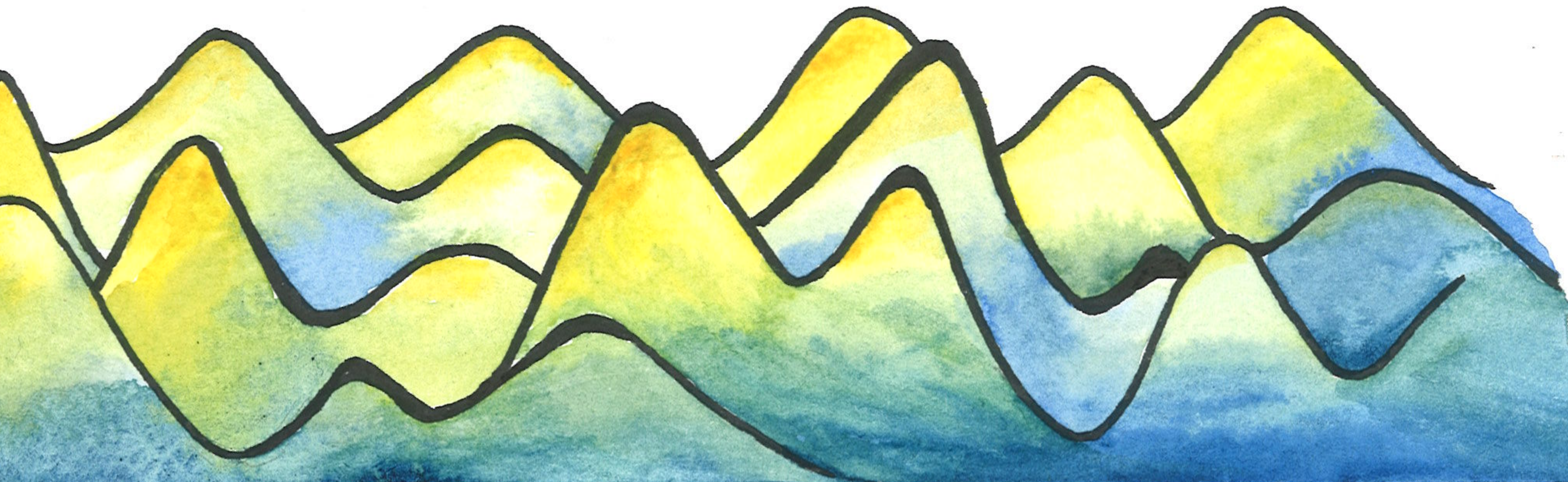
Potential for data science in string phenomenology

Mafalda Dias

with Alexander Westphal, Jonathan Frazer



The string landscape: dimensional reduction

String theory solutions with the potential to describe Einstein gravity & the standard model at low energies are theories in a 10D spacetime.

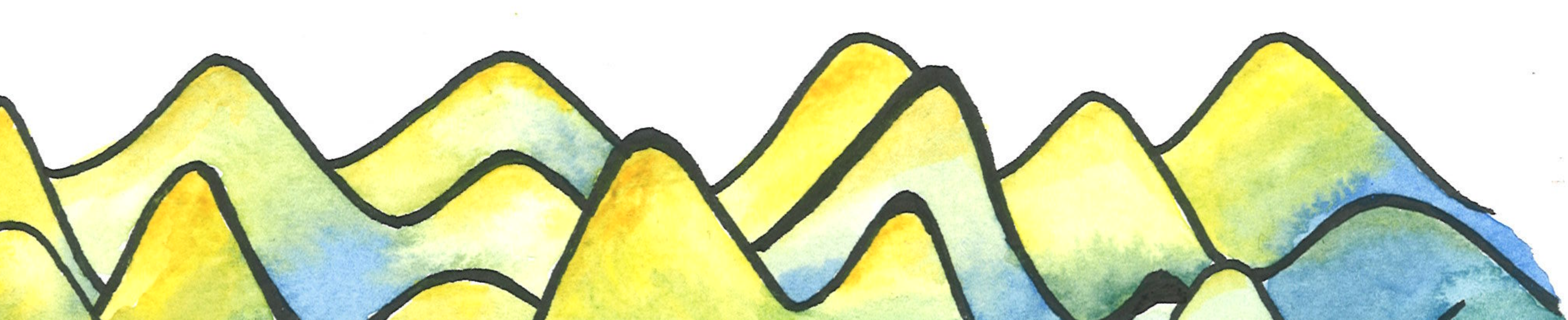
$$\mathcal{M}_{10} = \mathcal{M}_4 \times X_6$$

compact 6D manifold

$$G_{MN}dX^M dX^N = 2^{A(y)} g_{\mu\nu} dx^\mu dx^\nu + e^{-2A(y)} g_{mn} dX^m dX^n$$

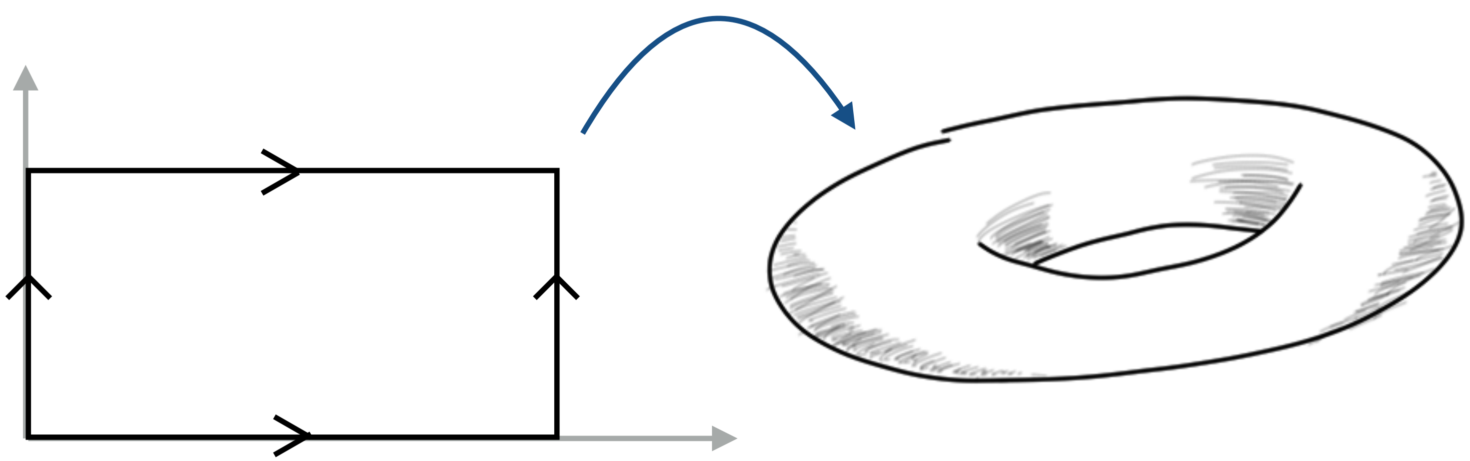
$$m, n = 1, \ldots, 6$$
$$\mu, \nu = 1, \ldots, 4$$

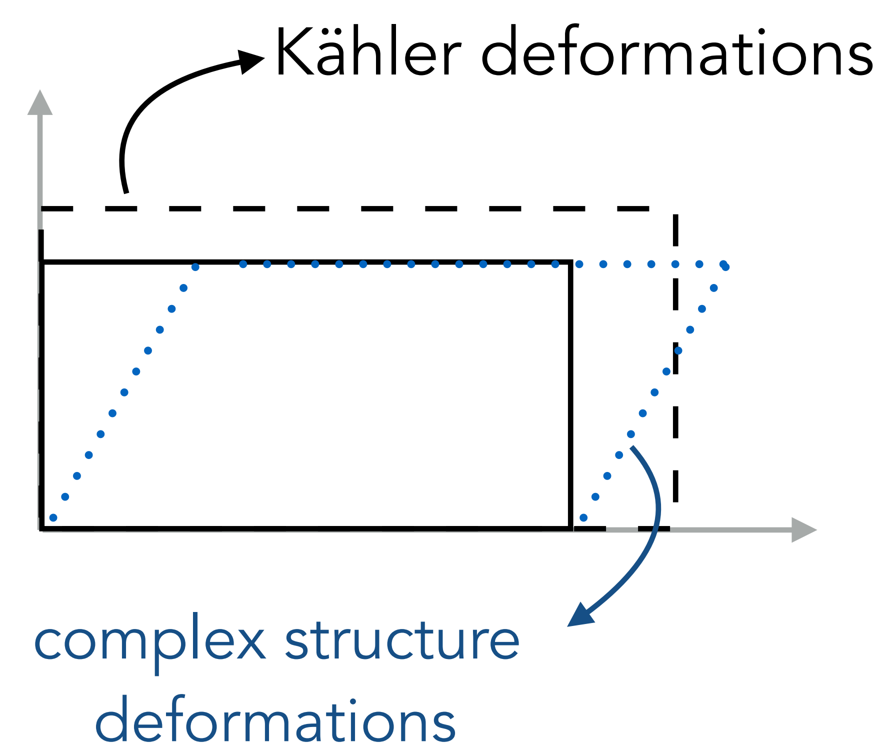
best understood non trivial Ricci flat manifolds are Calabi-Yau threefold

