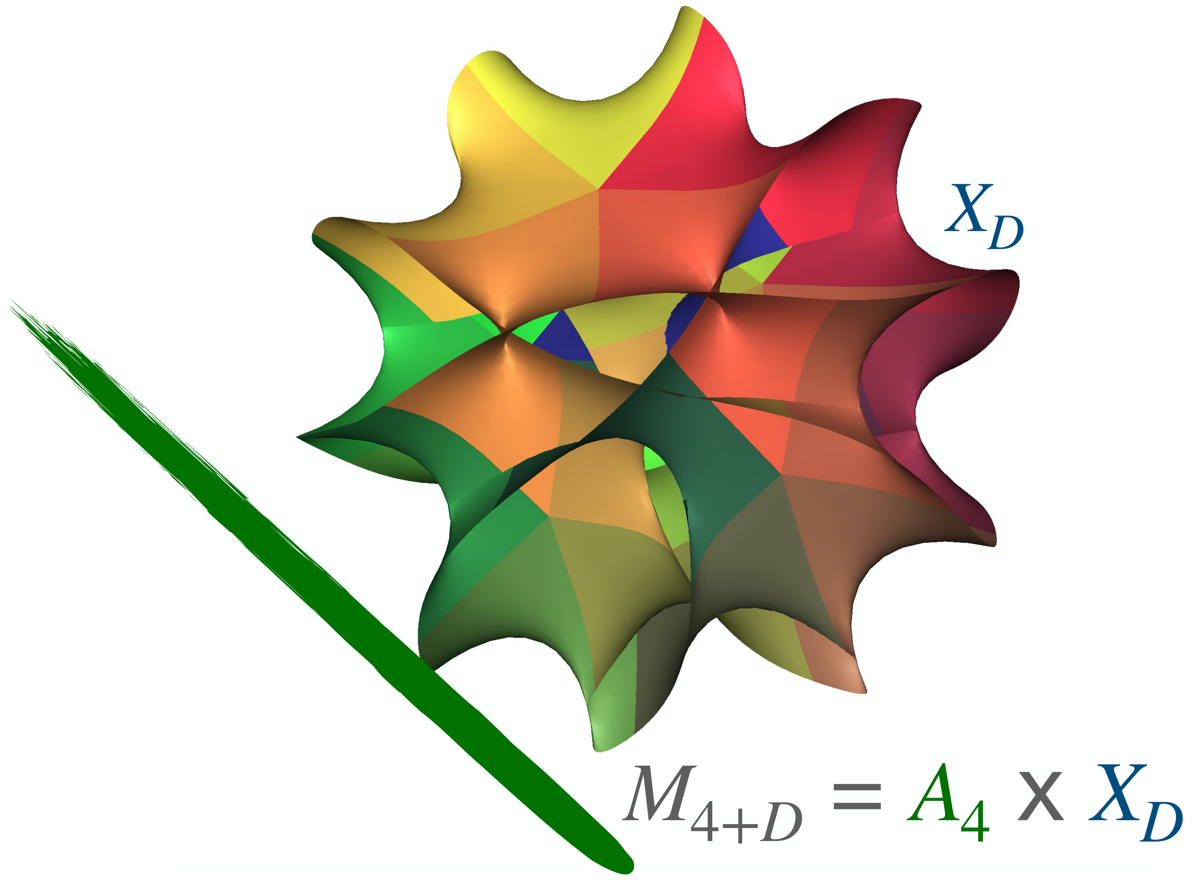

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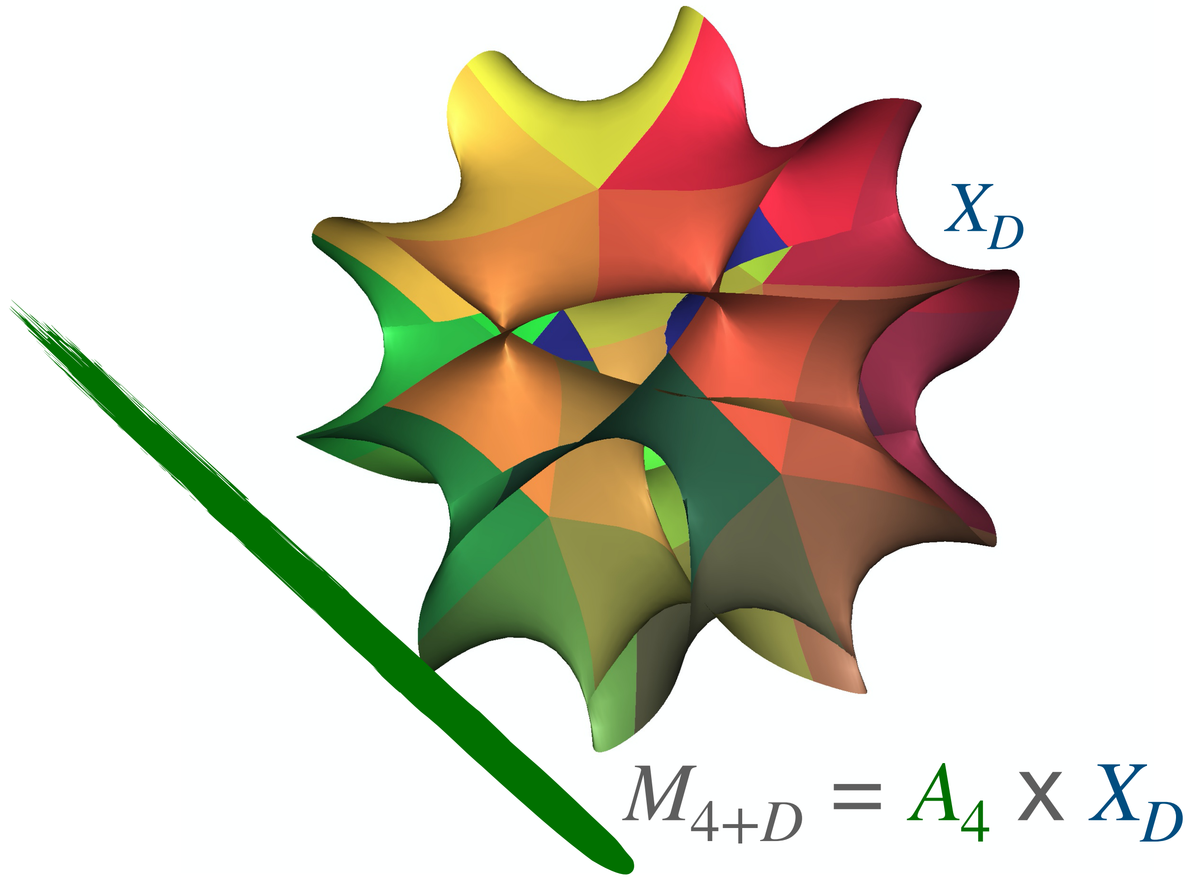

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Problem: no analytic solutions and existing numerical approaches are inefficient (single point in moduli space is expensive).

We are interested in efficiently obtaining metrics and their moduli dependence!

Anderson, Gerdes, Gray, Krippendorf, Raghuram, Ruehle: 2012.04656
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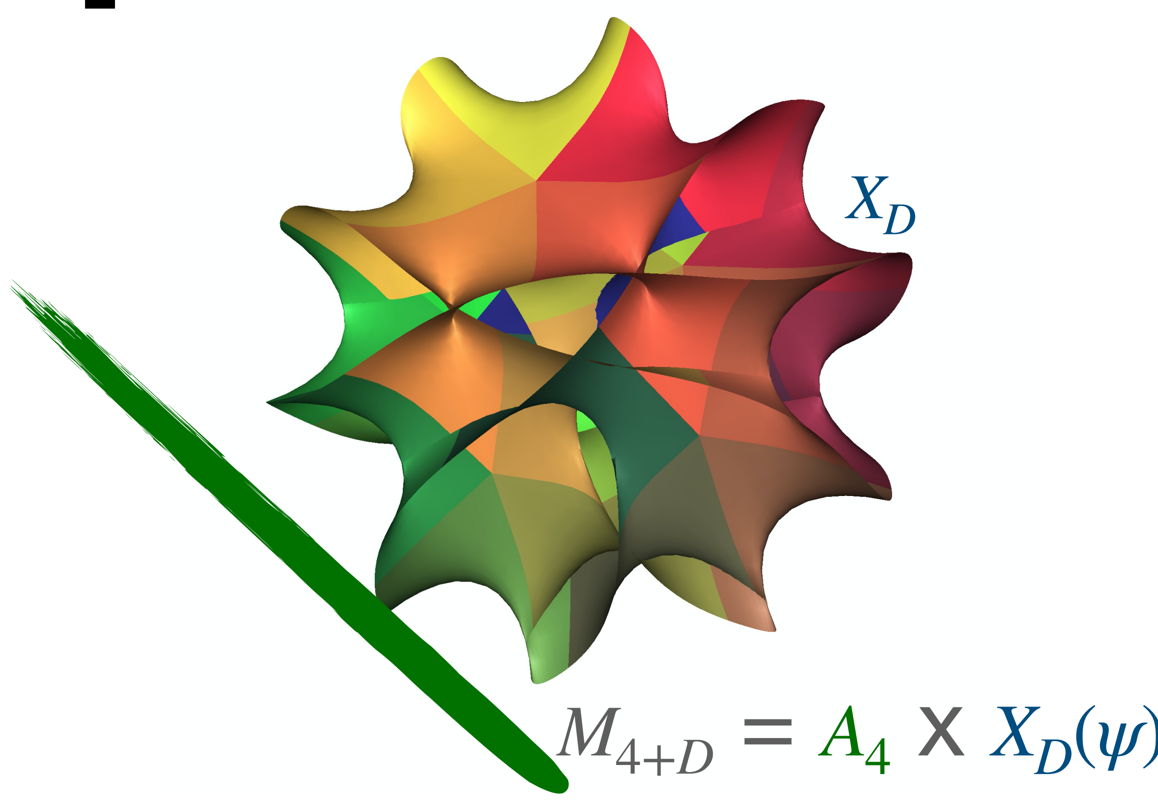
Which BSM physics does string theory predict?

Problem: Moduli-dependent Calabi-Yau metrics



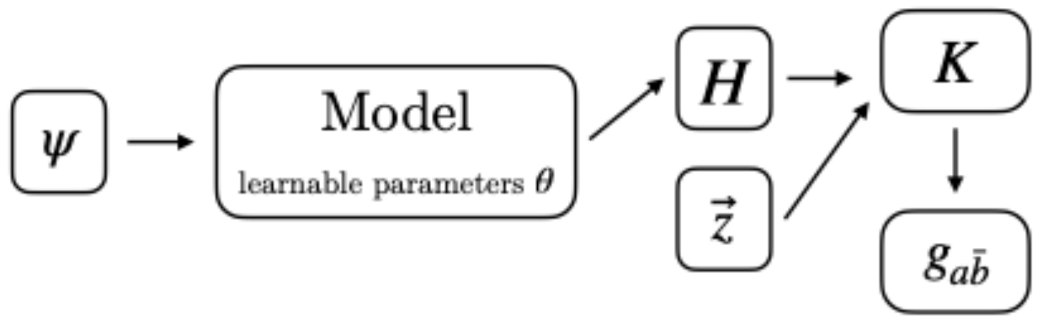
We need to solve Einstein's equations in higher dimensions as a function of moduli.

Optimisation problem: Guess a metric, measure deviation from Ricci-flatness (solving Einstein's equations), and change metric to minimise measure.

Class of metrics: K and derive g. Algebraic metric ansatz (guarantees solution to be Kähler and well-defined across patches, spectral method).

$$K = -\log\left(s_\alpha(z_a) H_{\alpha\bar{\beta}}(\psi) \bar{s}_{\bar{\beta}}(\bar{z}_b)\right), \; g_{a\bar{b}} = \frac{\partial K}{\partial z_a \partial \bar{z}_b}$$

Approximate $H(\psi)$ as a neural network:



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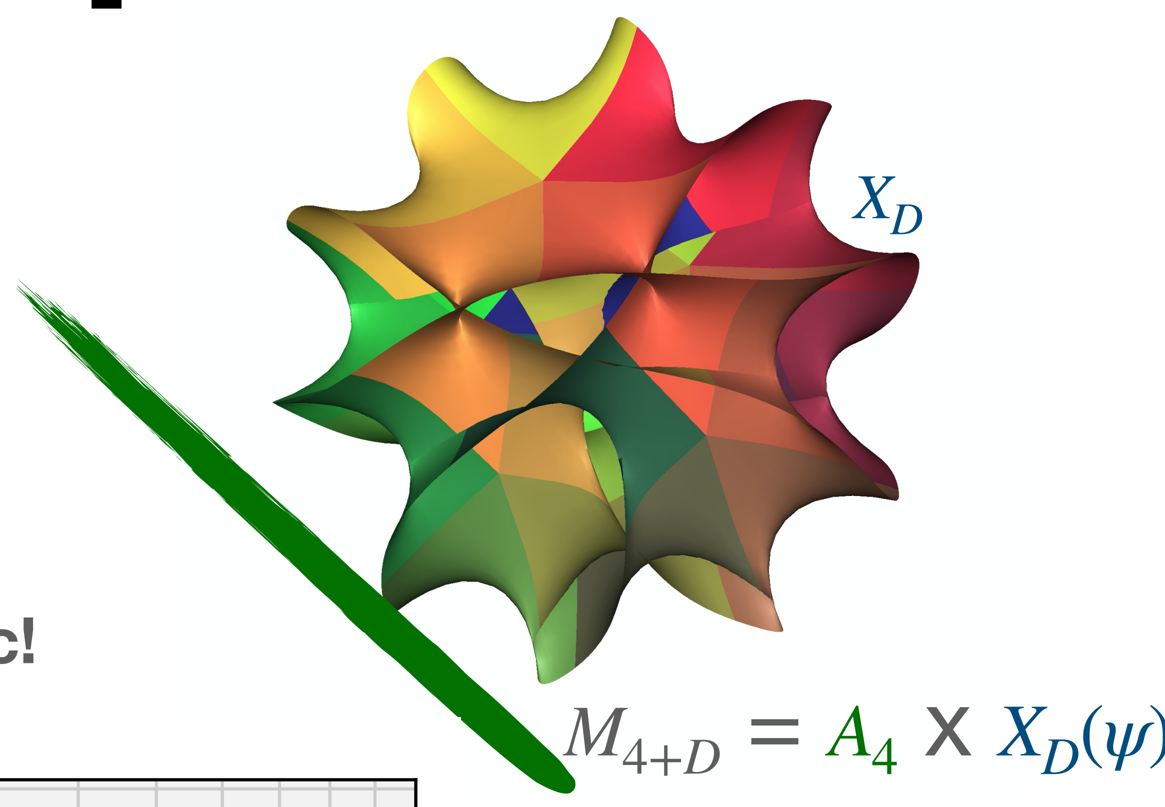

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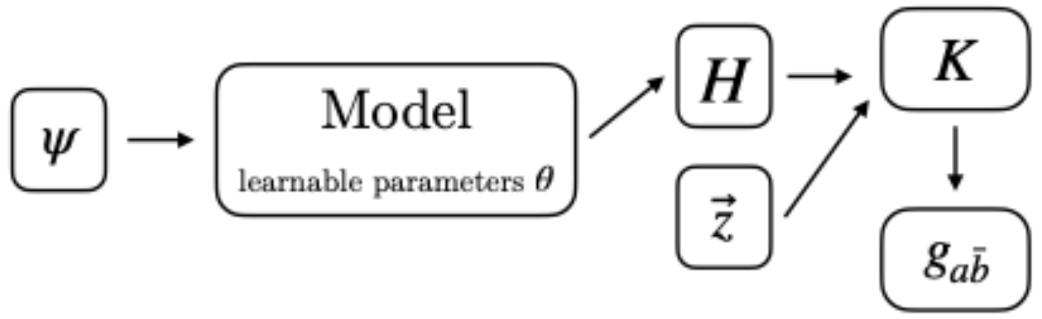
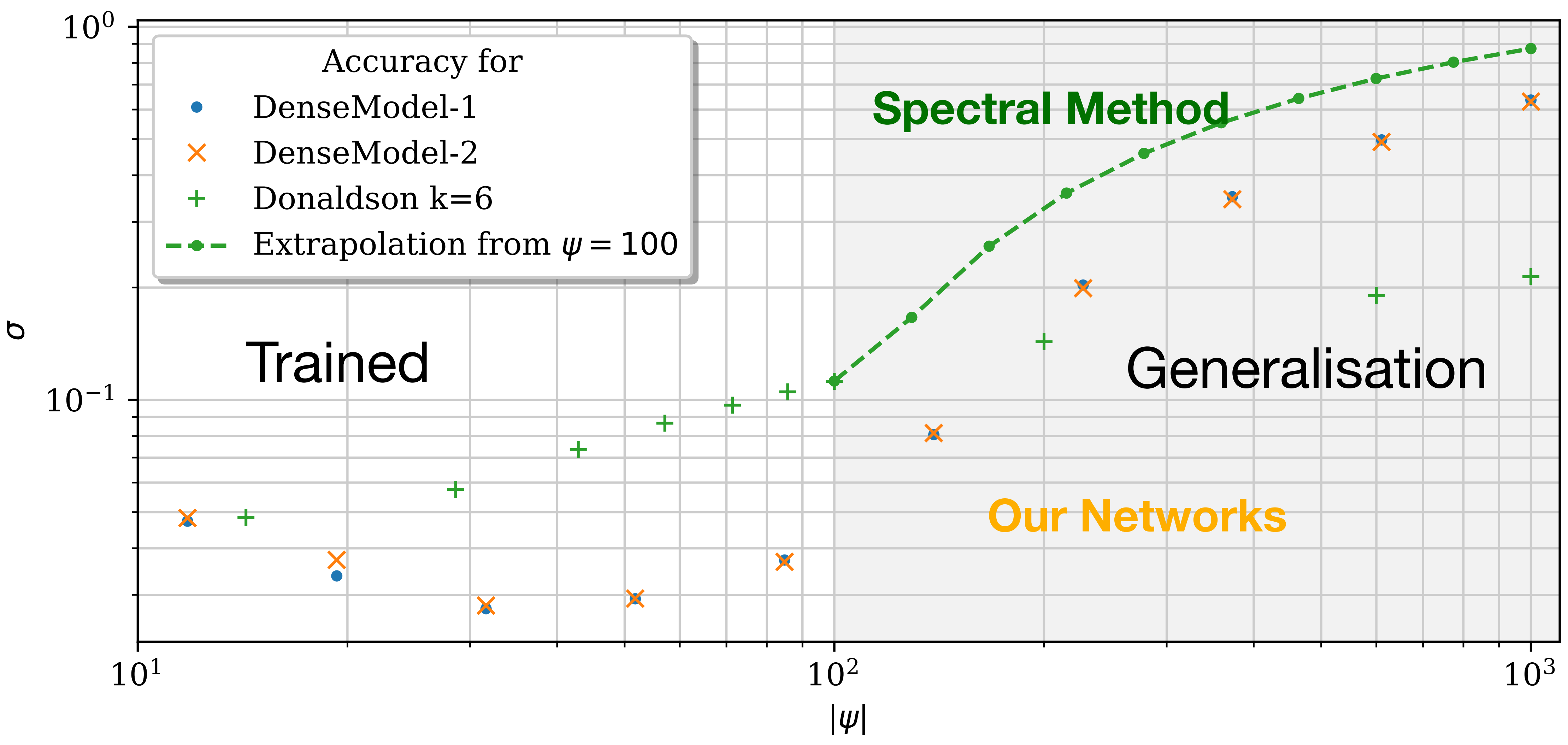


Habemus efficient moduli dependent CY metric!



