Exploration of string theory landscape

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String Landscape

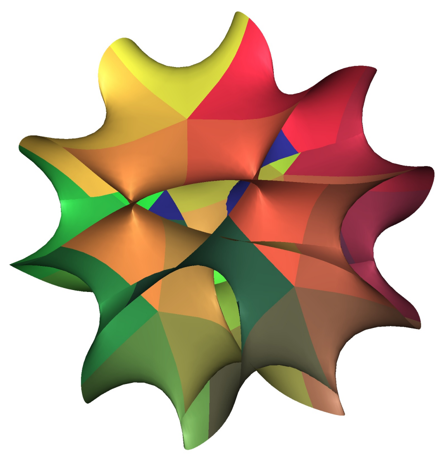
String theory is unique,
but admit many solutions.

Compatification

1+9 dimension — string theory

6d space X,

flux parameter $\vec{m} \in \mathbb{Z}^{\bullet}$.



Compactification

1+3 dimension — field theory

Depending on choice of X and $\vec{m}$, a lot of vacua are obtained though the number is finite [YH, Montero, Vafa, Valenzuela '21].

Choice of flux

There are cycles, where we can insert ``magnetic flux”.

Freedom to choose flux

Quantization number.

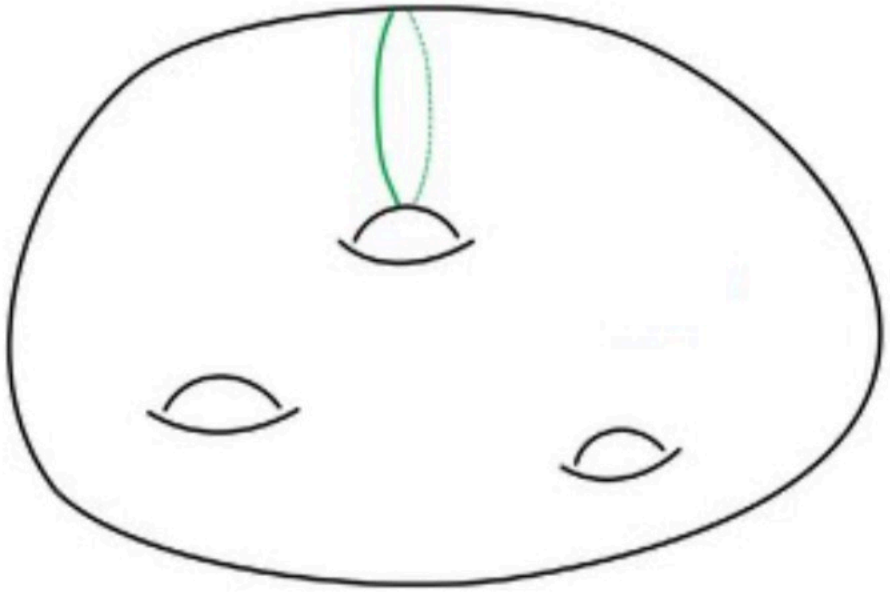
E.g. 10 choice of flux,

and #(cycle)=100,

then we have

$\mathcal{O}(10^{100})$ possibilities

[Douglas ‘03].



(Choice of CYs) $\times$ (Choice of fluxes) $=$ (Choice of models) .

Phenomenologically relevant vacua are extremely rare.

Most vacua have negative cosmological constant, or runaway solution.

So far, we do not find any solution close to our universe.

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Computational complexity of string vacua search was discussed in 2006.

Computational complexity of the landscape I

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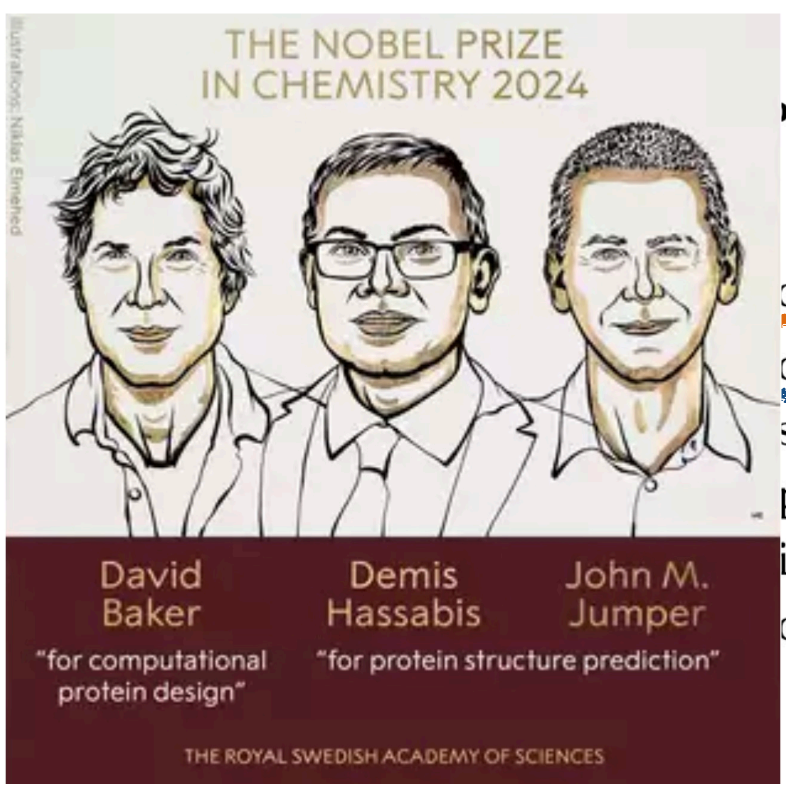

uglas[1,3]

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Setup

6d space:

‶degree 18 hypersurface in $\mathbb{CP}^4_{1,1,1,6,9}$ with discrete symmetry $\mathbb{Z}_6 \times \mathbb{Z}_{18}$“

From 4d EFT point of view,

we just have potential V for 3 complex scalar fields, (τ, Z_1, Z_2),

and flux parameters $(m_1, m_2, m_3, n_1, n_2, n_3)$.