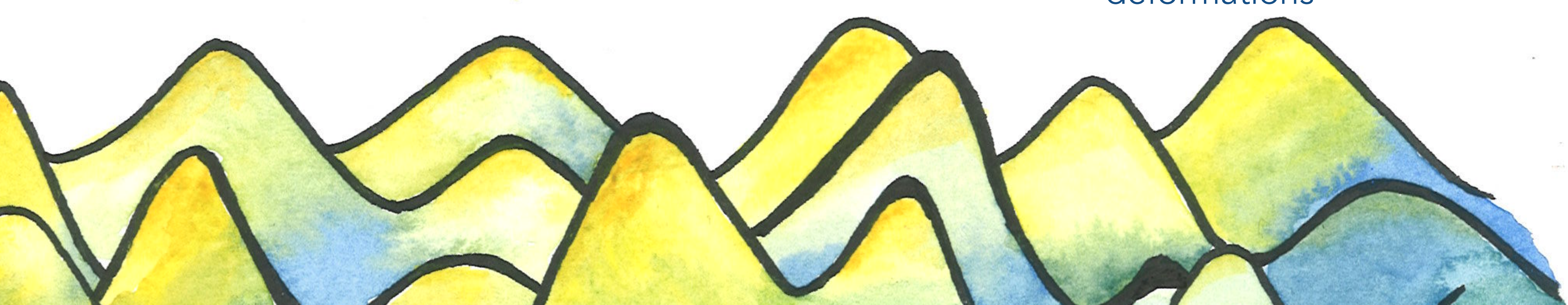


The string landscape: dimensional reduction

We need to study how the degrees of freedom of the 10D theory look like upon dimensional reduction in the 4D spacetime. In particular, deformations to g_{mn} that preserve the Calabi-Yau conditions give rise to hundreds or even thousands of scalar fields in the 4D theory with a geometric meaning — moduli.







The string landscape: pheno & challenges

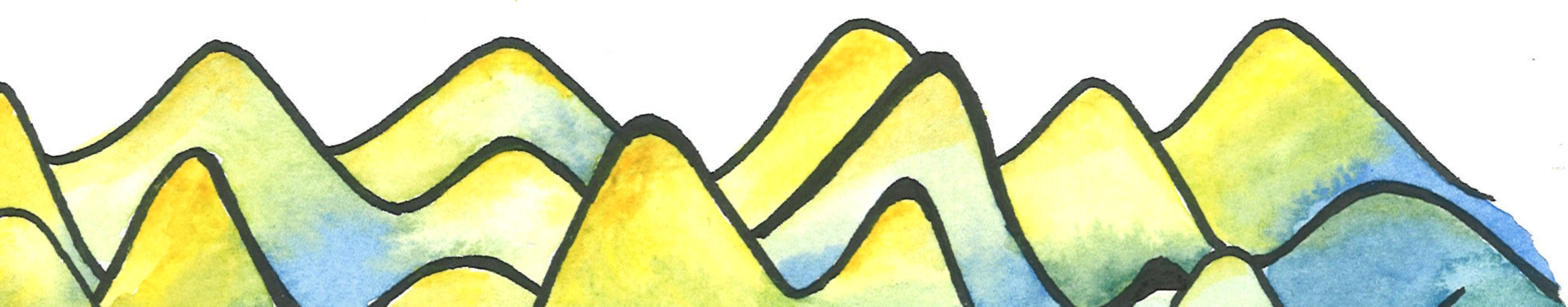
STRING LANDSCAPE

- All possible values for the hundreds/thousands of scalar fields in a given manifold
- All possible manifolds

OBJECTIVE

To build controlled models, be it for deSitter, inflation, dark matter, etc, where all fields have all corrections to their potential and kinetic sector under control.

Conjectures on the allowed values of some of the geometrical quantities.



The string landscape: pheno & challenges

Objective

To build controlled models, be it for deSitter, inflation, dark matter, etc, where all fields have all corrections to their potential and kinetic sector under control.

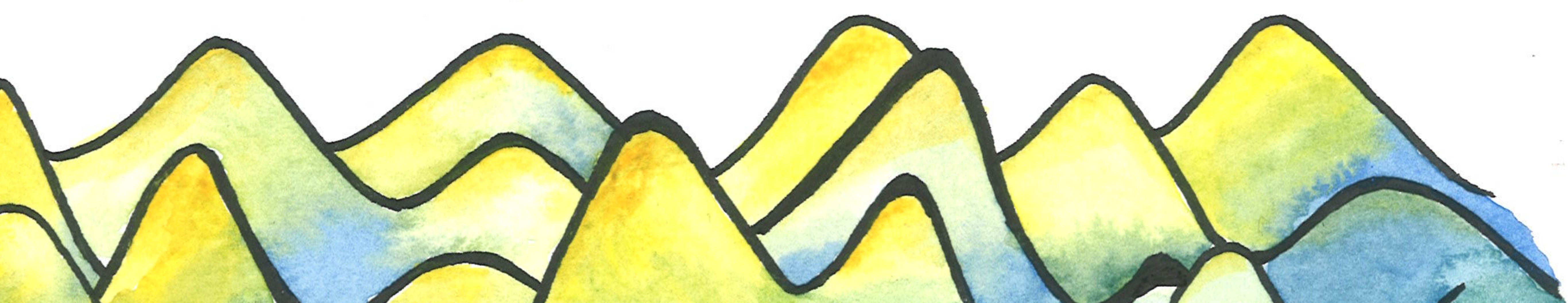
Conjectures on the allowed values of some of the geometrical quantities.

Challenges

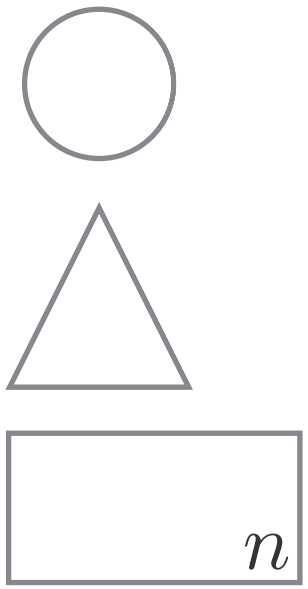
Extremely hard to work outside of very specific models — serious lamppost problem

Hard to make global predictions (not even mentioning the measure problem)

Hard to account for theoretical uncertainties even for the simplest models — no robust predictions