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Our accuracy measure:

$$\sigma = \frac{1}{\int_X \Omega \wedge \bar{\Omega}} \int_X \left| 1 - \frac{1}{\kappa} \frac{J^3}{\Omega \wedge \bar{\Omega}} \right|$$

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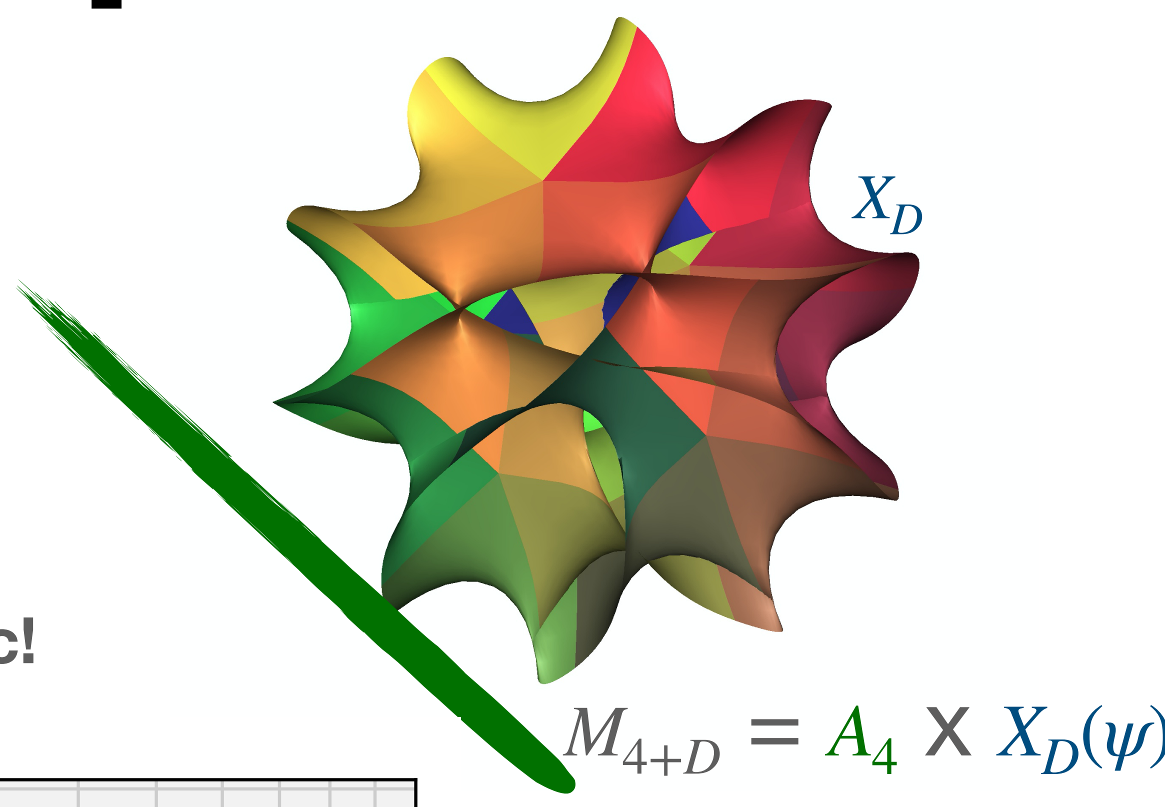

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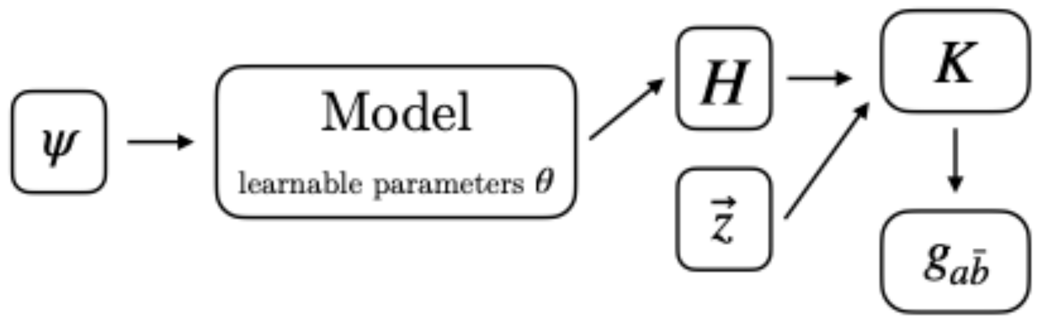

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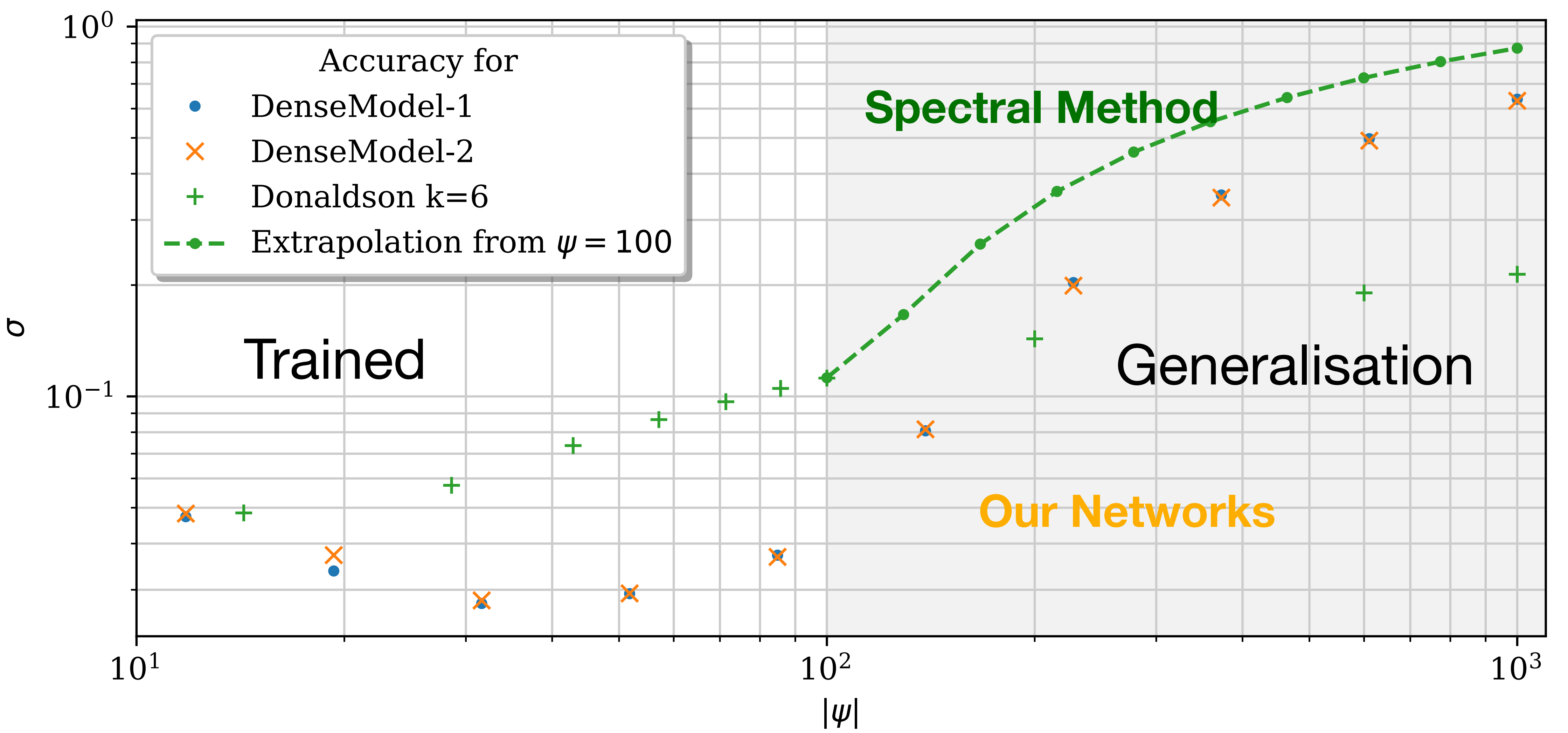

Developed efficient codebase ready for future science explorations.
Flexible code for 10d EOM solver:

- **General metrics (SU(3) structure)**
- **Backreaction of localised sources in compact CY**

CYJAX

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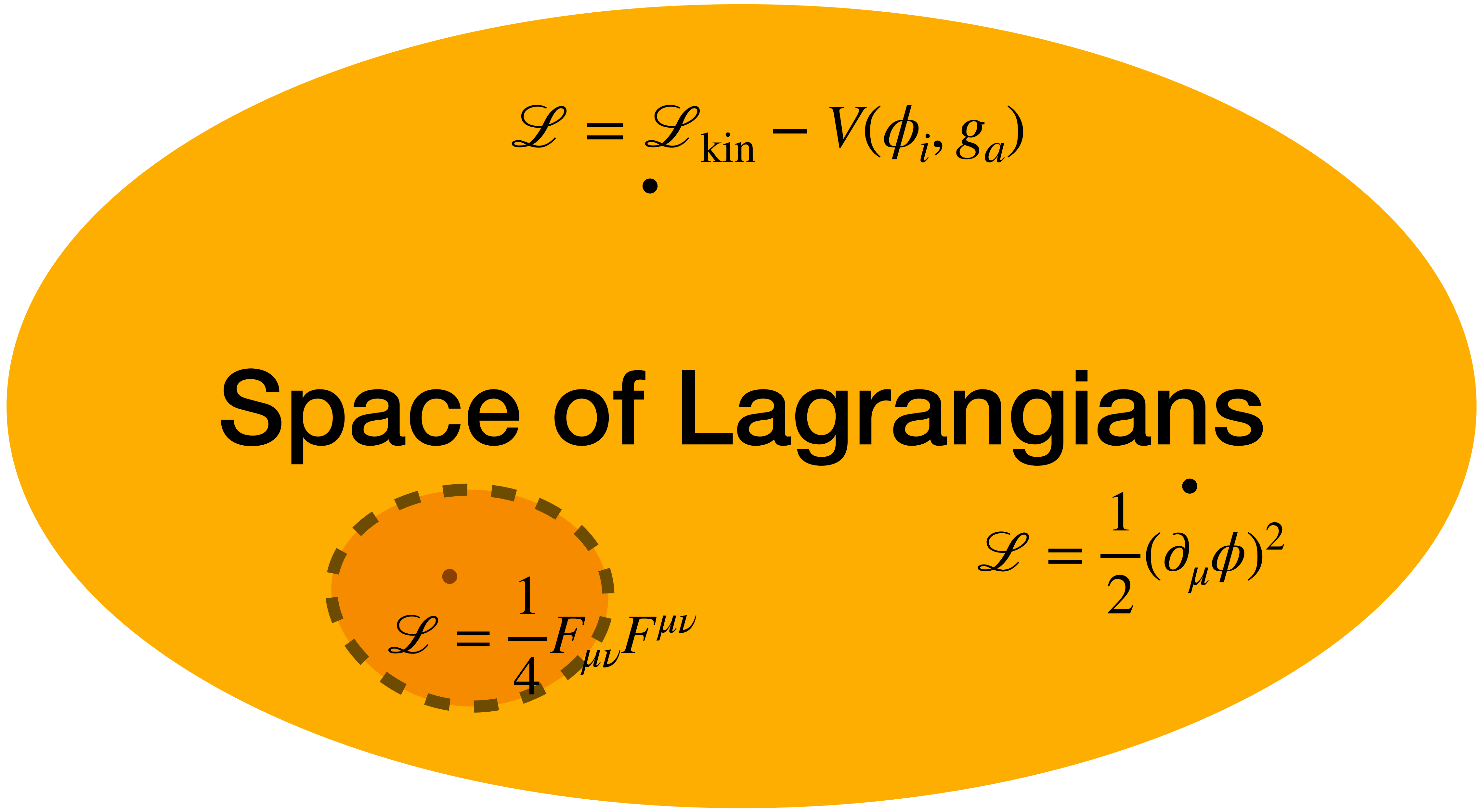
Part 2: AI infrastructure (differentiable programming) for essential tools…

Tools to understand string theory predictions

QG model

e.g. fields, spacetime, interactions: $\mathscr{L}_{\text{EFT}}$



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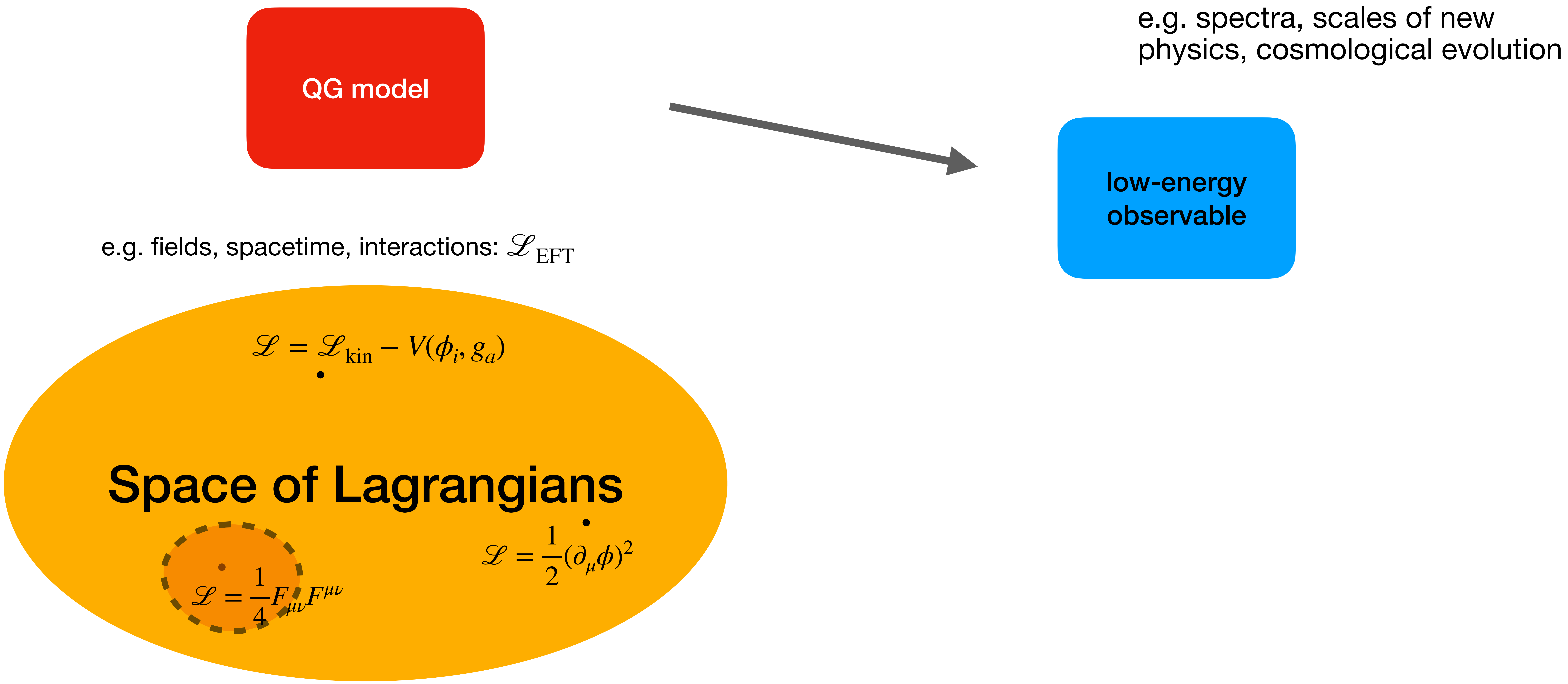


Tools to understand string theory predictions

QG model

e.g. spectra, scales of new physics, cosmological evolution

low-energy observable

e.g. fields, spacetime, interactions: $\mathscr{L}_{\mathrm{EFT}}$

$\mathscr{L} = \mathscr{L}_{\mathrm{kin}} - V(\phi_i, g_a)$

Space of Lagrangians

$\mathscr{L} = \frac{1}{2}(\partial_\mu \phi)^2$

$\mathscr{L} = \frac{1}{4} F_{\mu\nu} F^{\mu\nu}$

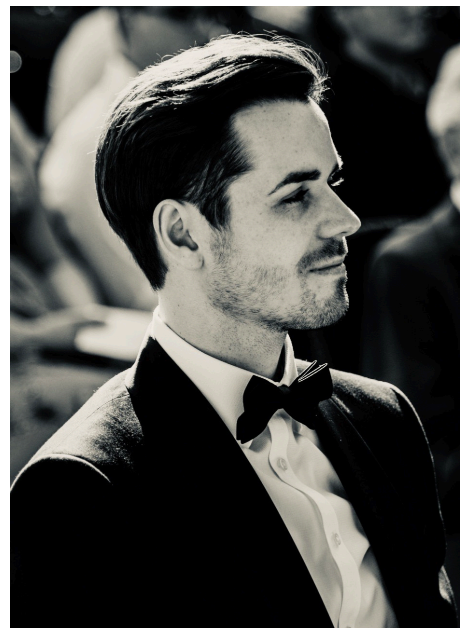
Forward problem:

How can we understand the physics of QG models?

For many questions we have the formalism but no efficient computational tools.

JAXVacua

Tools for understanding flux vacua of type IIB



with Andreas Schachner

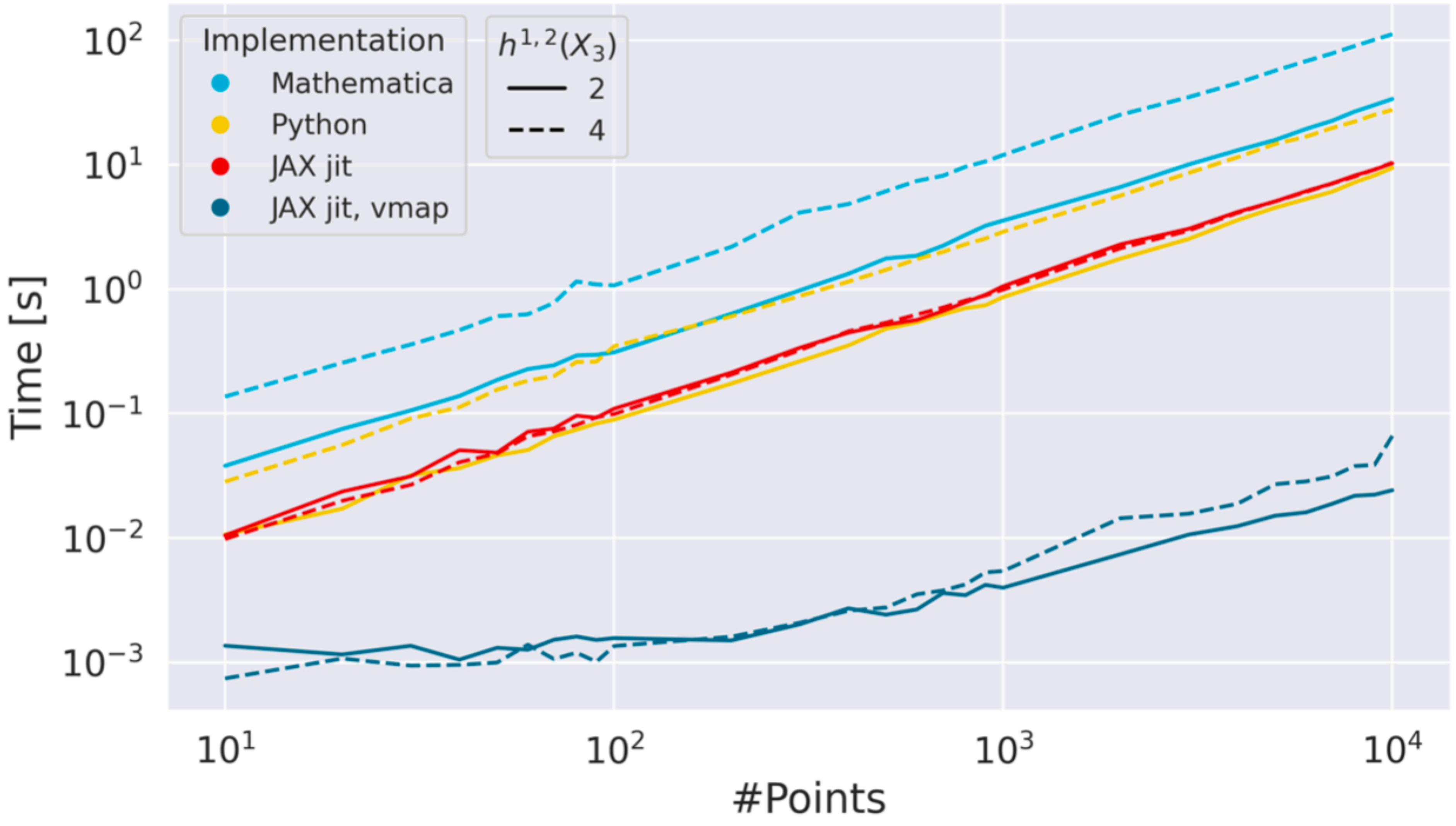
Dataset D: Kreuzer-Skarke database (4.7×10^8 polytopes)
x large combinatorial choices for $\vec{N}_{\text{flux}}$

For each $d \in D$:

- Determine and evaluate EFT (e.g. scalar potential) [supergravity formalism, methods from 90s (e.g. for prepotential at large complex structure), **our result: efficient numerical implementation now**]
- Evaluate phenomenology, e.g. find minima
  Our work: from $O(1)$ minima (1312.0014) $\rightarrow O(10^6)$ minima with similar computational resources ($h^{1,1} \leq 15$)

Timing for evaluating $D_I W$

Orders of magnitude speed improvements!



Technology:

- autodiff: differentiable code (allows fast evaluation of)
- JIT: automatically generate C++ code
- VMAP: automatically parallelise code (CPU and GPU)
- Different numerical optimisers

Completeness

"What is the number of flux vacua with $|W_0| = 100$ **and** $N_{\text{flux}} < 10$**?"**

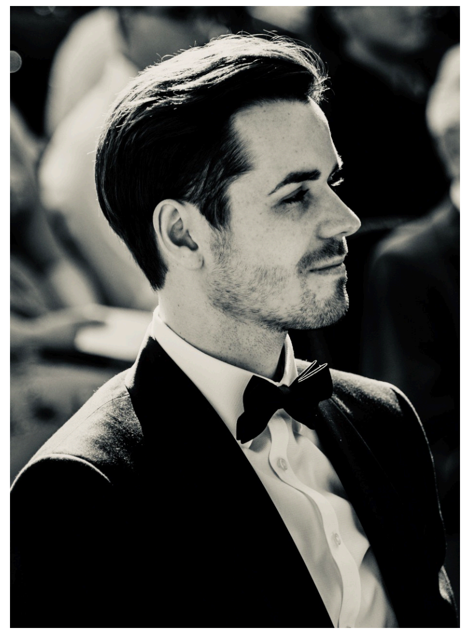
Deep observations of regions of moduli space in $\mathbb{P}_{1,1,1,6,9}$

work in collaboration with (2501.03984):

Aman Chauhan

Michele Cicoli

Anshuman Maharana



Andreas Schachner

Pelegrino Piantadosi

How do #fluxes become manageable?

cf. Plauschinn
[here slightly stronger bounds]

- Rewriting the ISD condition $\star_6 G_3 = \mathrm{i}G_3$:

Fluxes: $f, h \in \mathbb{Z}^{2h^{2,1}+2}$

$$f = \left(s\,\Sigma \cdot \mathcal{M} + c_0 \mathbf{1}\right) \cdot h$$

$$\mathcal{M} = \begin{pmatrix} -\mathcal{I}^{-1} & \mathcal{I}^{-1}\mathcal{R} \\ \mathcal{R}\mathcal{I}^{-1} & -\mathcal{I} - \mathcal{R}\mathcal{I}^{-1}\mathcal{R} \end{pmatrix}$$

$$\mathcal{N} = \mathcal{R} + \mathrm{i}\mathcal{I}$$

Prepotential

$$\mathcal{N}_{IJ} = \overline{F}_{IJ} + 2\mathrm{i}\,\frac{\mathrm{Im}(F_{IL})X^L\,\mathrm{Im}(F_{JK})X^K}{X^M\mathrm{Im}(F_{MN})X^N}\;,\; F_{IJ} = \partial_{X^I}\partial_{X^J}F\,.$$

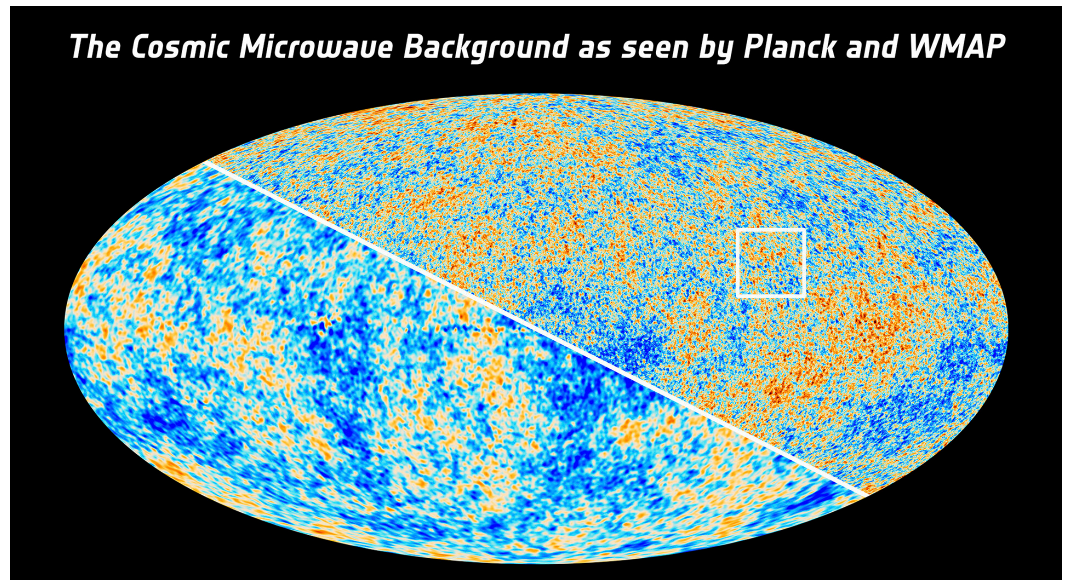
- Finite region of moduli (eigenvalues of M) and tadpole constrain allowed fluxes:

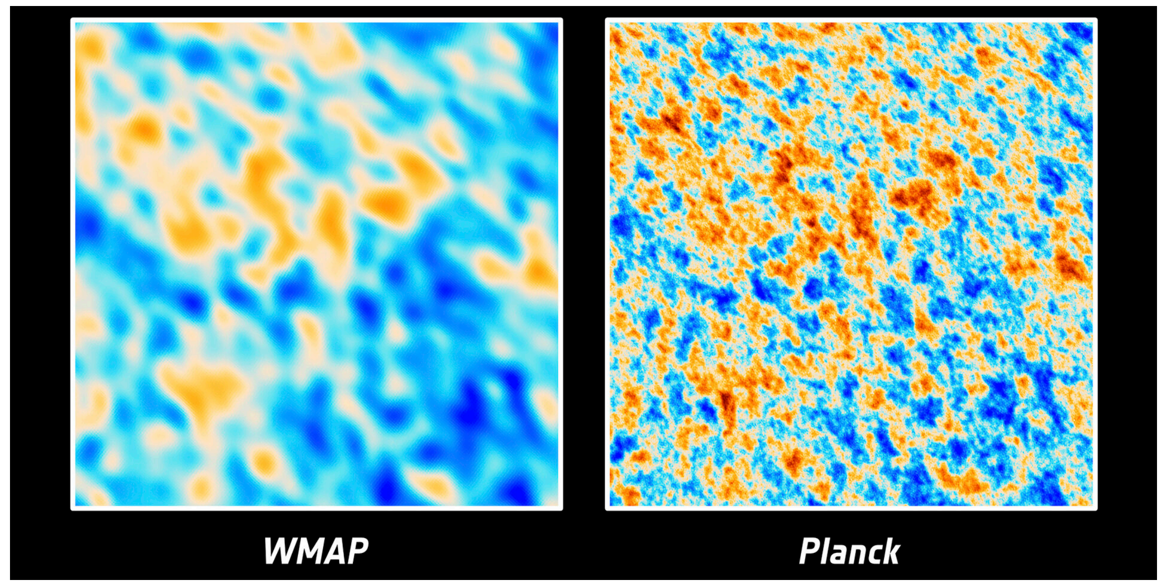
$$|h|^2 \leq \frac{2N_{\mathrm{flux}}\lambda_{\mathrm{max}}}{\sqrt{3}} \qquad \frac{\sqrt{3}}{2}\,\frac{N_{\mathrm{flux}}}{\lambda_{\mathrm{max}}} \leq |f|^2 \leq \frac{\lambda_{\mathrm{max}}^2 N_{\mathrm{flux}}^2}{|h|^2} + \frac{|h|^2}{4}\,.$$

The flux vacua universe

Comparison with astrophysical observations

- Simple nearby objects (i.e. numerically straight-forward): rigid, toroidal, …
- Coarse observations: possible with appropriate codes (e.g. JAXvacua)
- What do we find in deep observations?





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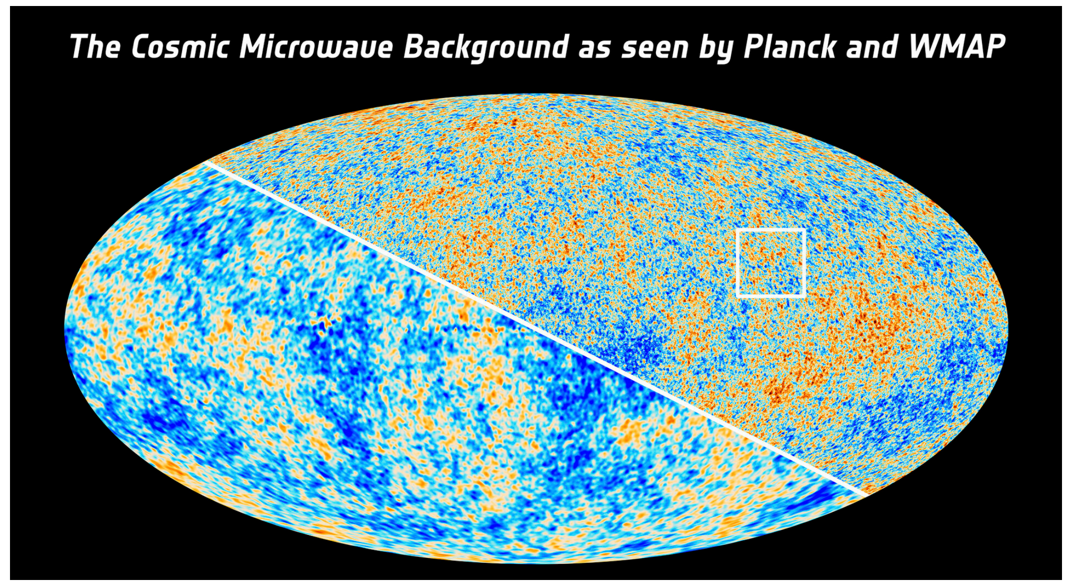

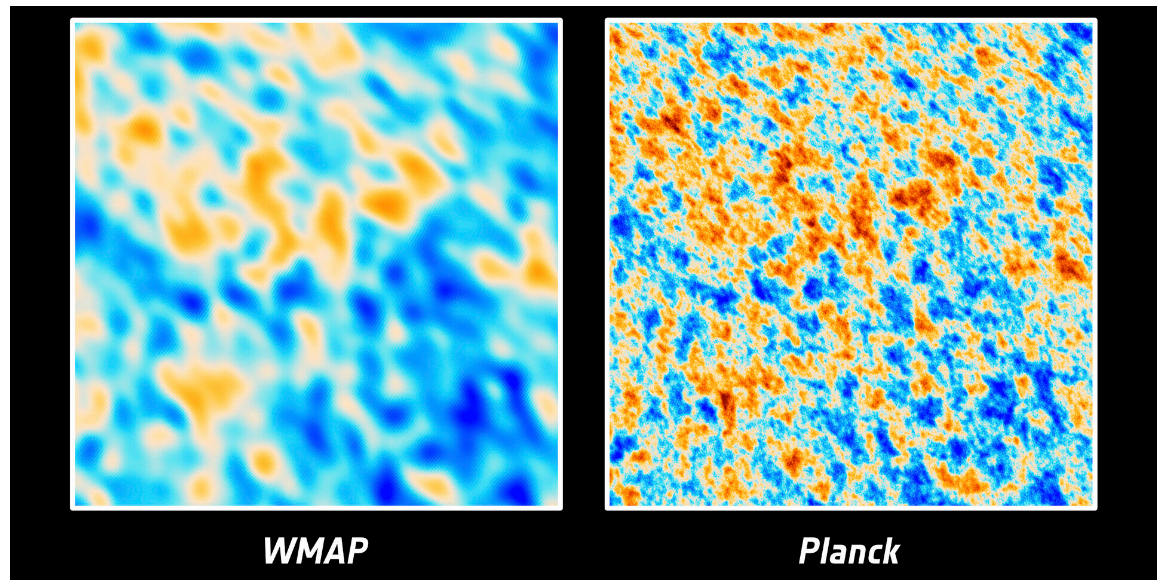

The flux vacua universe

Models meet observations

Statistical models (continuous flux approximation):

$$\mathcal{N}_{\text{stat}}(N_{\text{flux}} \leq N_{\text{max}}) = \frac{(2\pi N_{\text{max}})^6}{6!} \int_{\mathcal{M}_\tau \times \mathcal{M}_{\text{cs}}} \mathrm{d}^6 z \, \det(g) \, \rho(z)$$

$$\rho(z) = \pi^{-6} \int \mathrm{d}^2 X \, \mathrm{d}^4 Z \, \mathrm{e}^{-|X|^2 - |Z|^2} \, |X|^2 \left| \det \begin{pmatrix} \delta^{IJ} \, \overline{X} - \frac{\overline{Z}^I Z^J}{X} & F_{IJK} \, \overline{Z}^K \\ \overline{F}_{IJK} \, Z^K & \delta^{IJ} X - \frac{Z^I \, \overline{Z}^J}{\bar{X}} \end{pmatrix} \right|$$

Do deep observations of flux landscape reproduce such estimates?

Algorithmic biases in observed ensembles? Can we quantify those biases?

Douglas, Ashok, Denef

Deep explorations

- Fix tadpole and region in moduli space (fixes range for eigenvalue spectrum of matrix in ISD).
- Generate box of flux vectors for h (sample points in region of moduli space), f fixed from ISD.
- Find flux vacua using JAXvacua.
- Check equivalences, consistency (masses, LCS valid)

$$f = \left(s\,\Sigma \cdot \mathscr{M} + c_0 \mathbf{1}\right) \cdot h$$

$$|h|^2 \leq \frac{2N_{\text{flux}}\lambda_{\text{max}}}{\sqrt{3}}$$

$$\frac{\sqrt{3}}{2}\,\frac{N_{\text{flux}}}{\lambda_{\text{max}}} \leq |f|^2 \leq \frac{\lambda_{\text{max}}^2 N_{\text{flux}}^2}{|h|^2} + \frac{|h|^2}{4}\,.$$

Our deep observations

Our deep observations

Four datasets

- Old friend: $\mathbb{P}_{[1,1,1,6,9]}$ symmetric locus, large complex structure.