A network perspective for string model building



stochastic variable

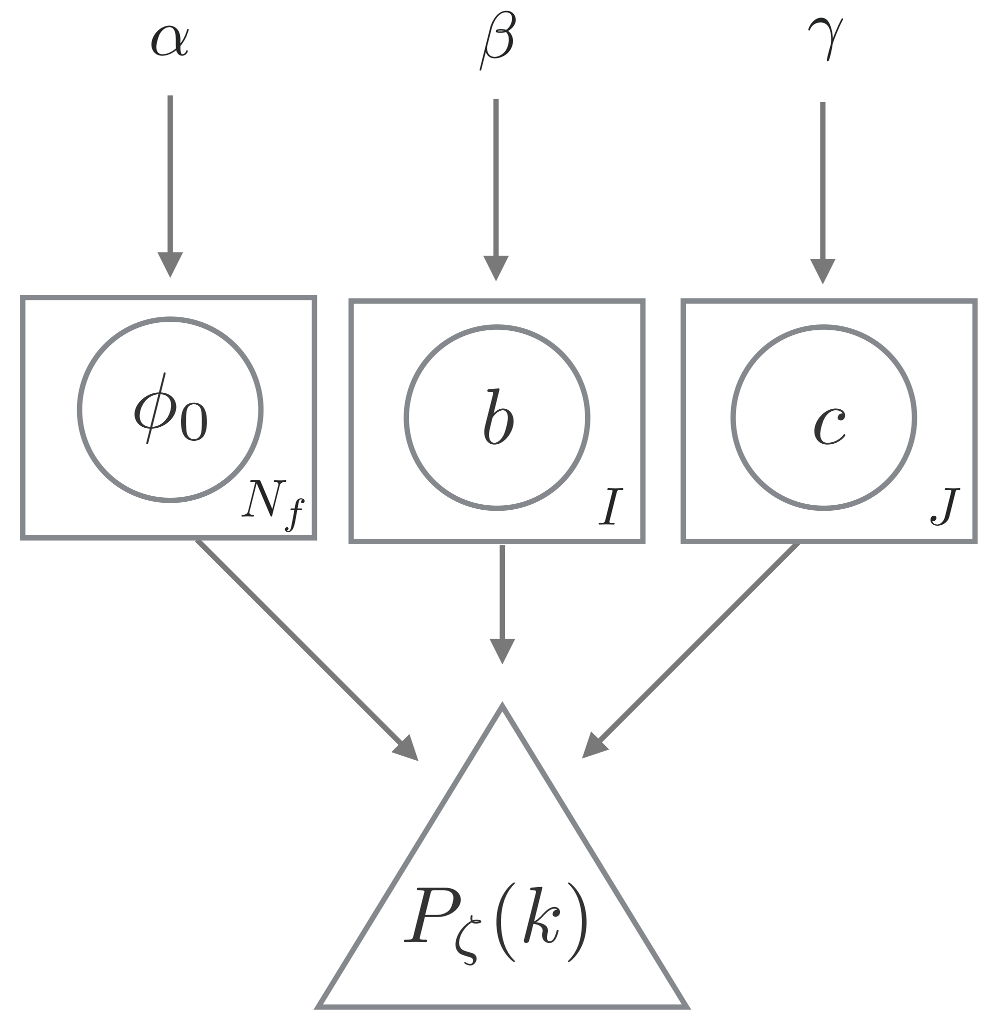
deterministic variable

Plate: repeat n times

$\alpha\ \beta$ hyperparameters

ϕ_0 initial conditions

$b\ c$ parameters appearing in $\mathcal{L}$



$$p(P_\zeta, \phi_0, b, c) = p(P_\zeta | \phi_0, b, c) p(\phi_0) p(b) p(c)$$

More generally

$$p(X_1, \ldots, X_n) = \prod_{i=1}^{n} p(X_i | X_{\mathrm{pa(i)}})$$

parent nodes

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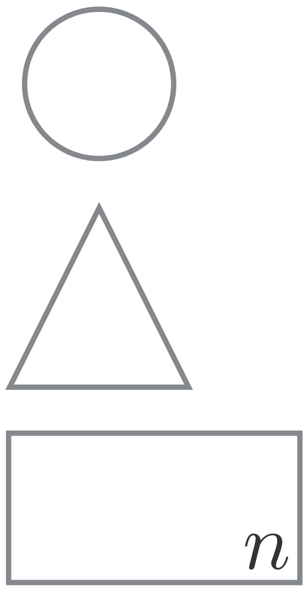

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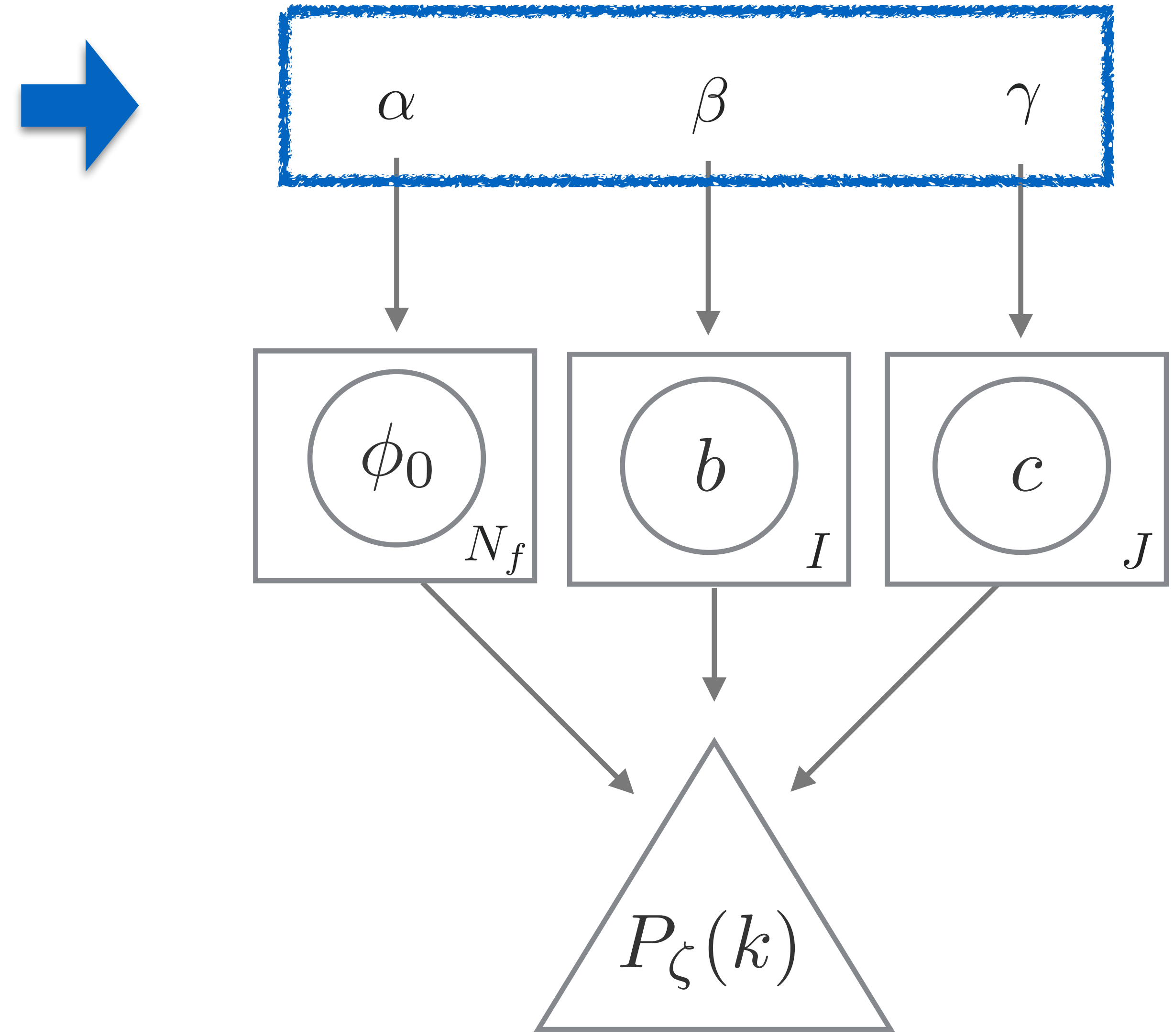