Name	$\mathrm{Im}(z^i)$	s	$N_{\max}$	$\#h$	$\#f$	$\#(f,h)$	$\mathcal{N}_{\mathrm{vac}}$	exhaustive
A	$[2,3]$	$[\frac{\sqrt{3}}{2},20]$	34	82,082	1,849,426	5,134,862	5,140,872	✓
B	$[2,5]$	$[\frac{\sqrt{3}}{2},10]$	10	1,900	6,340	12,160	12,196	✓
C	$[1,10]$	$[\frac{\sqrt{3}}{2},50]$	34	3,652,744	21,043,832	50,652,686	50,884,086	×
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coarse study e.g. 1212.4530 (Westphal et al.)

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Dilaton solutions

Dataset A

- Structures in string couplings revealed when filtering individual N_{flux} values.
- Scale of the structures changes when changing N_{flux}.

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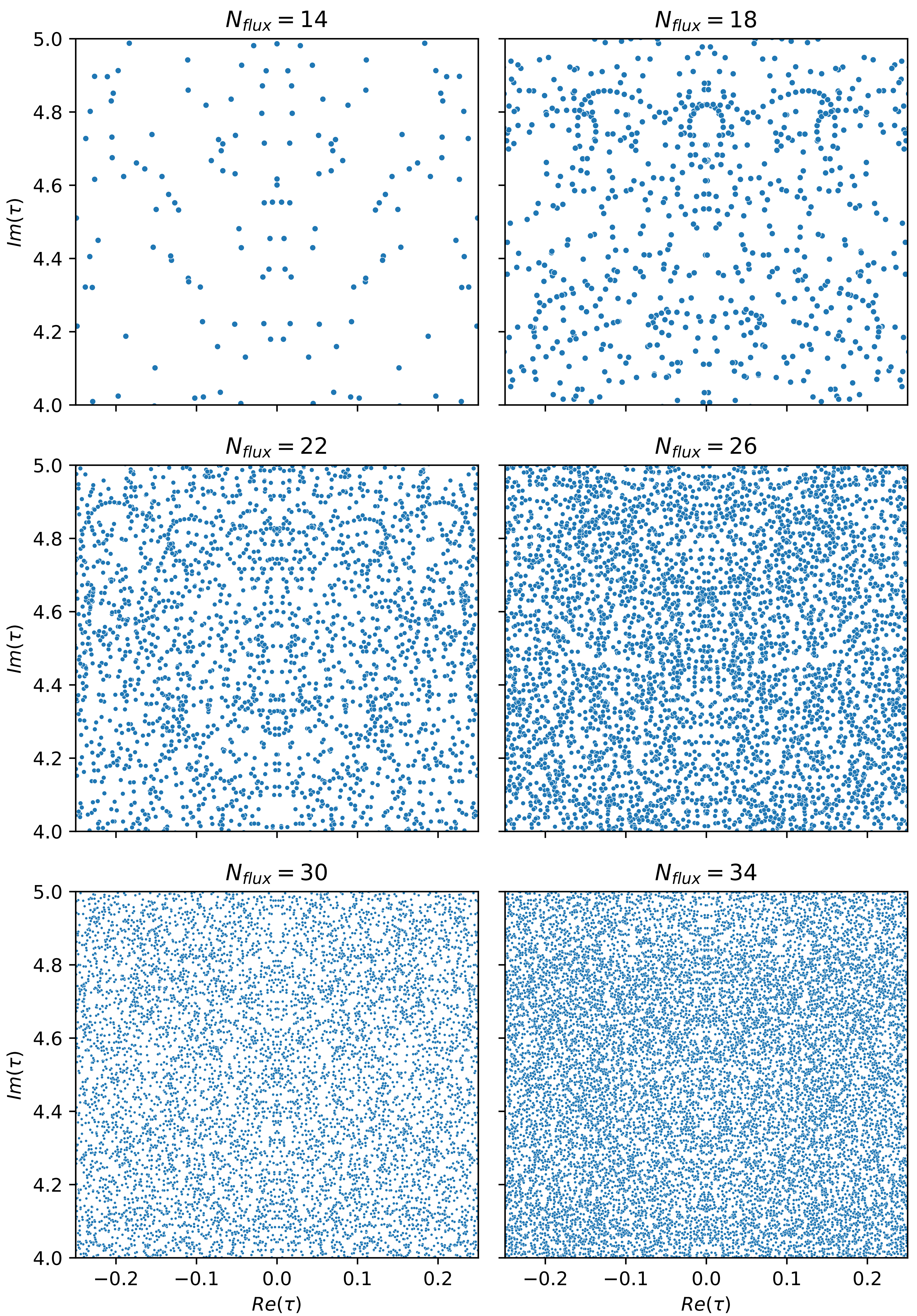
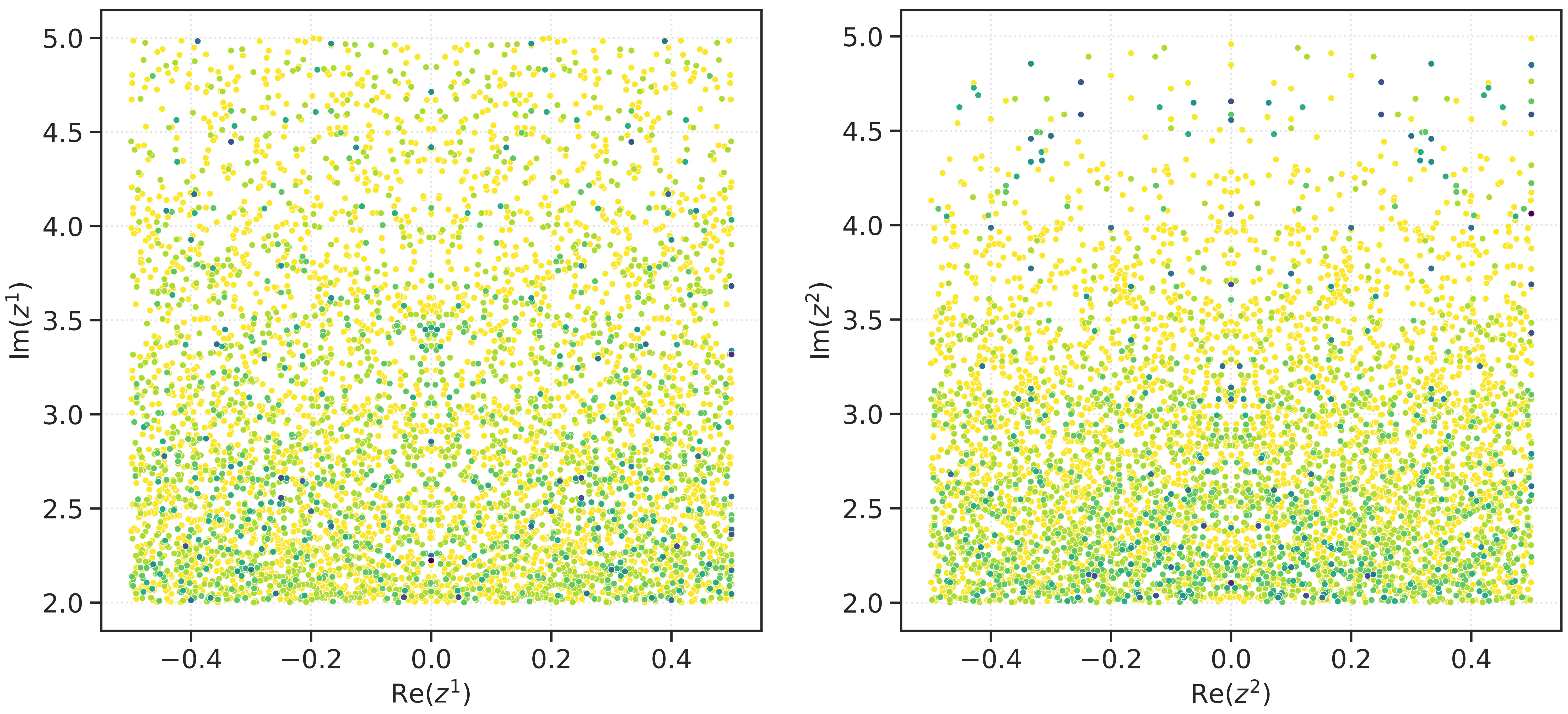
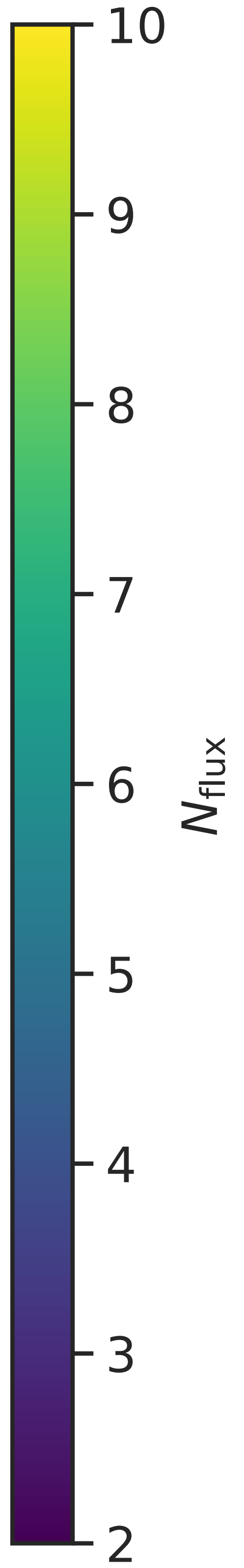
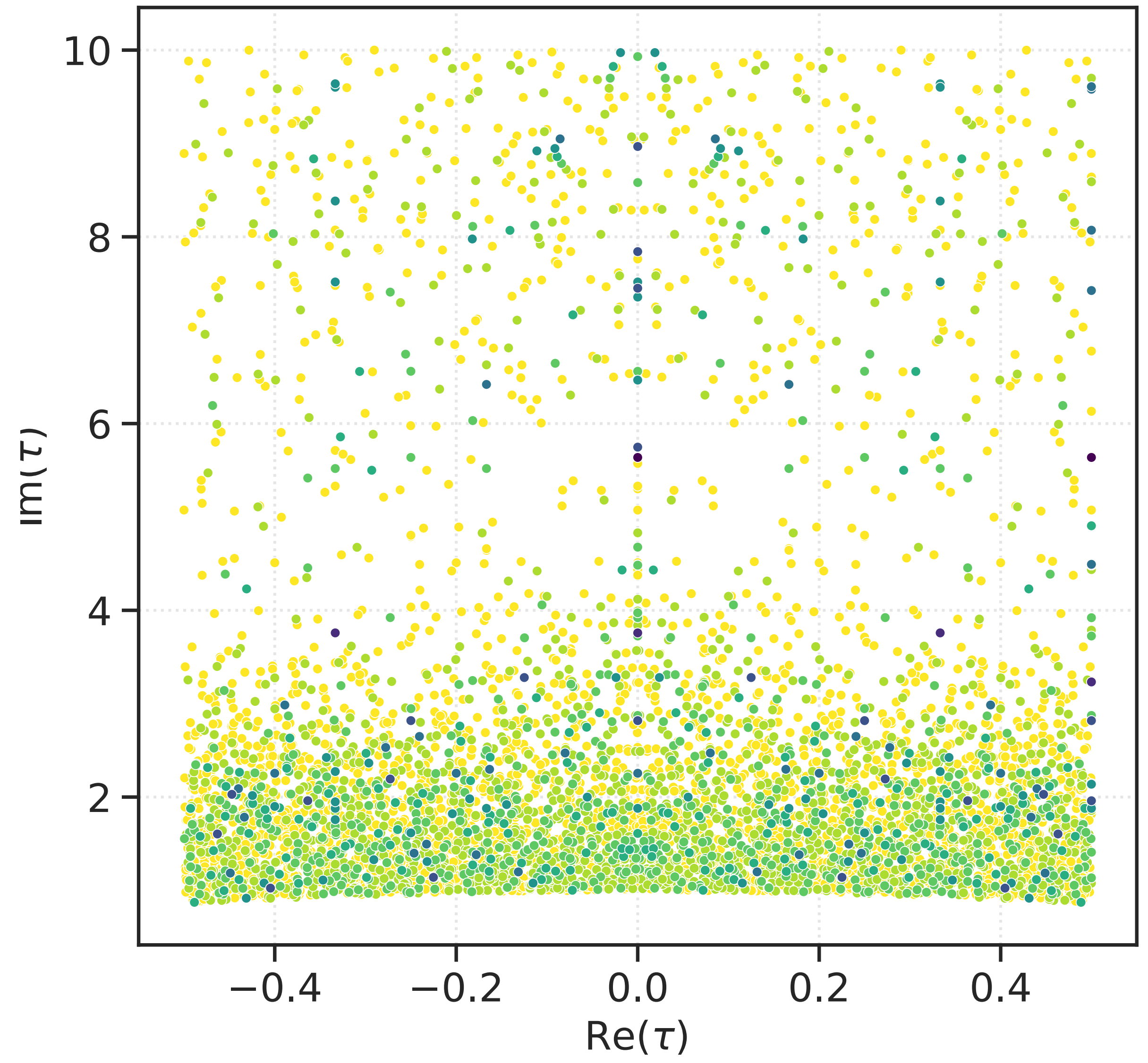
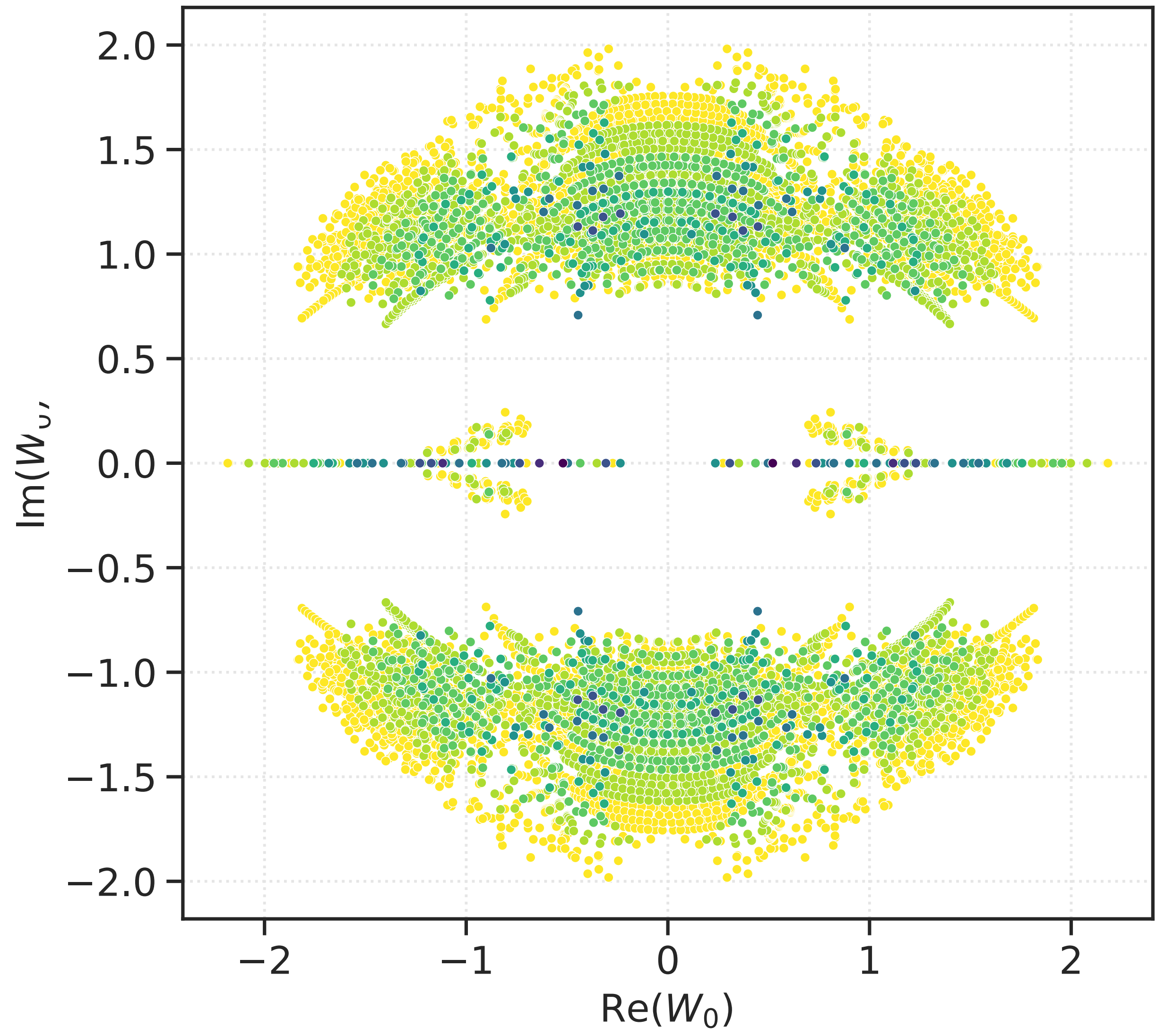


Distribution of solutions (dataset B)









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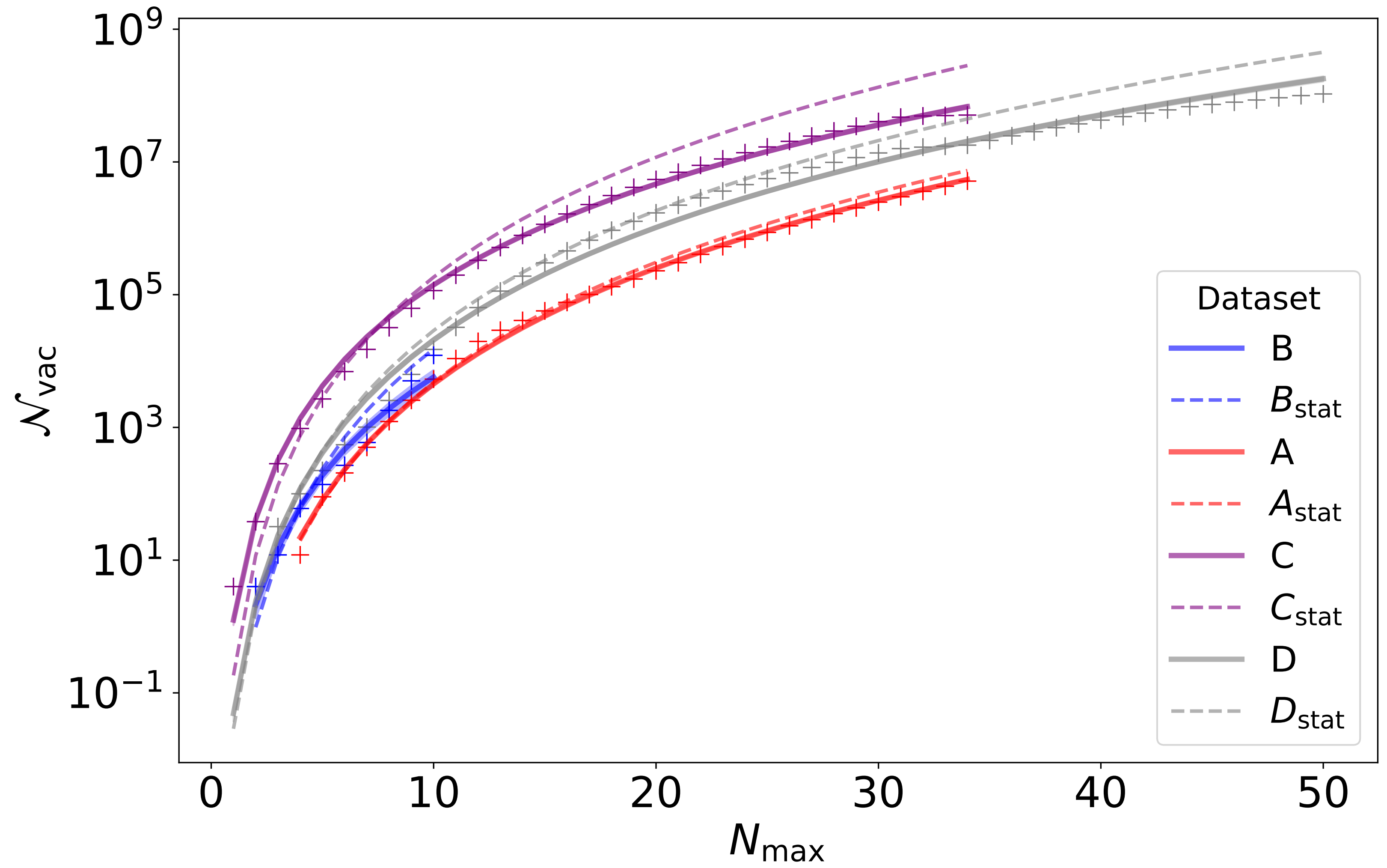
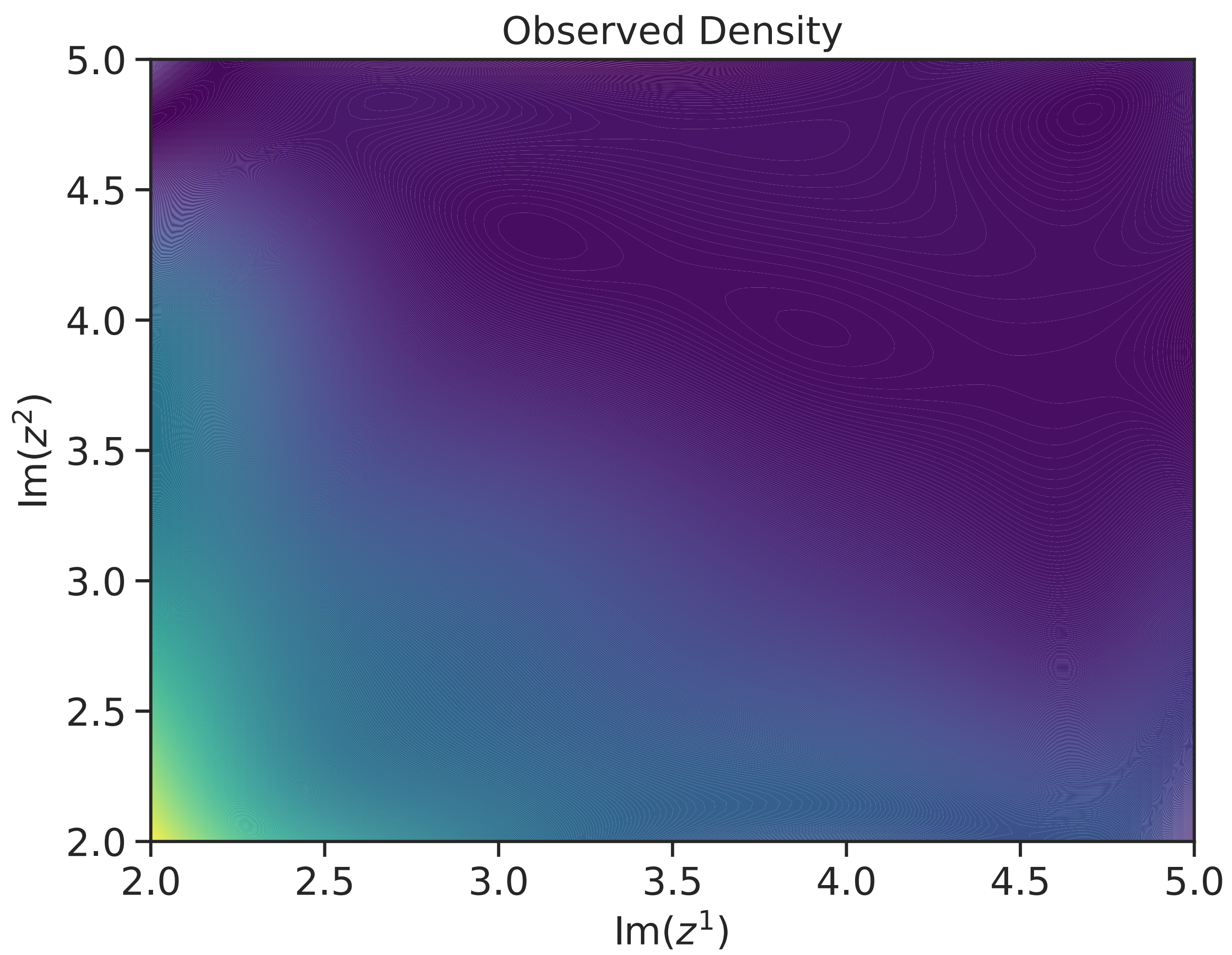
Local deviations from statistical expectations

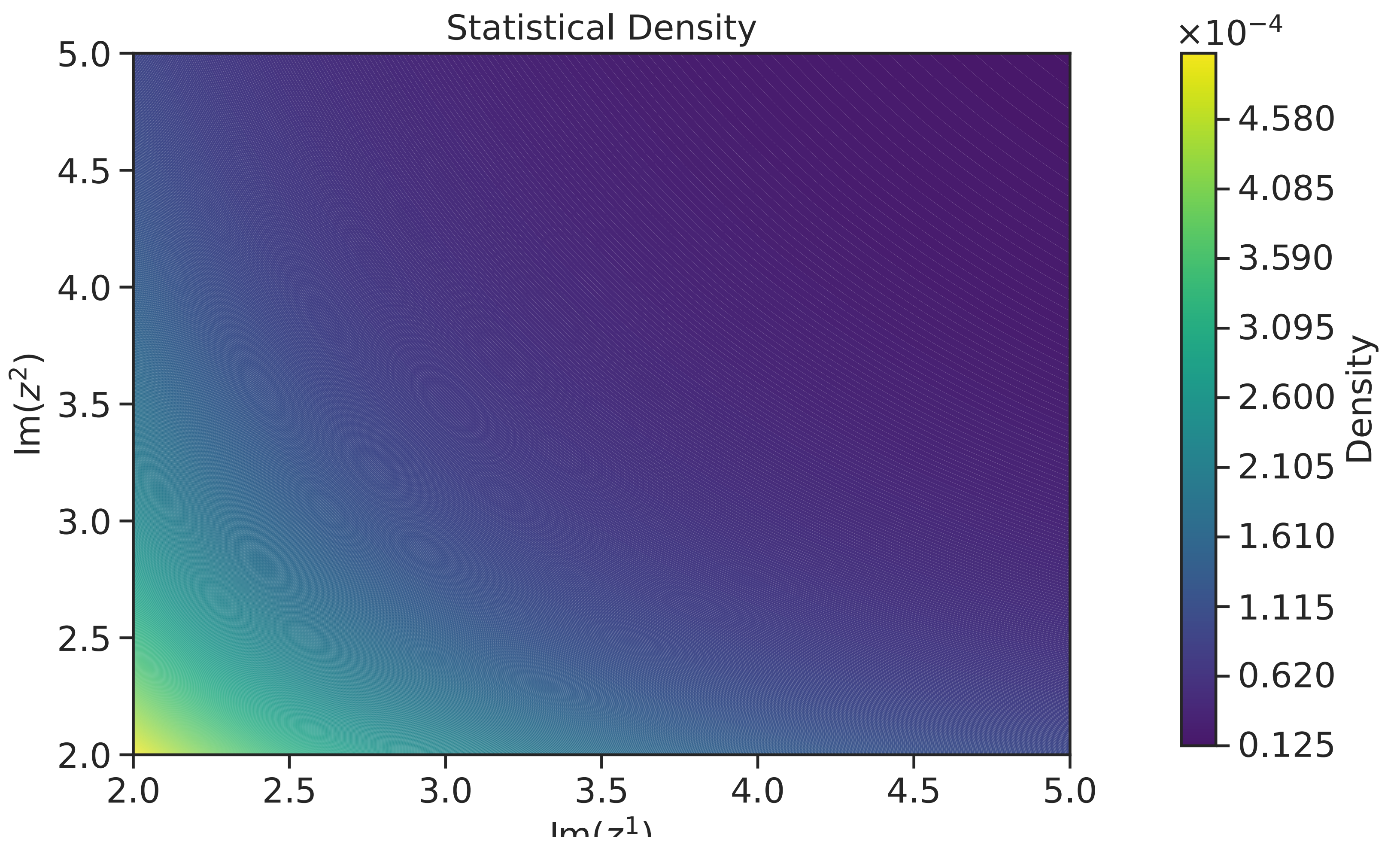
Expectations vs. observed total numbers



Continuous flux density expectation



Observed flux density



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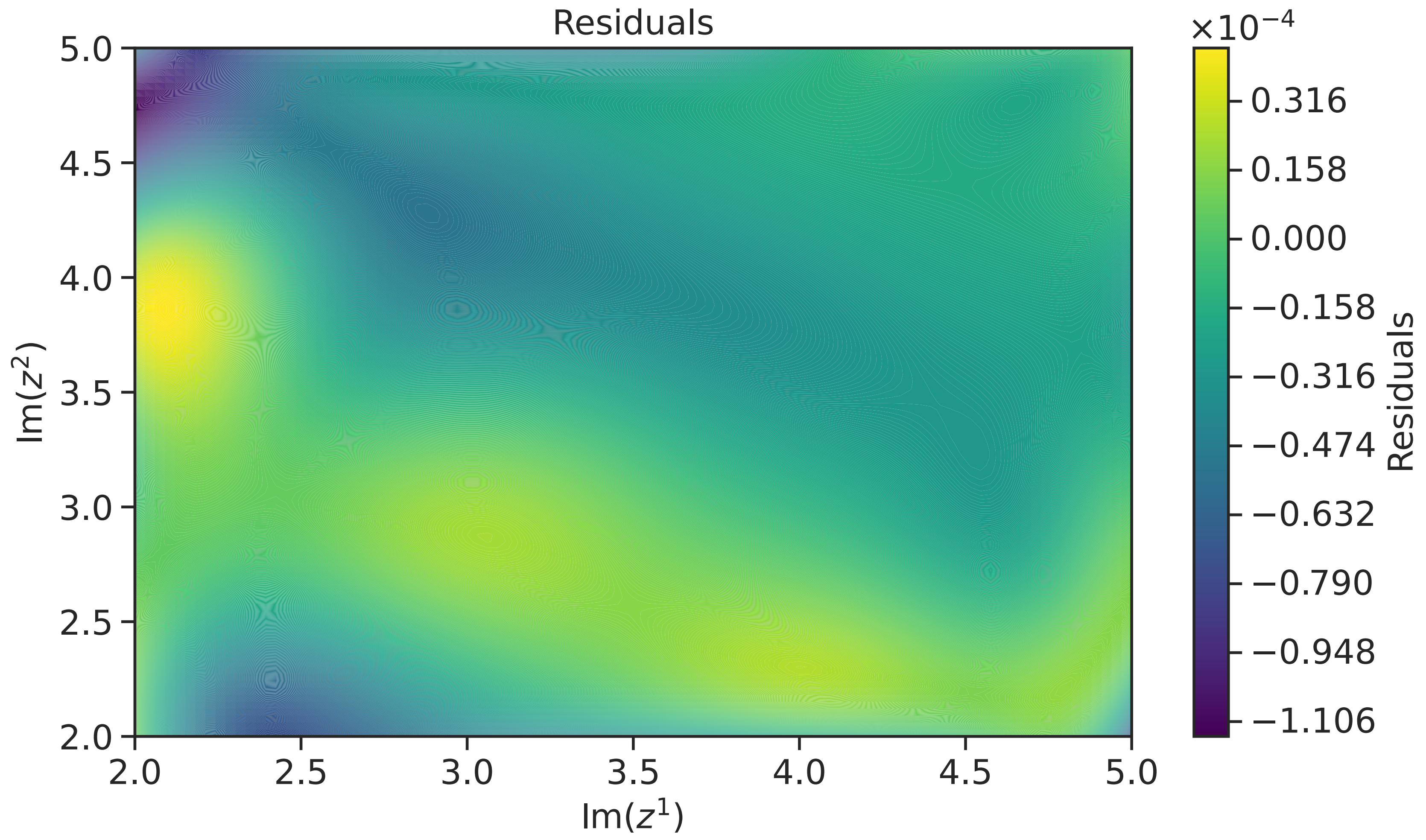
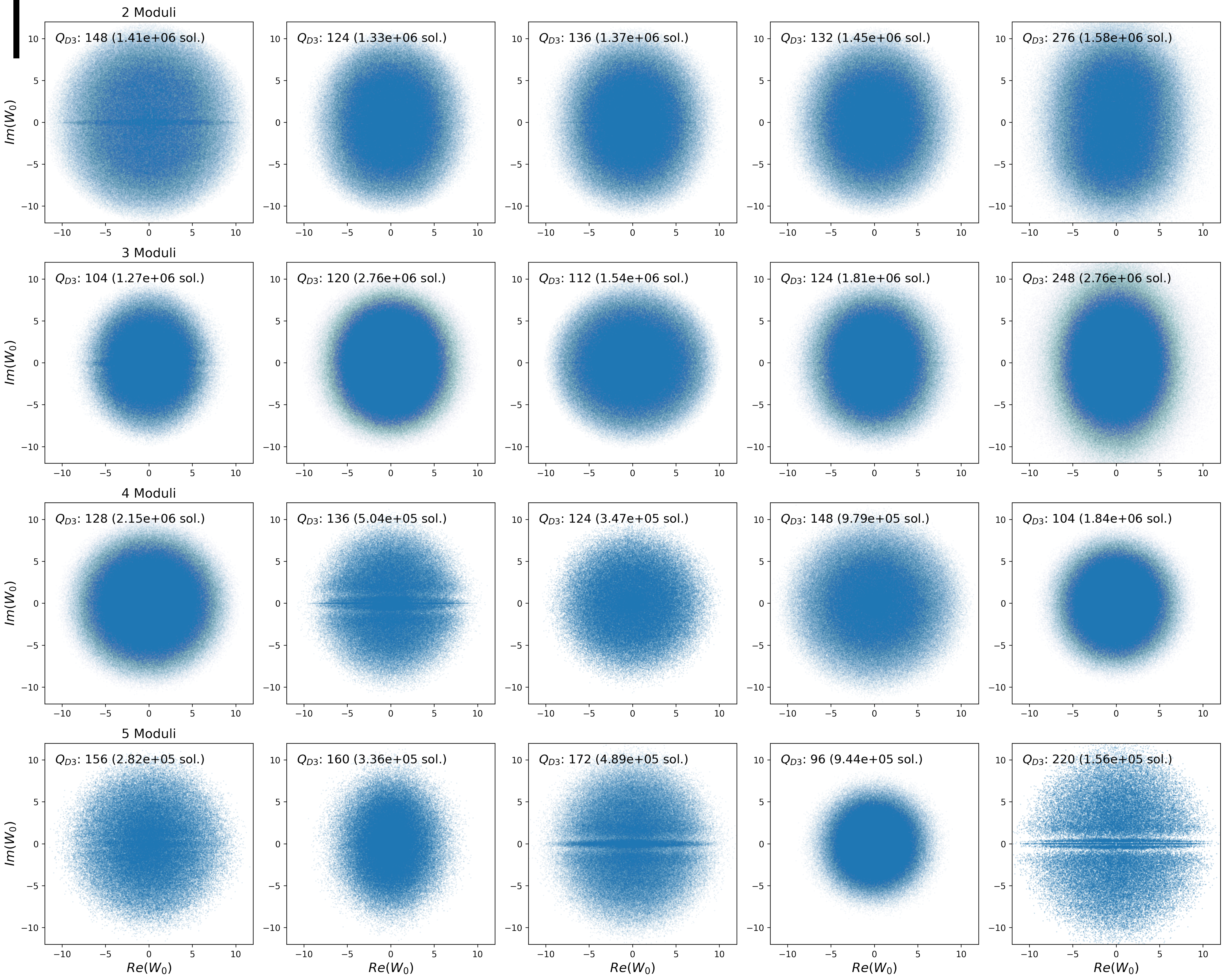


Distribution of $|W_0|$

- Coarse scan for various geometries showed universal behavior (2307.15747 with J. Ebelt).
- Structures around $\mathrm{Im}(W_0) = 0$ unclear.