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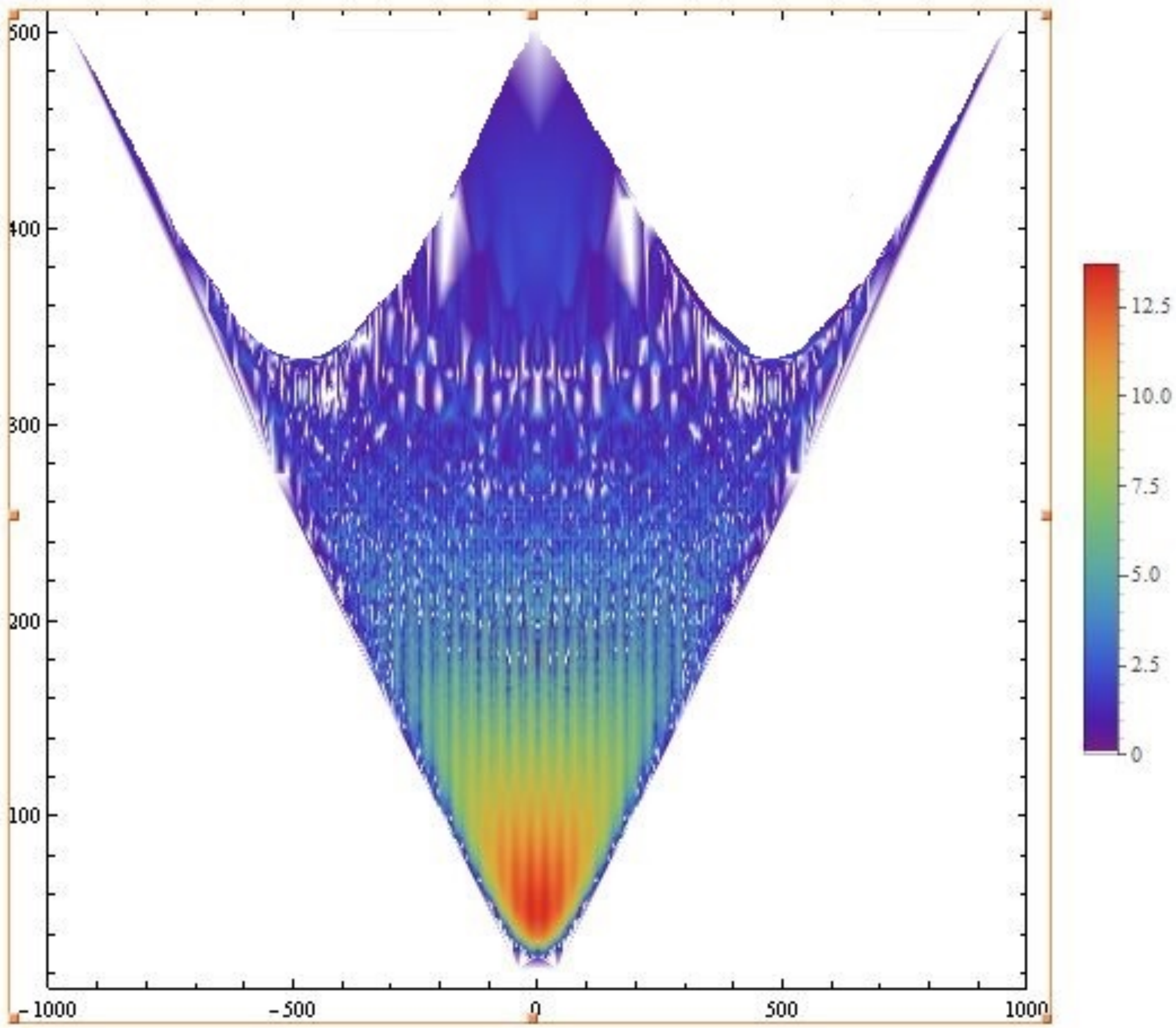
A data set of Calabi-Yau threefolds — Kreuzer-Skarke database and others

Number of Kähler and complex structure moduli



Seems perfect training ground for some pattern recognition/ classification problems!

Exploring Calabi-Yau data sets with machine learning

CLASSIFICATION / CONJECTURE IDENTIFICATION

- Compute geometrical quantities algorithmically, which map out to effective 4D potentials for scalar moduli. These computations are hard for most CYs but known for some which can be used as training data.
- Identification of new patterns that can be analytically investigated as a way of building new conjectures

High Energy Physics – Theory

Machine Learning CICY Threefolds

Kieran Bull, Yang-Hui He, Vishnu Jejjala, Challenger Mishra

(Submitted on 8 Jun 2018)

The latest techniques from Neural Networks and Support Vector Machines (SV

High Energy Physics – Theory

Machine Learning in the String Landscape

Jonathan Carifio, James Halverson, Dmitri Krioukov, Brent D. Nelson

(Submitted on 3 Jul 2017)

We utilize mach
machine learni
arising from re
conjecture for
for when E_6 ari
appearance of

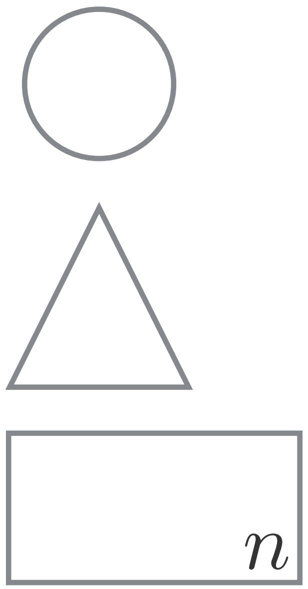
High Energy Physics – Theory

Learning non-Higgsable gauge groups in 4D F-theory

Yi-Nan Wang, Zhibai Zhang

(Submitted on 19 Apr 2018 (v1), last revised 1 May 2018 (this version, v3))

A network perspective for string model building



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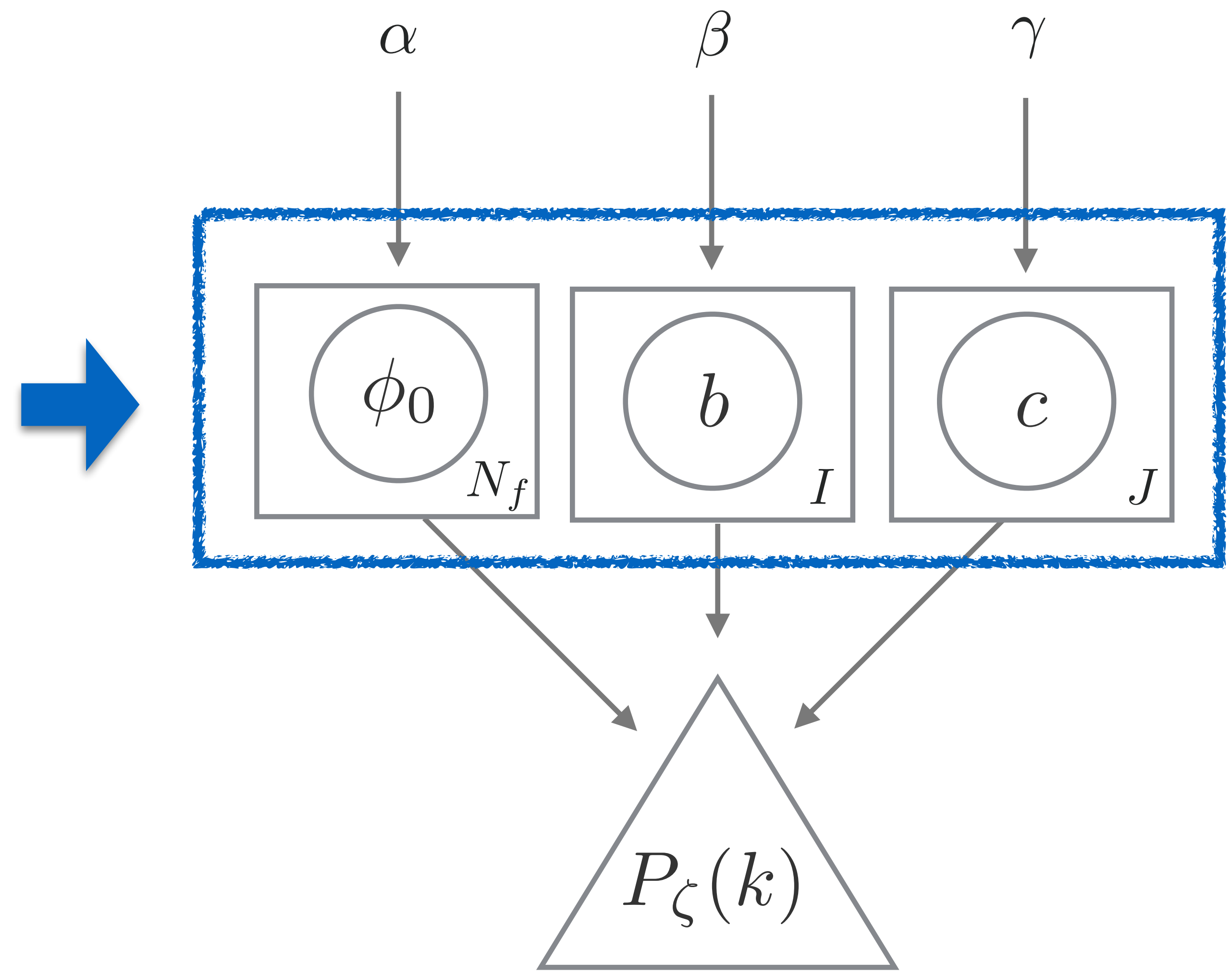

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parent nodes

Exploring Calabi-Yau data sets with machine learning

GENERATION/ SEARCH FOR WORKABLE EXAMPLES

- Discover new workable lamppost examples. Understand and find the specific anomalies that make these workable examples.