$$W_0 = \sqrt{2/\pi}\; e^{K/2}\; W$$

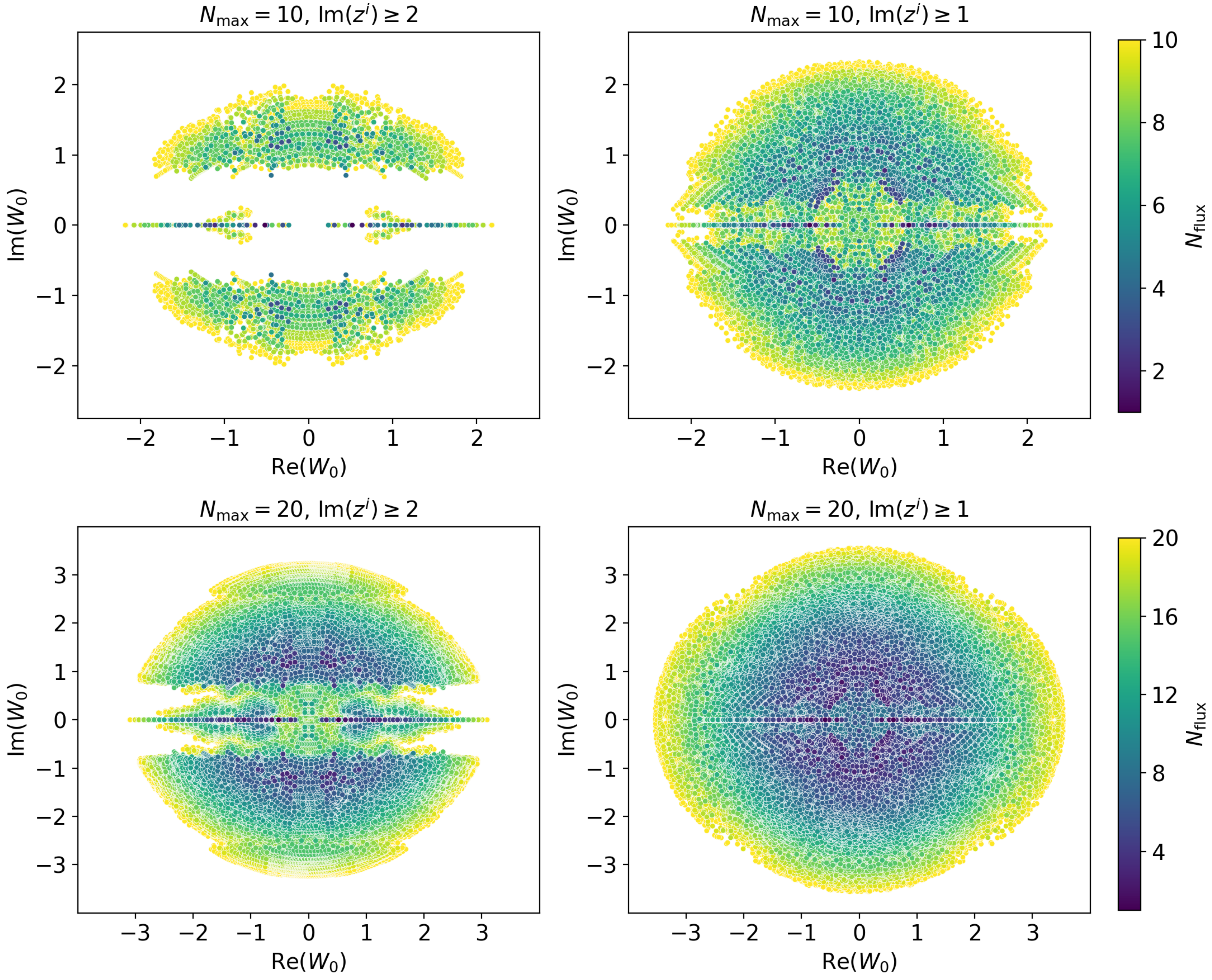
2307.15747

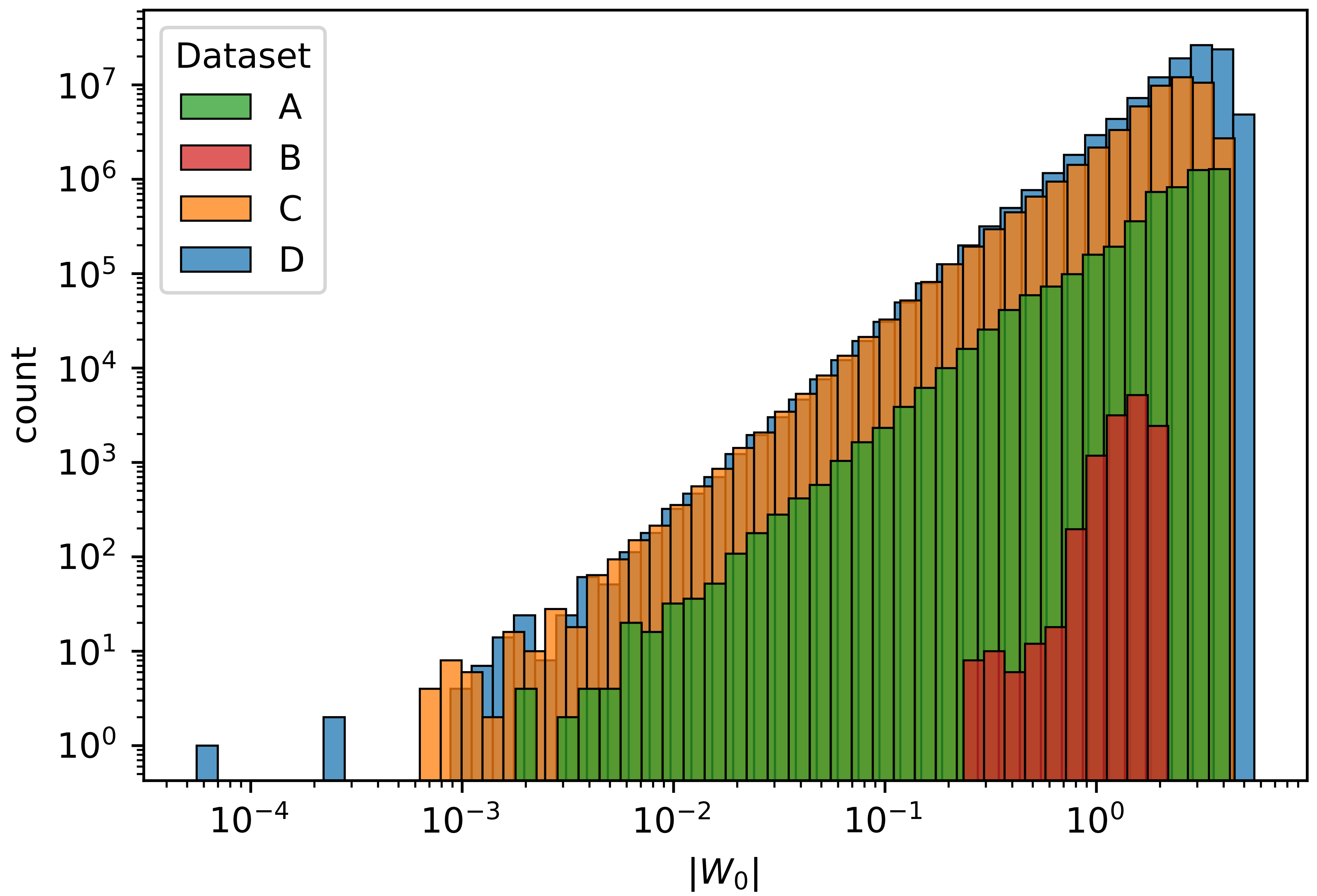


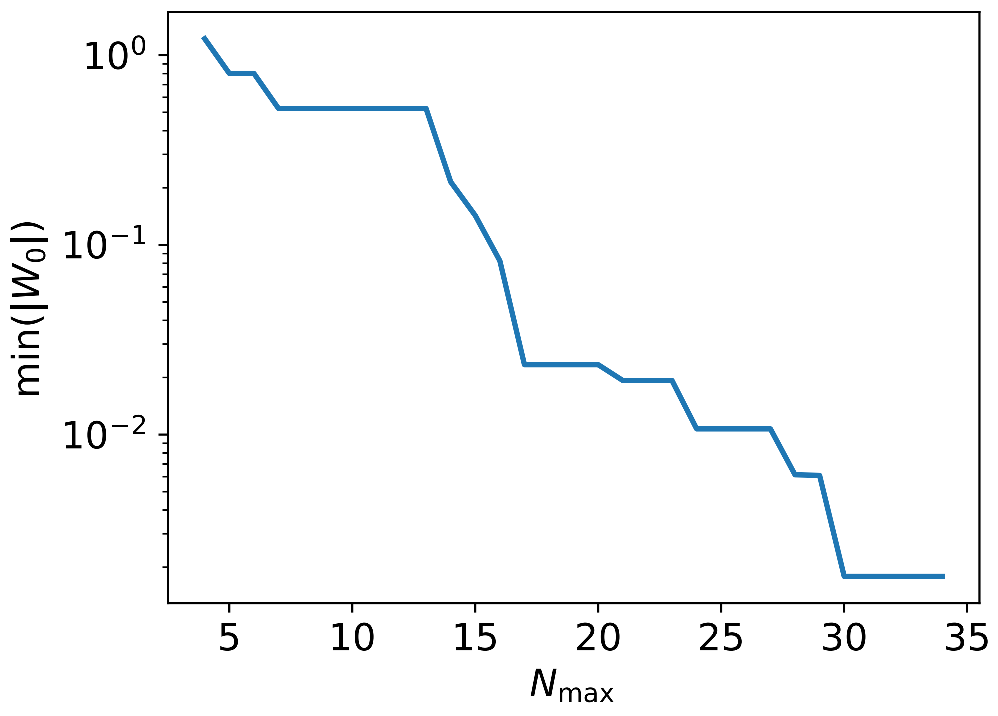
Distribution of $|W_0|$

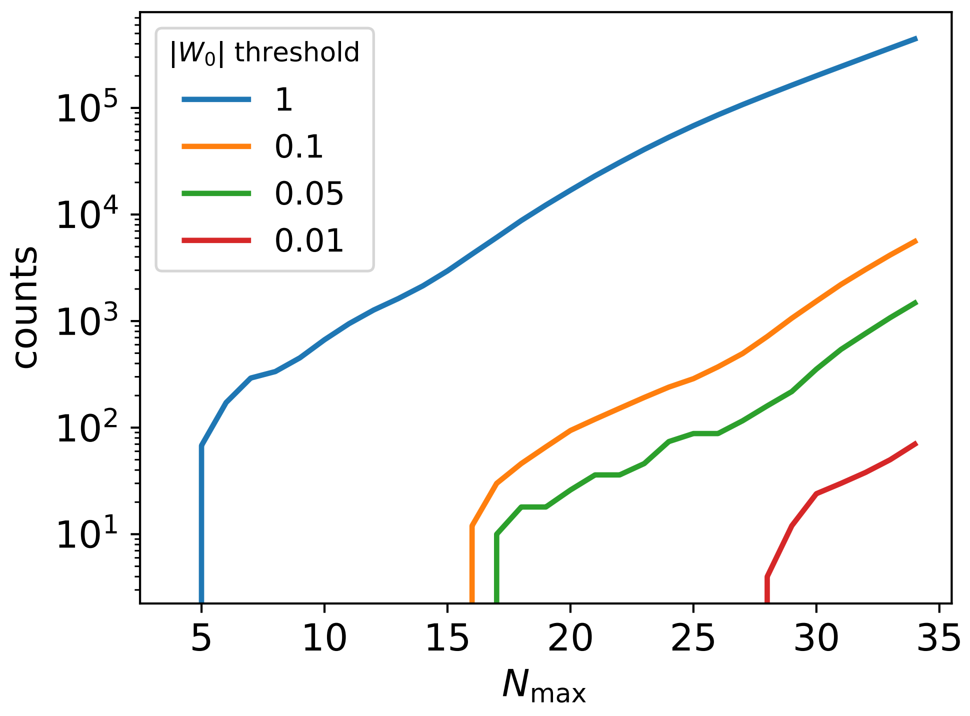
Structures depend on sample construction (region & tadpole)