Data creation with Generative Adversarial Networks

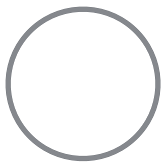
FABIAN RUEHLE (UNIVERSITY OF OXFORD)

string_data 2018

Anomaly Detection: Mapping the IIB Lamppost with Reinforcement Learning

Jim Halverson
Northeastern University

Making robust predictions by exploring universality



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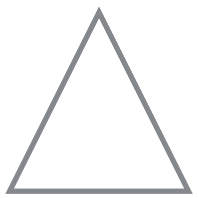

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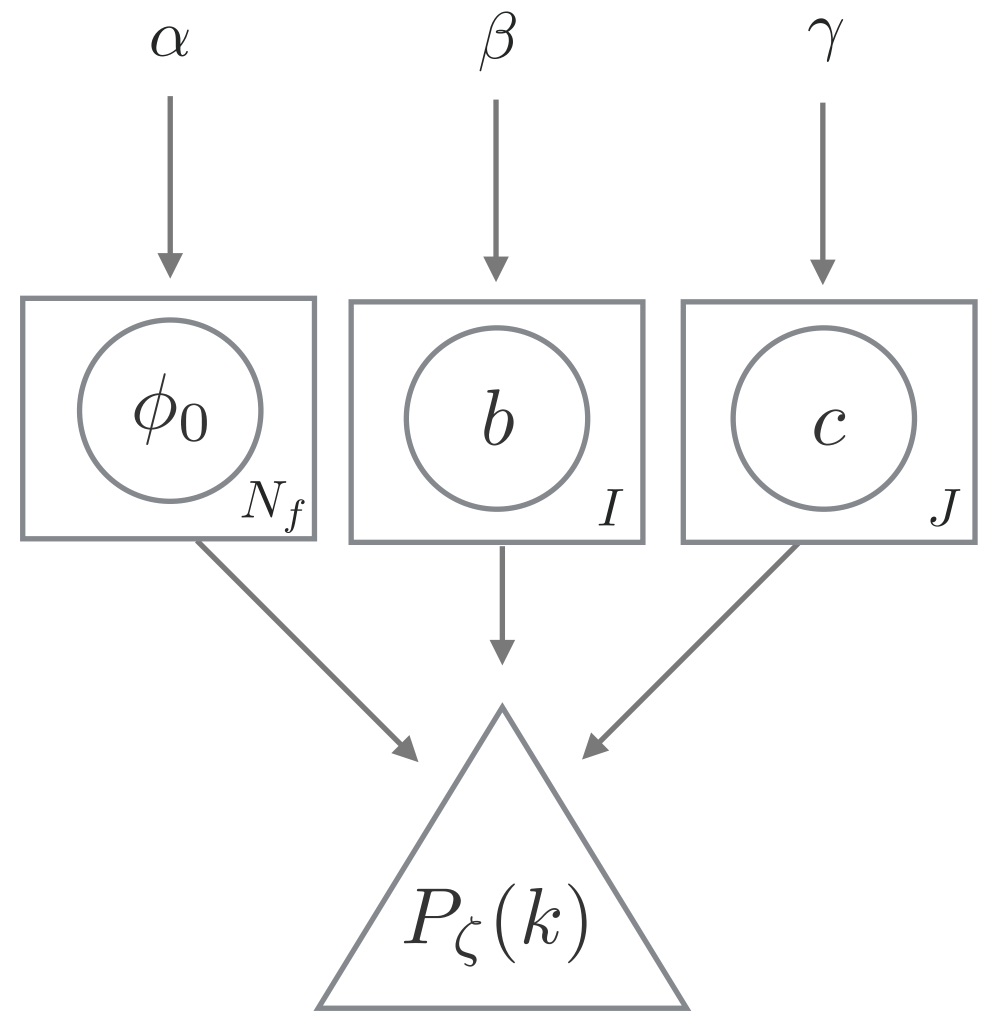
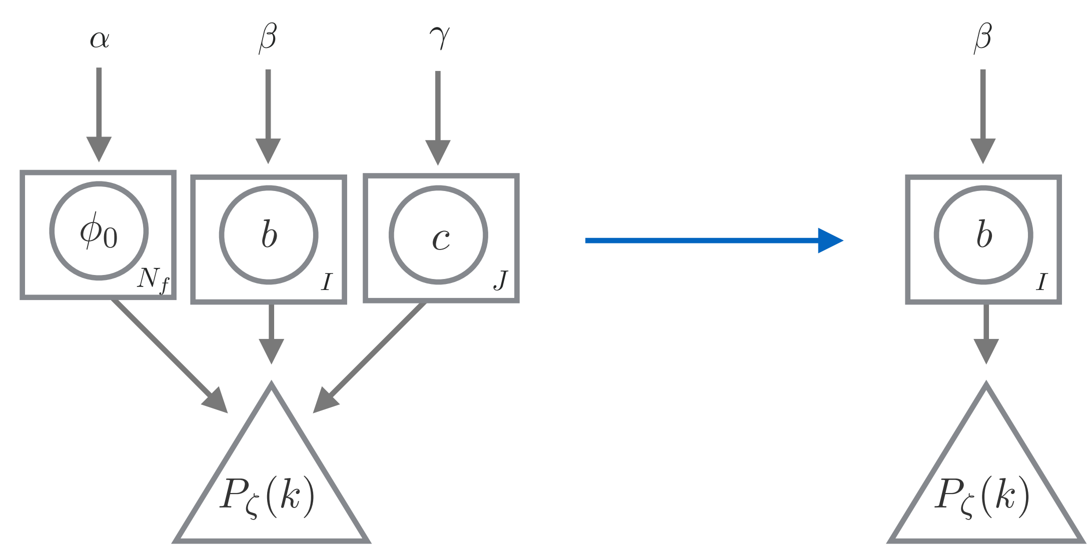


The task of making robust predictions is greatly simplified if we can show that some nodes can be safely "integrated out"