-



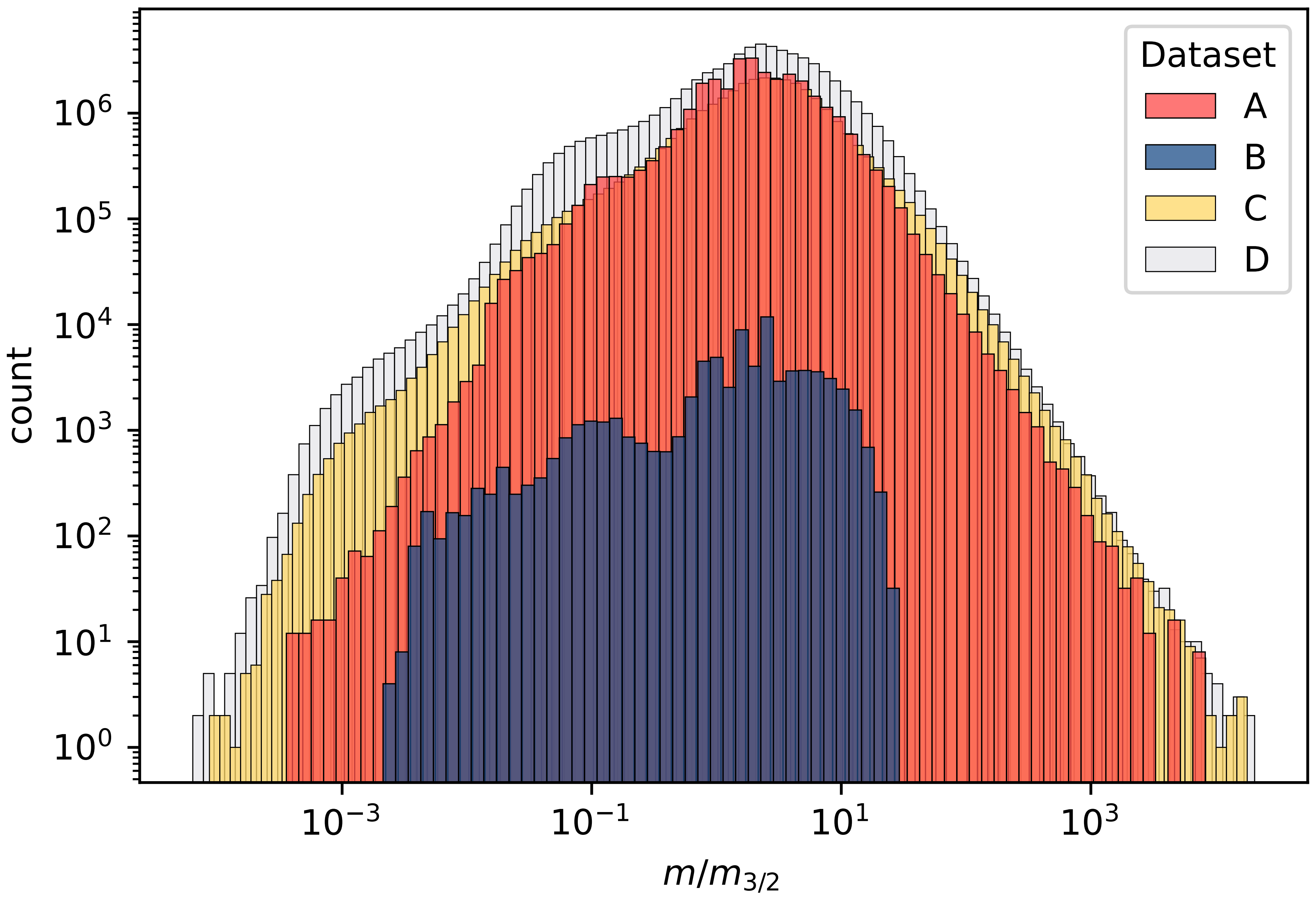






Distribution of moduli masses

Hierarchies are present

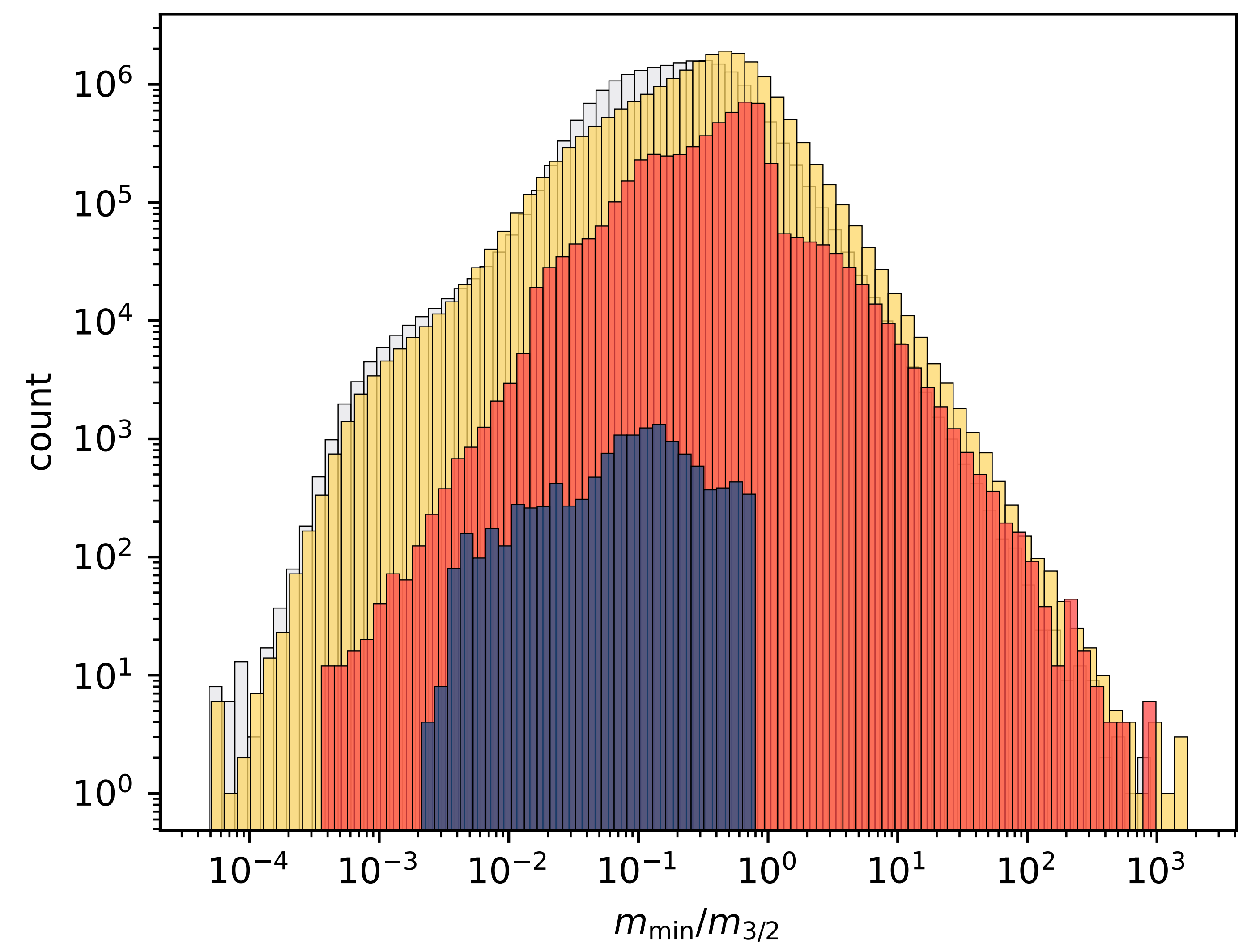


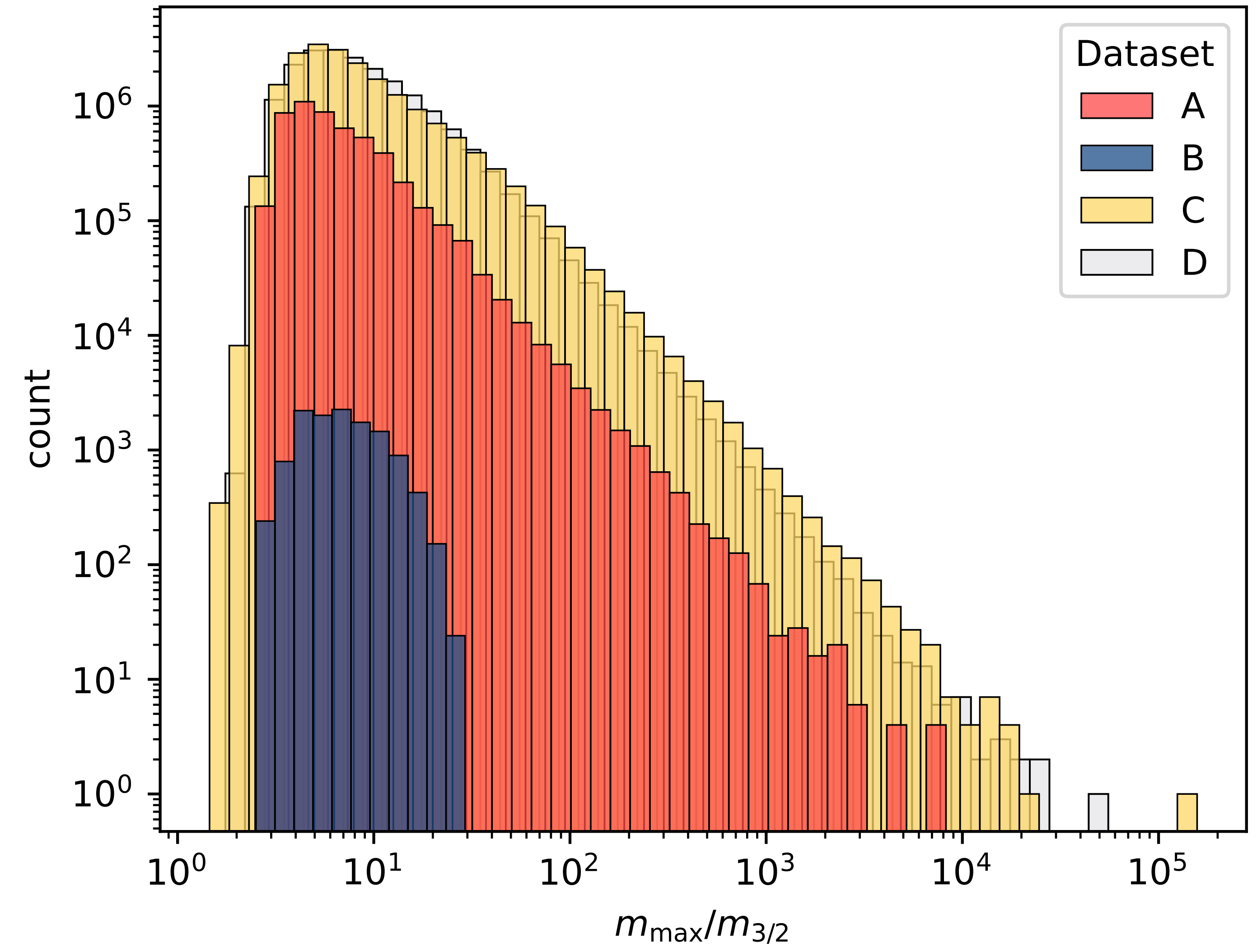
Explicit solution with: $|W_0| \sim 10^{-5}$

$$f = (4,12,2,-1,0,-1),\ h = (36,-1,0,0,1,-1)$$

$$z^1 = 0.5 + 2.3682\,\mathrm{i} z^2 = 0.5 + 2.5118\,\mathrm{i} \tau = 0.5 + 1.4812\,\mathrm{i}$$

$$m_A = (9.1505, 9.1513, 97.7826, 97.7853, 138.5255, 138.5287)$$





Part 3: Generative AI to find (string) models with desired phenomenology

Why tools for flux vacua — which physics?

Broader physics motivation

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"Give me string models that realise $|W_0| = 100$."

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Model builder

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"What is the conditional density of flux vectors $P(\mathbf{x} \,|\, W_0)$?"

"What is the number of flux vacua with $|W_0| = 100$ and $N_{\mathrm{flux}} < 10$?"

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Definite and probabilistic answers

“What is the conditional density of flux vectors $P(\mathbf{x} \,|\, W_0)$?”

“What is the number of flux vacua with $|W_0| = 100$ and $N_{\text{flux}} < 10$?”

Why tools for flux vacua — which physics?

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Model builder

“Give me string models that realise $|W_0| = 100$.”

“Give me BSM models that solve the Hubble tension.”

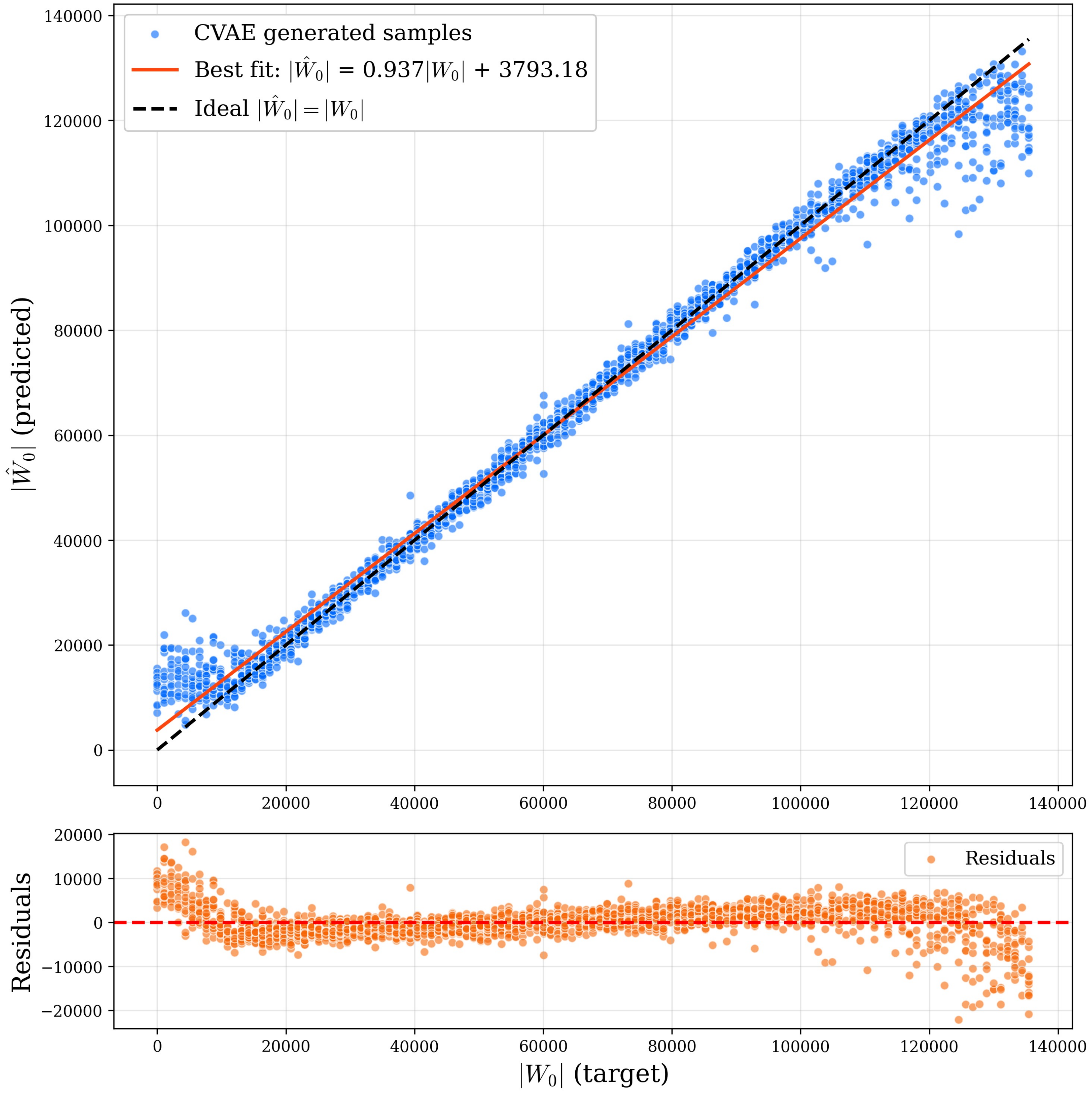
Definite and probabilistic answers

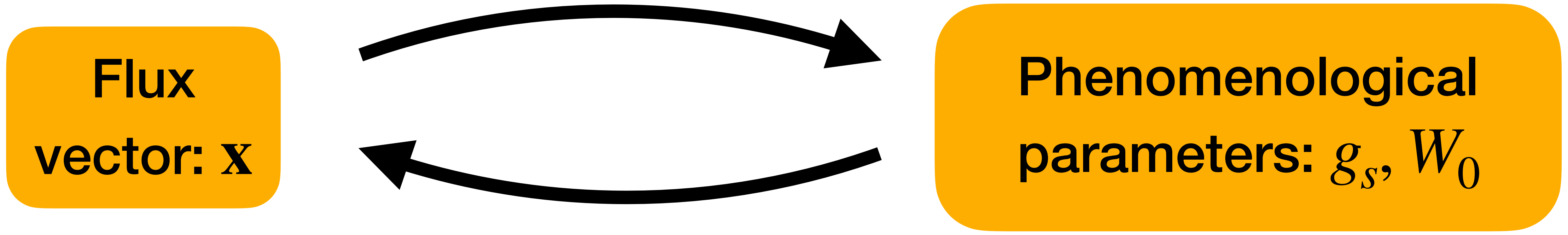
“What is the conditional density of flux vectors $P(\mathbf{x}\,|\,W_0)$?”

“What is the number of flux vacua with $|W_0| = 100$ and $N_{\text{flux}} < 10$?”

“What is the probability of primordial GWs at high frequencies from a consistent theory of quantum gravity?”

Our contribution: the AI string model builder





A model in realistic situations for questions like:
$P(\mathbf{x} \,|\, W_0)$

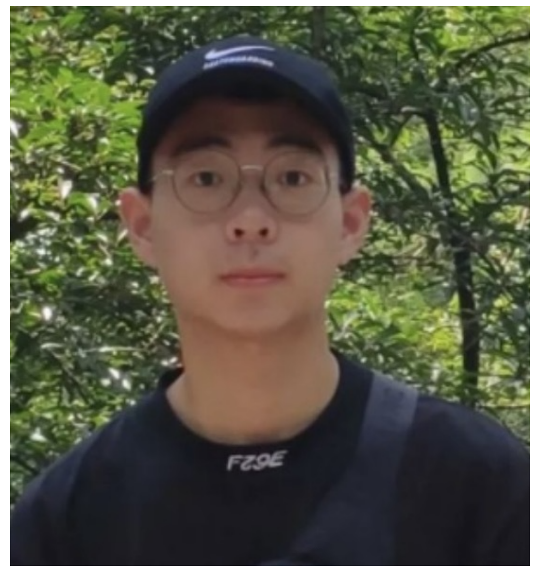
see Zhimei's poster!

Solving inverse problems of Type IIB flux vacua with conditional generative models (conditional VAE)

SK, Liu: 2506.22551

Part 4: LLMs and tools to overcome resource limitations

Theoretical physicists can only finish a few projects a year. How to scale?

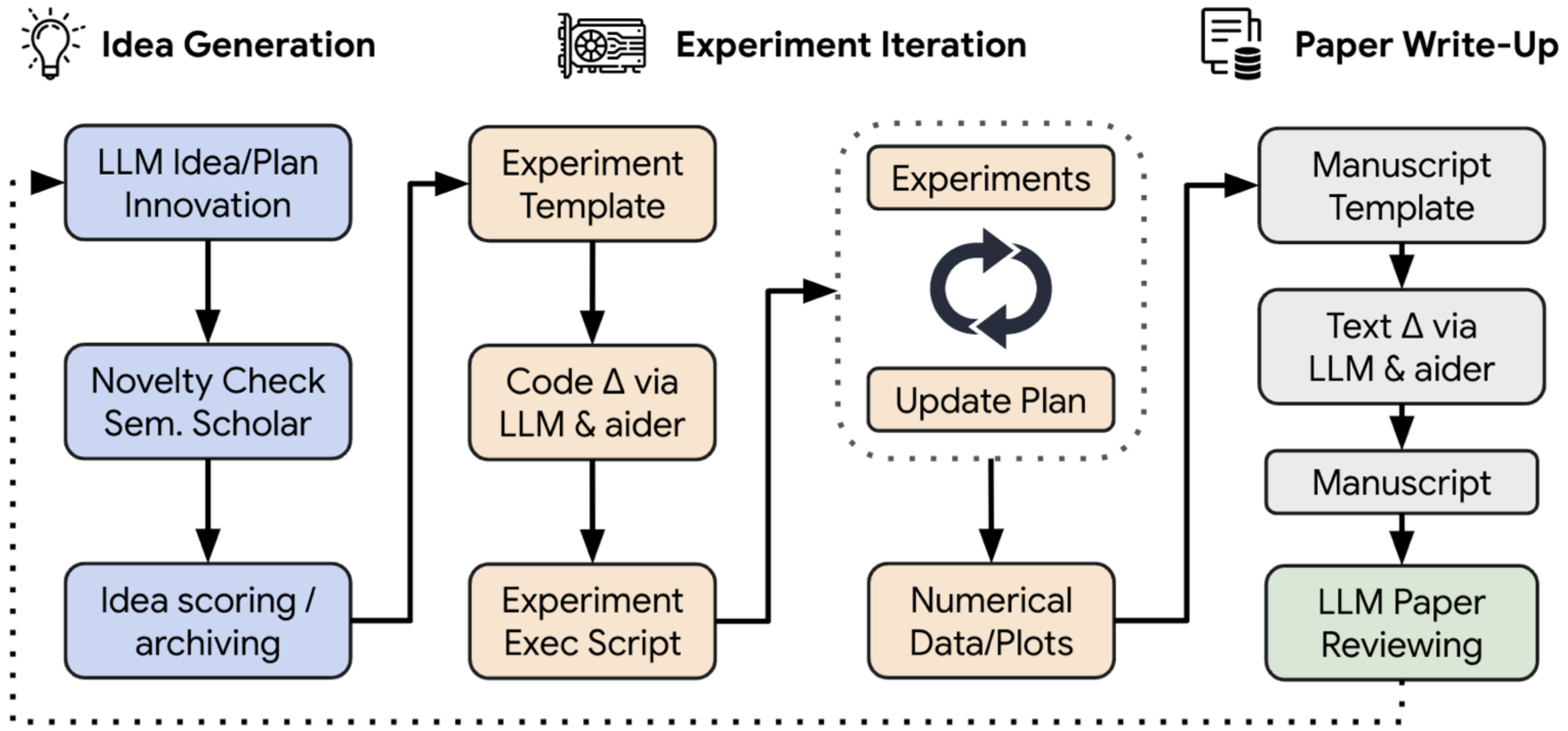


work with Zhimei Liu and Yi Gu

Agents and LLMs

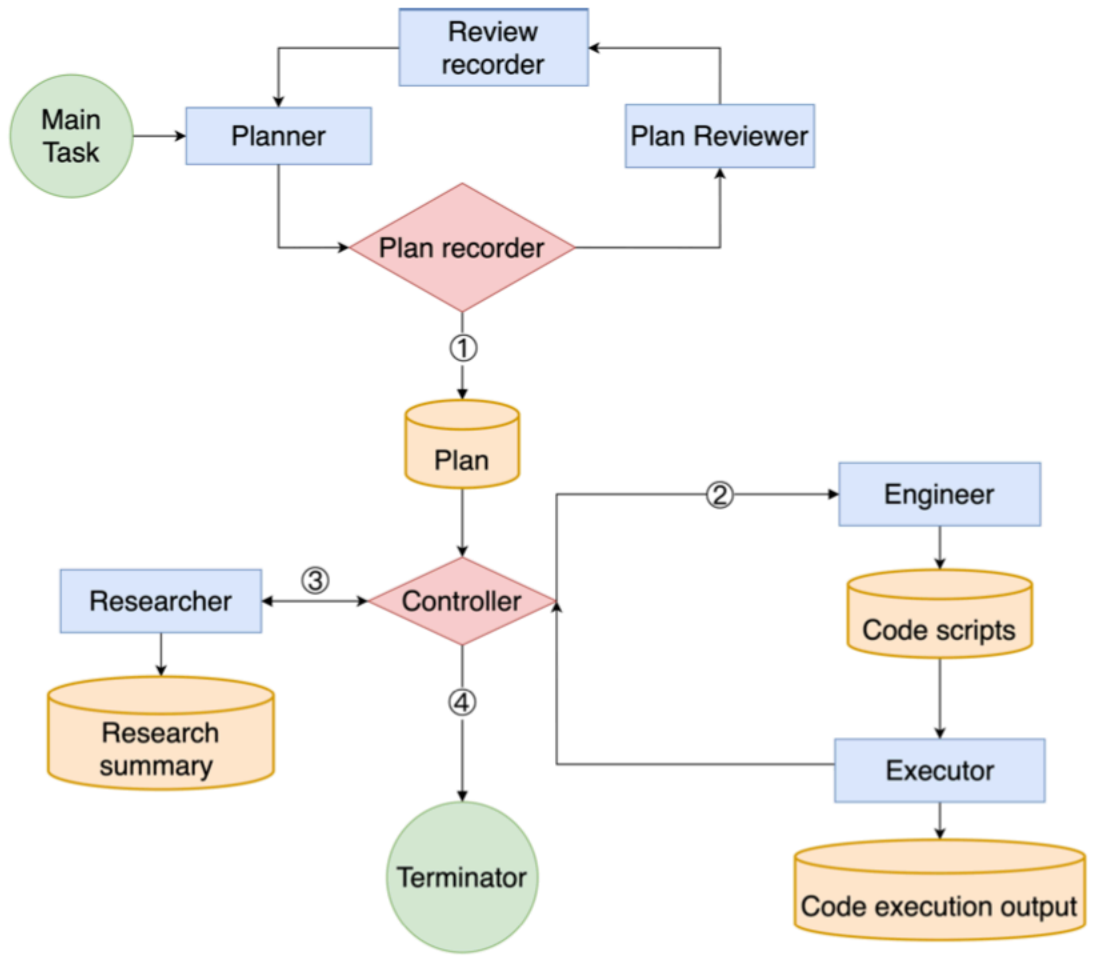
Automated scientific discovery: the ingredients