Towards robust predictions despite incomplete knowledge

LARGE N UNIVERSALITY

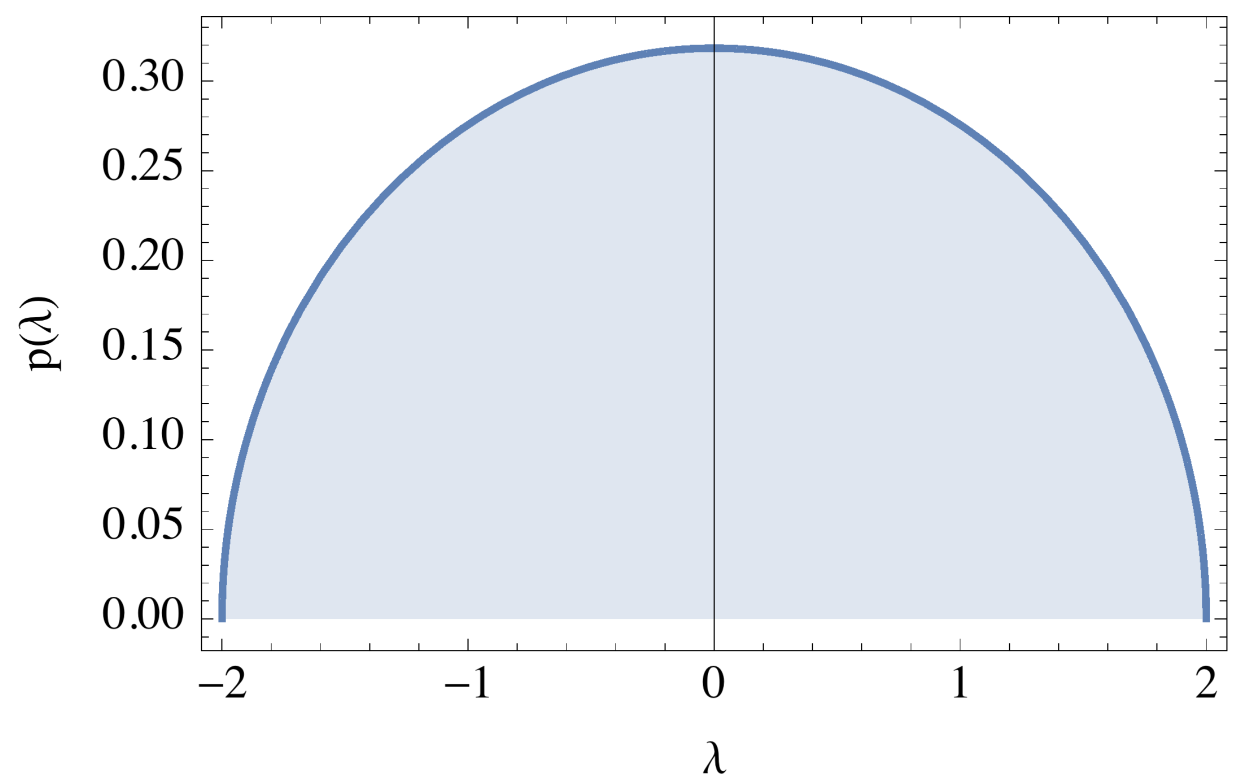
Emergent simplicity is ubiquitous in complex systems and there are many powerful tools to take advantage of it.

Example: Random Matrix Theory

Random matrices first introduced to physics by Eugene Wigner. He modelled the nuclei of heavy atoms.

Postulated that the spacings between the lines in the spectrum of a heavy atom nucleus should resemble the spacings between the eigenvalues of a random matrix, and should depend only on the symmetry class of the underlying evolution

Gaussian orthogonal ensemble

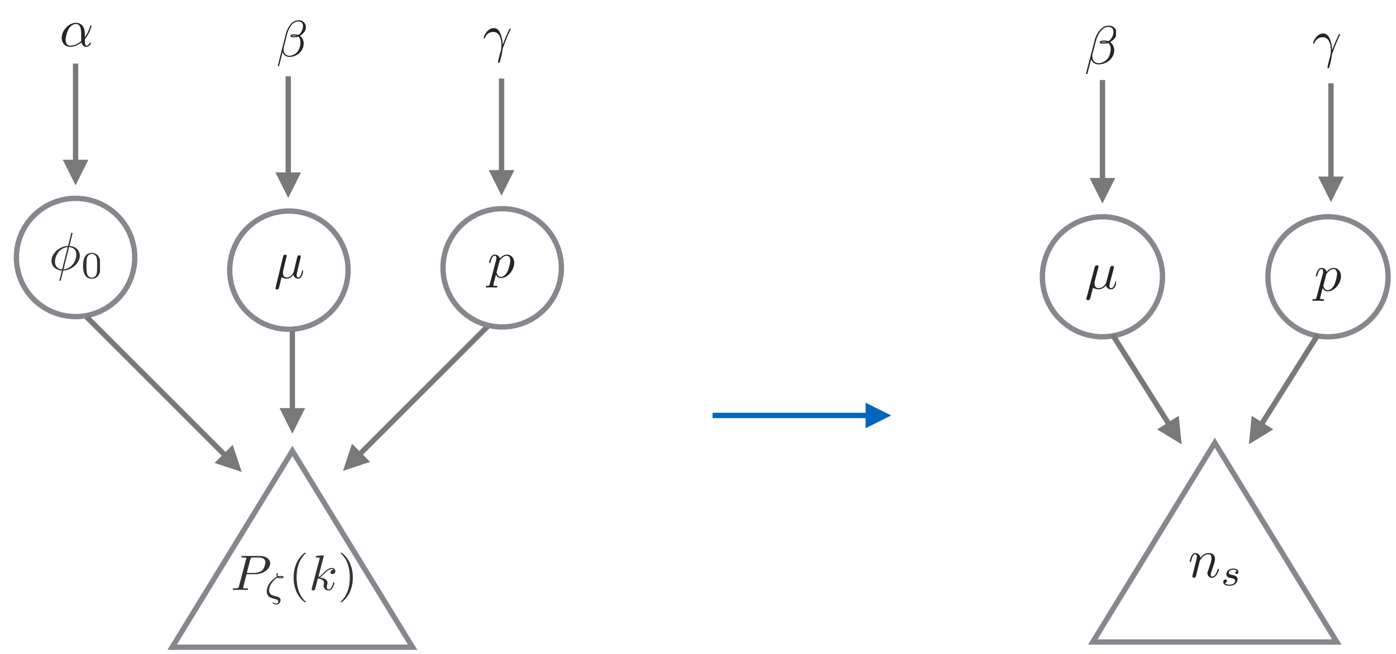


$$p(M)\mathrm{d}M = p(M')\mathrm{d}M'$$
$$M' = O^T M O$$

Mehta: Random Matrices

MINIMAL WORKING EXAMPLE: AXION MONODROMY

$$\mathcal{L} = -\frac{1}{2}(\partial\phi)^2 - \Lambda^4\left[\left(1 + \left(\frac{\phi}{\mu}\right)^2\right)^{\frac{p}{2}} - 1\right]$$



See Baumann and McAllister “Inflation and String Theory” for a review

MINIMAL WORKING EXAMPLE: AXION MONODROMY

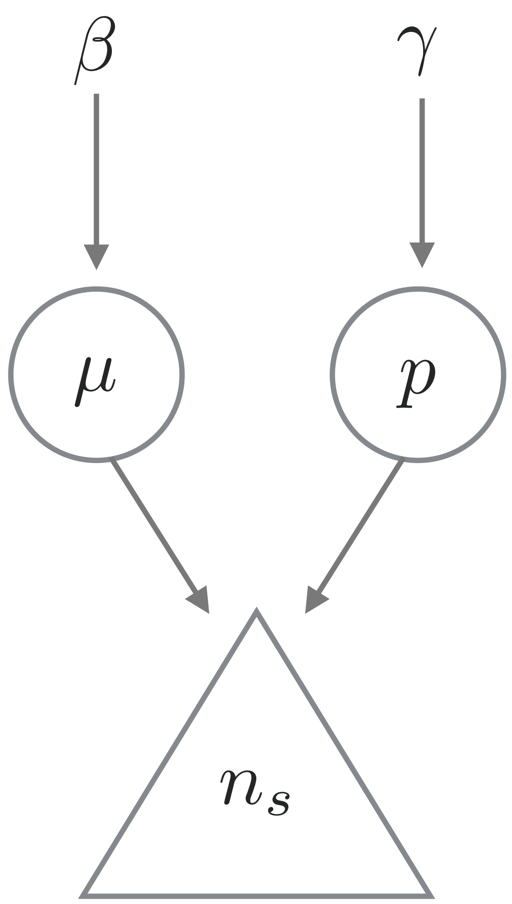
Steps:

1. Identify relevant scales (class of models)
2. Learn the mapping from parameters to observables
3. Study how predictions change according to prior choice

Model dependent but often one can obtain order of magnitude estimates for model parameters.

μ $\quad \mu \in [0.1, 1]$

p $\quad p \in [0.1, 2]$



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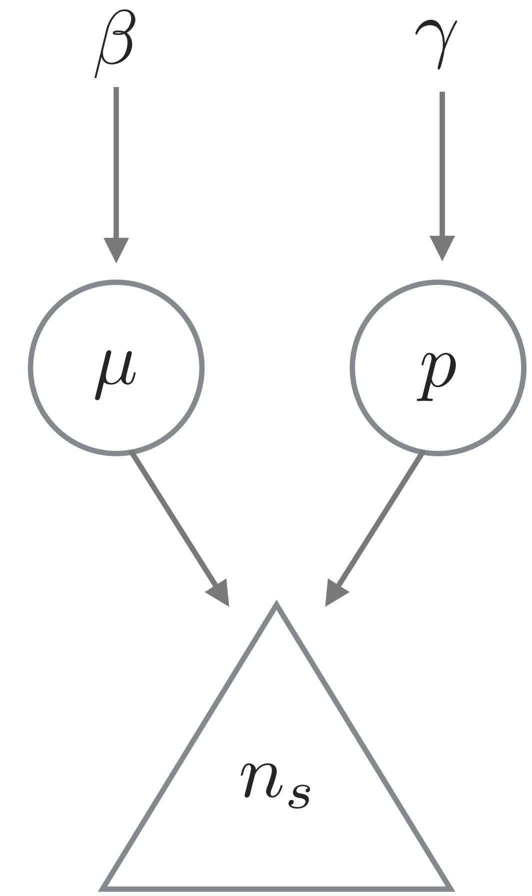
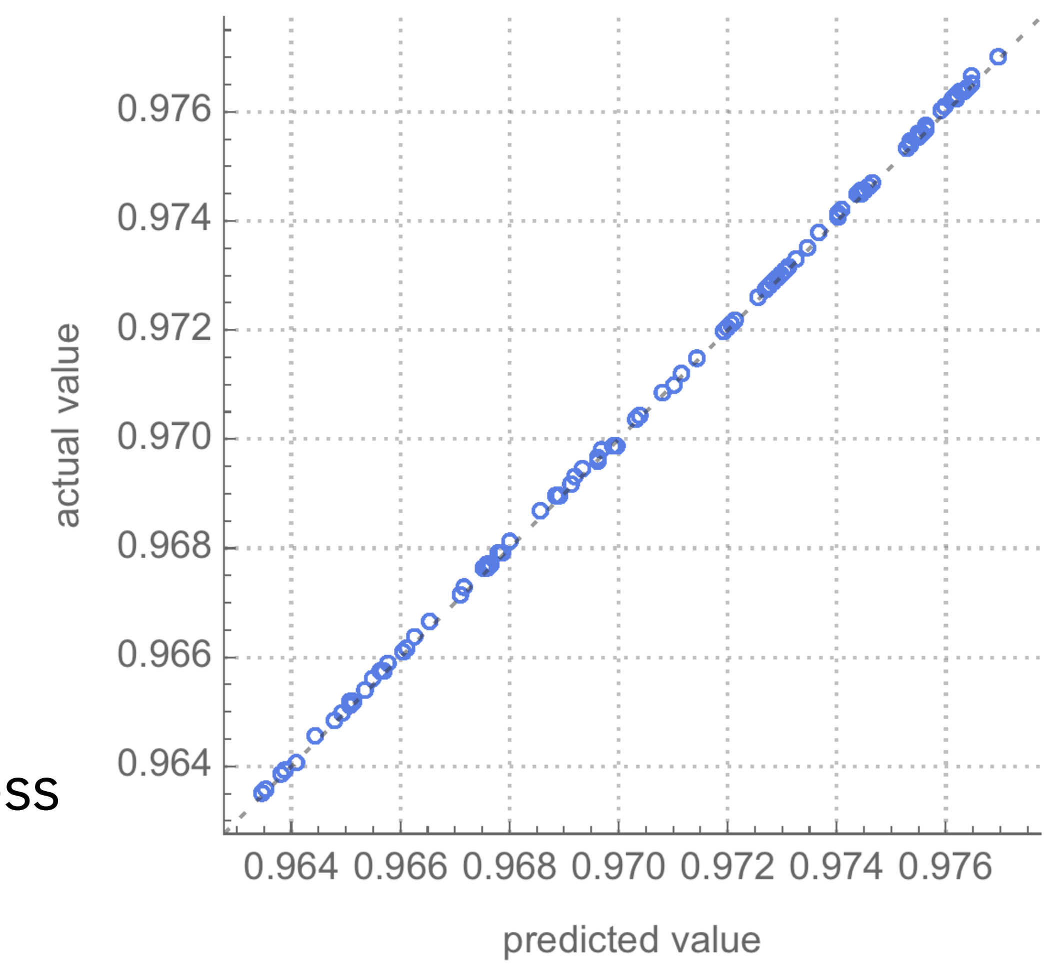


We can use publicly available code to compute observables for large sample of model parameters BUT it is extremely expensive!
Use machine learning methods to learn this mapping.

$$\mu \sim \mathcal{U}(0.1, 1) \qquad p \sim \mathcal{U}(0.1, 2)$$

$$n_s(\mu, p)$$

Gaussian Process



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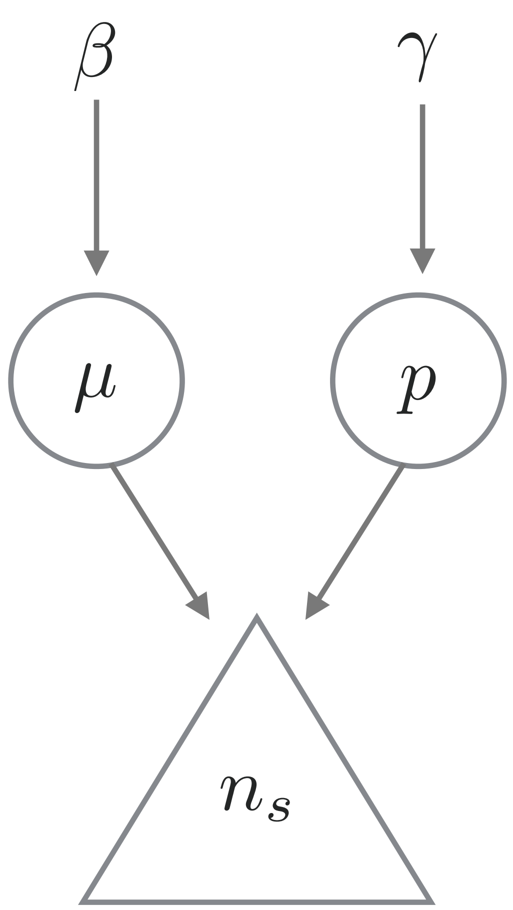

One approach is to use information theory.

Consider a range of priors and compute the mutual information (but we have been also using the KL divergence)

$I(n_s;\mu) \quad I(n_s;p)$

$$I(n_s;\mu) = \sum_{n_s}\sum_{\mu} p(n_s,\mu)\log\left[\frac{p(n_s,\mu)}{p(n_s)p(\mu)}\right]$$

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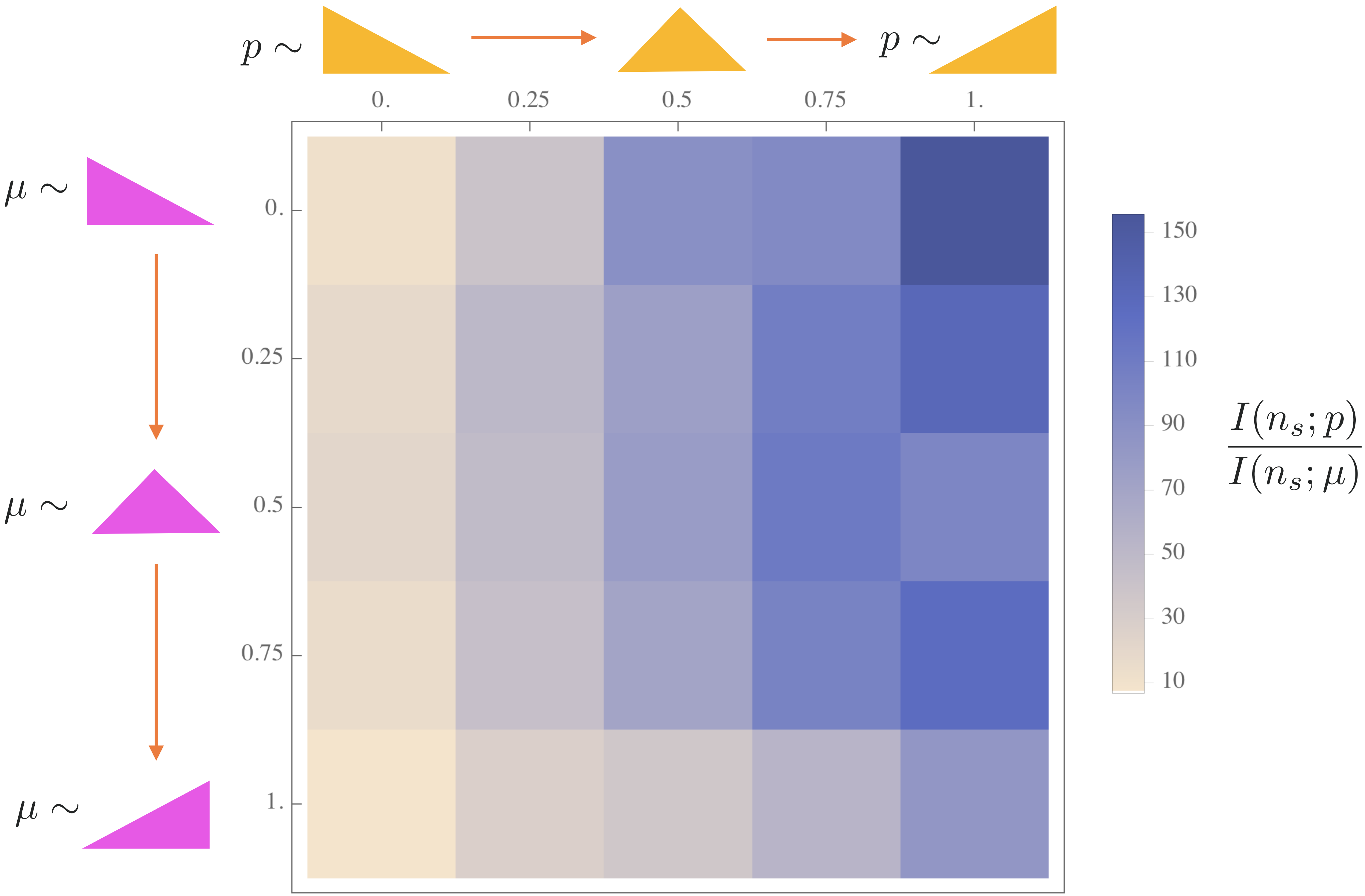
MINIMAL WORKING EXAMPLE: AXION MONODROMY