- LLMs can write code.
- LLMs can plan projects.
- LLMs can improve answers by critiquing themselves.
- Such systems can conduct some research and write up their results.
- Conjecture: systems using current LLMs and running code produced by them will be capable of doing most of our research within the next 12-24 months.



from AI Scientist

multi-agent systems for autonomous discovery



Lu et al.: The AI Scientist 2408.06292
Laverick et al.: Multi-Agent System for Cosmological Parameter Analysis 2412.00431
Moss: The AI Cosmologist I: An agent system for automated data analysis 2504.03424
TPBench (Münchmeyer et al.): tpbench.org
...

2507.07257

Work in progress

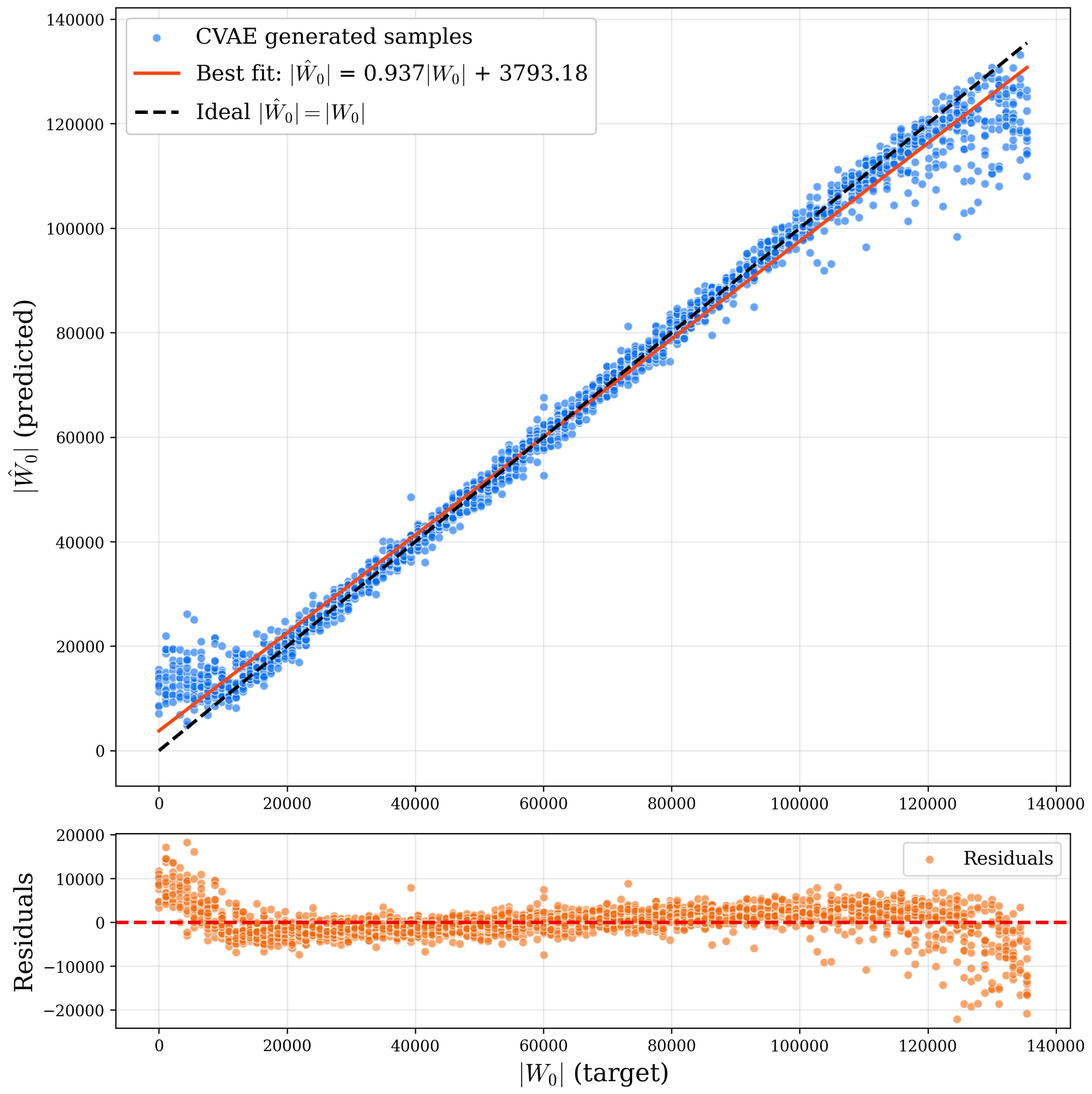
We can have systems that reason like smart physicists…

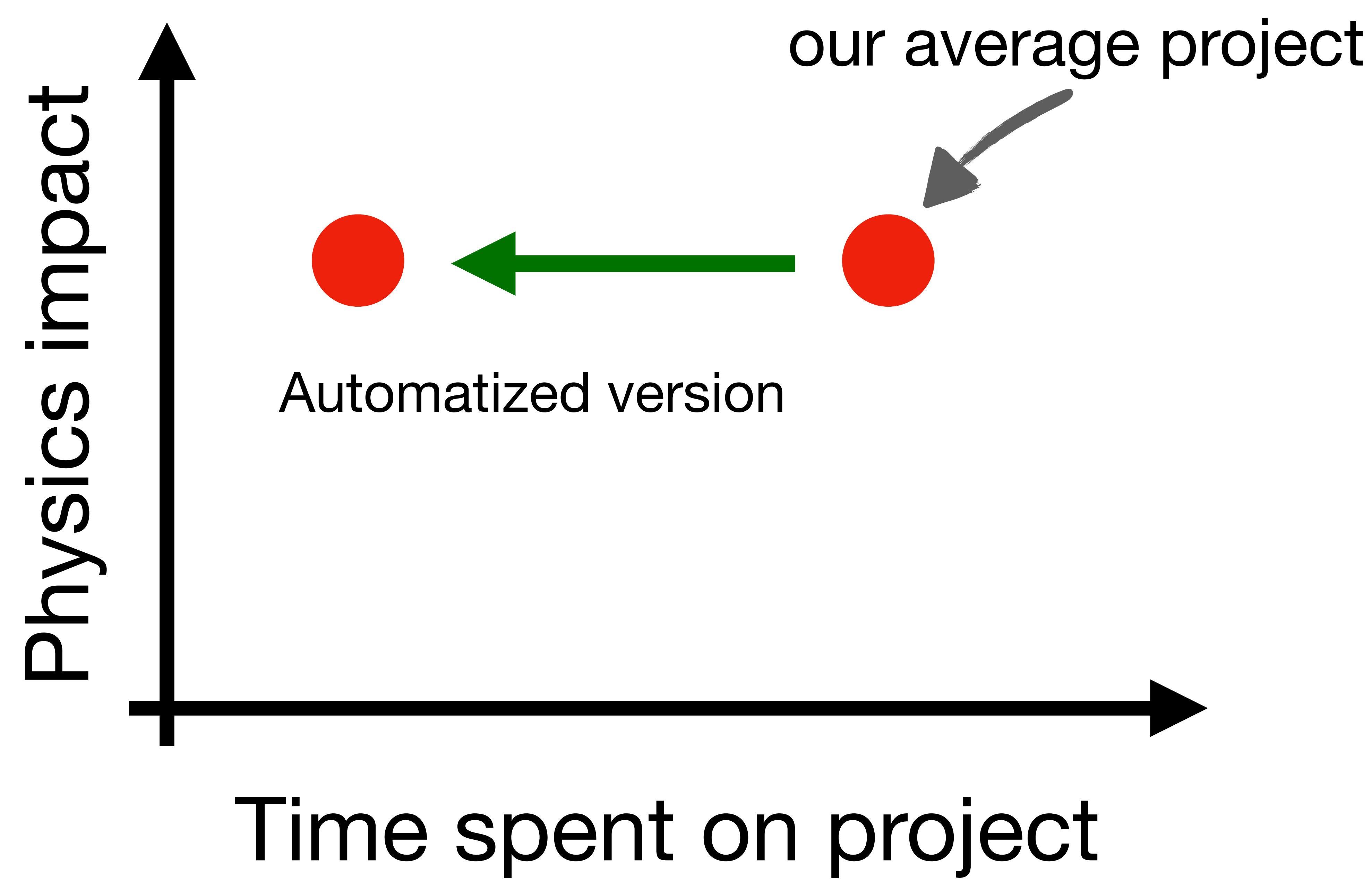
Work in progress

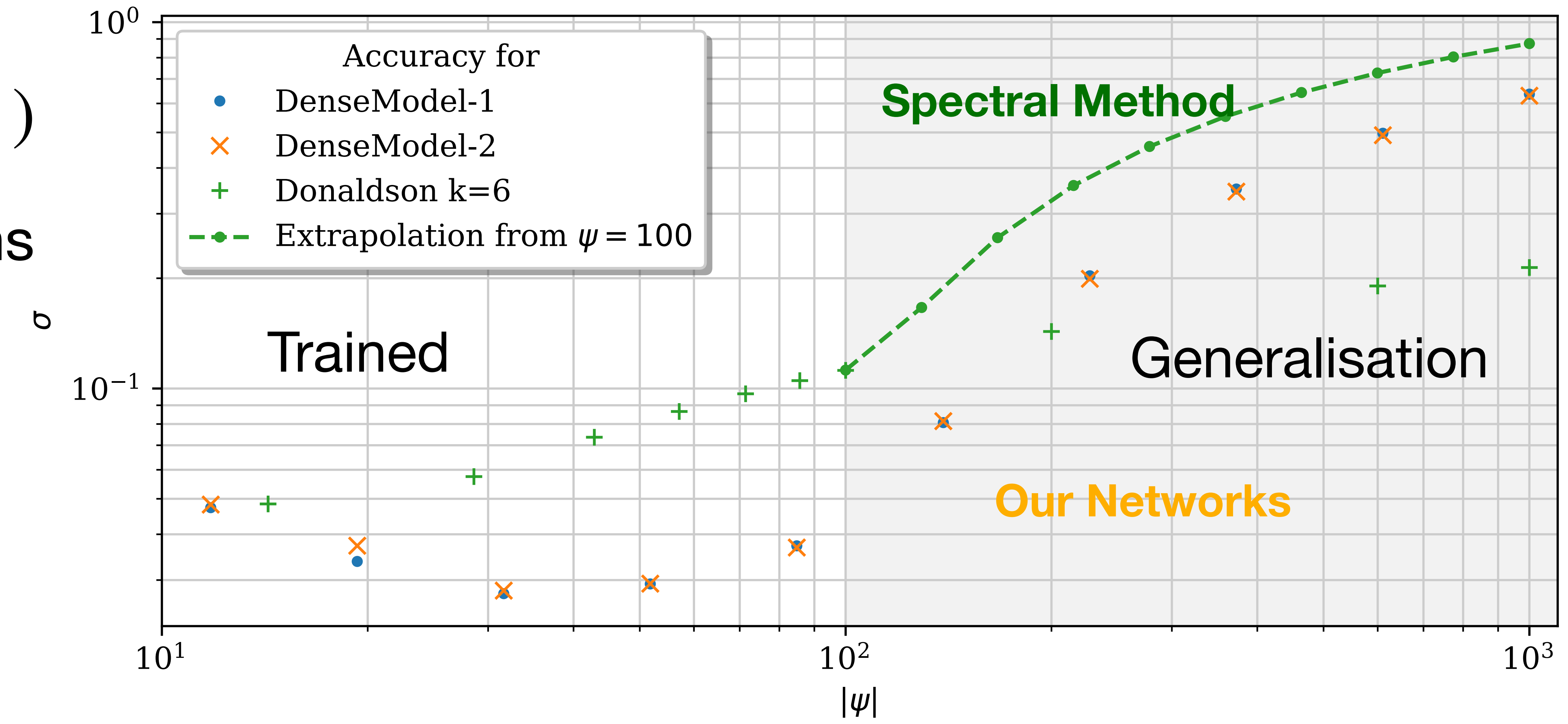
We can have systems that can do literature review across multiple papers…

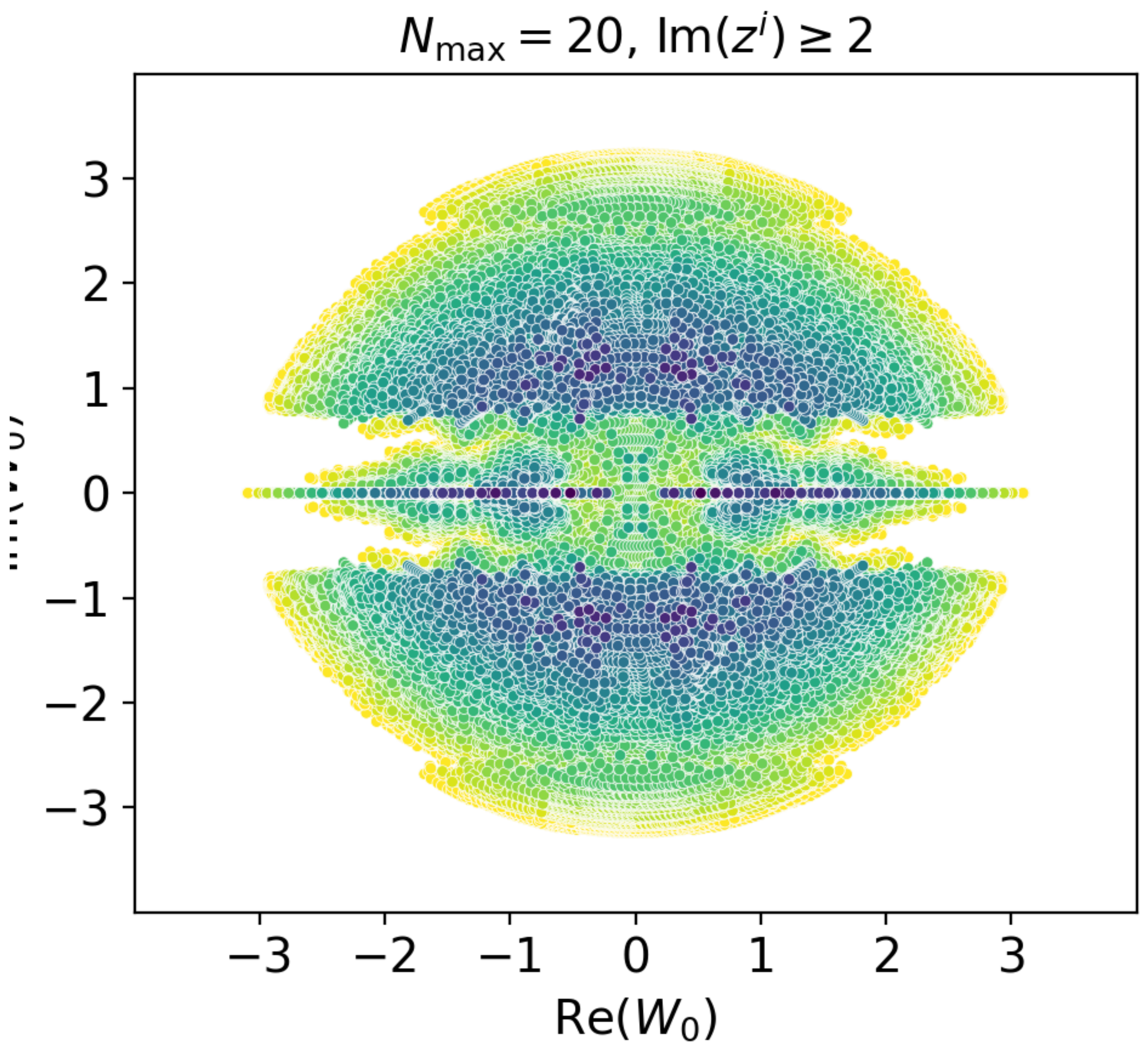
Conclusions

- Using customized ML models we can gain new insights in BSM physics:
- Finding solutions to differential equations using appropriate NNs
- Statistical models of string theory EFTs, e.g. $P(\mathbf{x}\,|\,|W_0|)$
- Deep observations of regions in the string landscape are possible
- Which discoveries lie ahead with agents using LLMs and tools?









Thank you!