The spectral index contains significantly more information about p than μ

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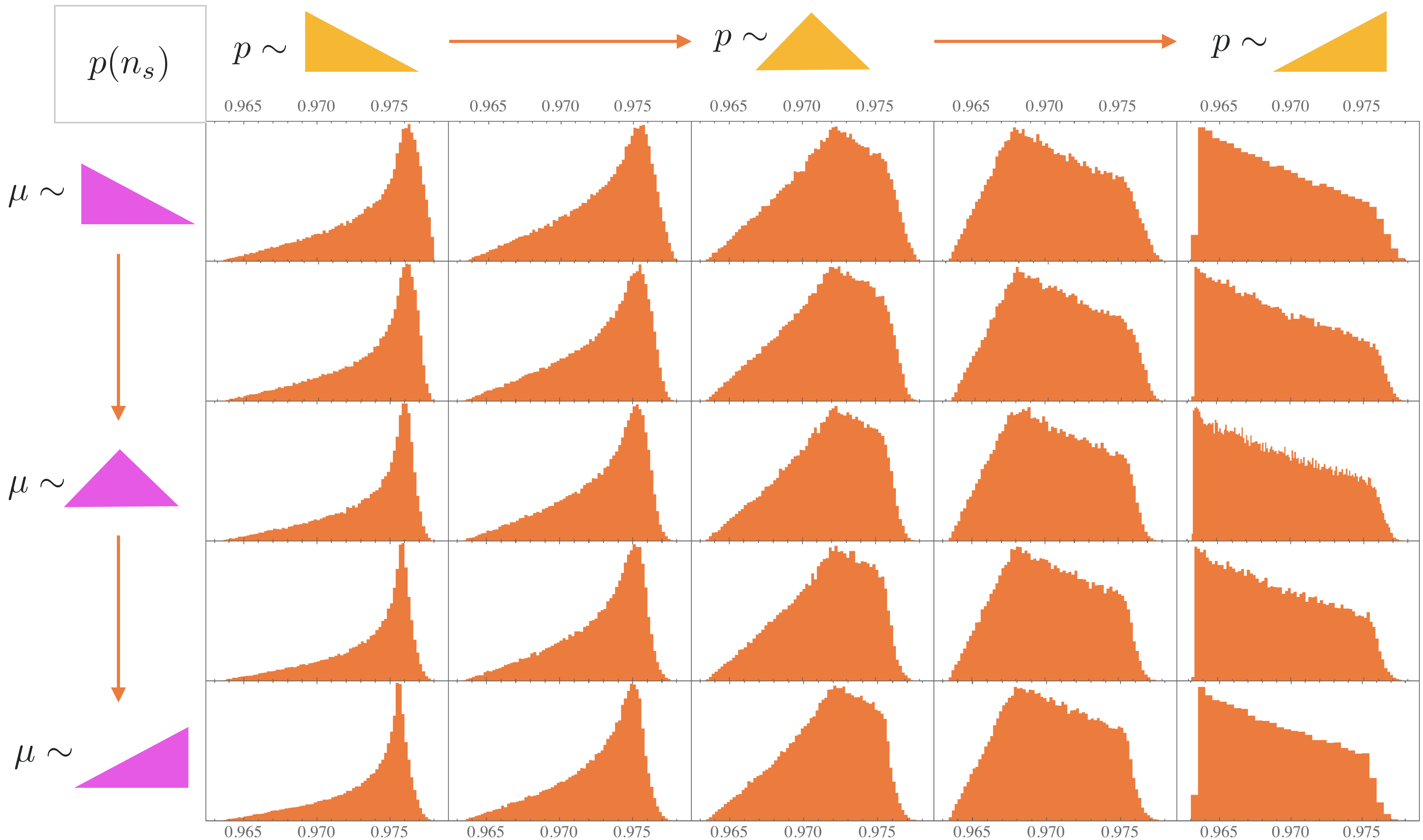

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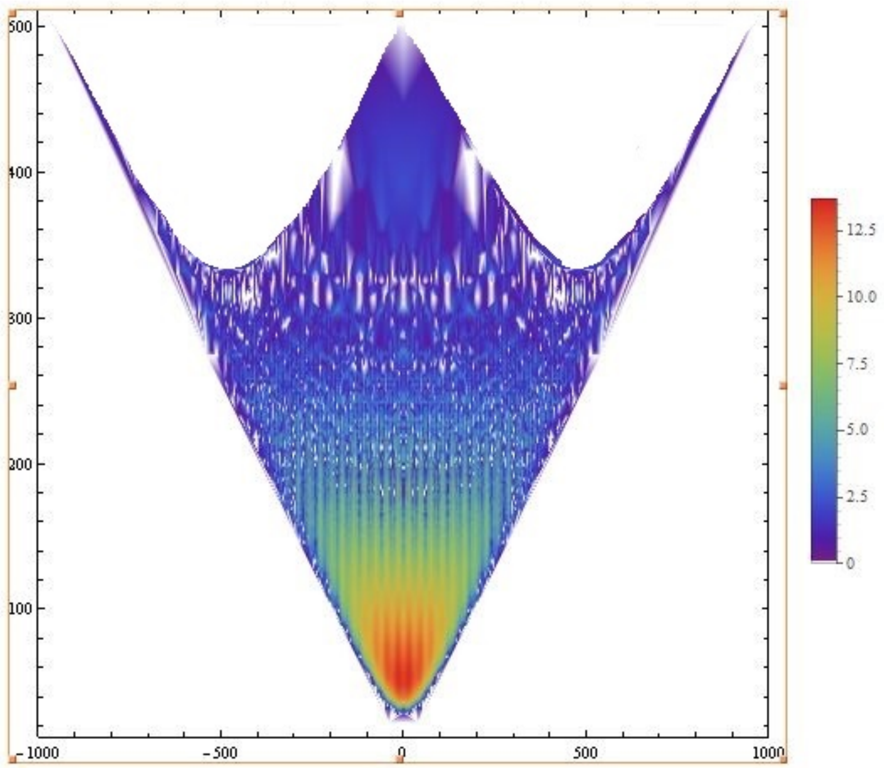
Take away messages



String phenomenology faces many challenges which can be handled/ alleviated from the point of view of data science — the string landscape

Classification of the known geometrical datasets / identify patterns

Identify and explore workable examples

Explore universality of “information bottle-neck” as a way to make robust predictions