Potential V

$$V = V\left(\tau, Z_1, Z_2; m_1, m_2, m_3, n_1, n_2, n_3\right).$$

- Solution of string theory is (local) minimum of V.

- V is positive semidefinite.

- SUSY solution: $V = 0$, SUSY solution: $V > 0$.

- Many solution depending on integers $m_{1,2,3}$, $n_{1,2,3}$,

under condition $m_1^2 + m_2^2 + m_3^2 + n_1^2 + n_2^2 + n_3^2 \leq 276$.

Our work [YH, Uematsu, Yamazaki, to appear]:

1: Scan of $\mathcal{O}(10^8)$ vacua.

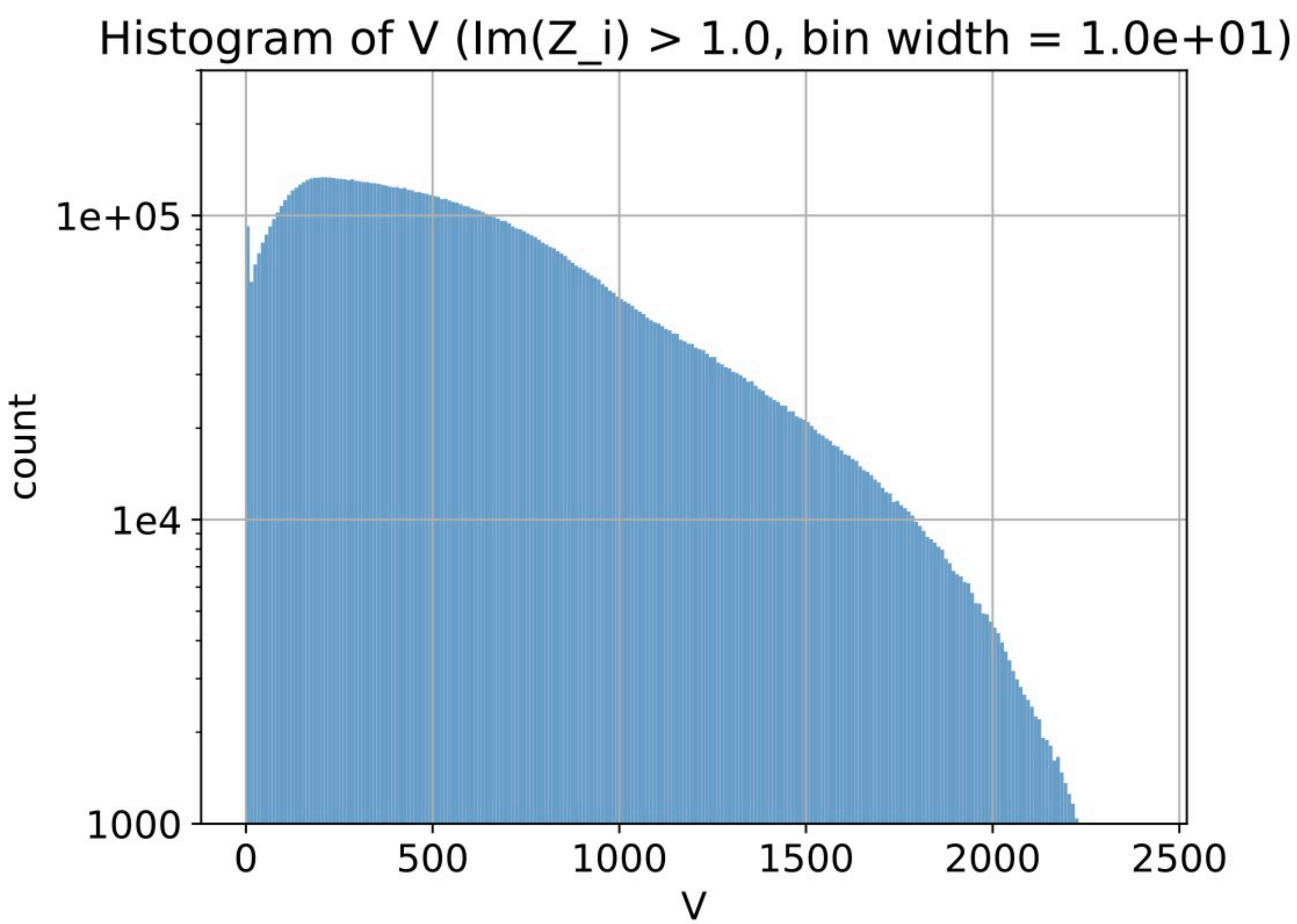
2: Test of effectiveness of machine-learning technique for regression tasks.

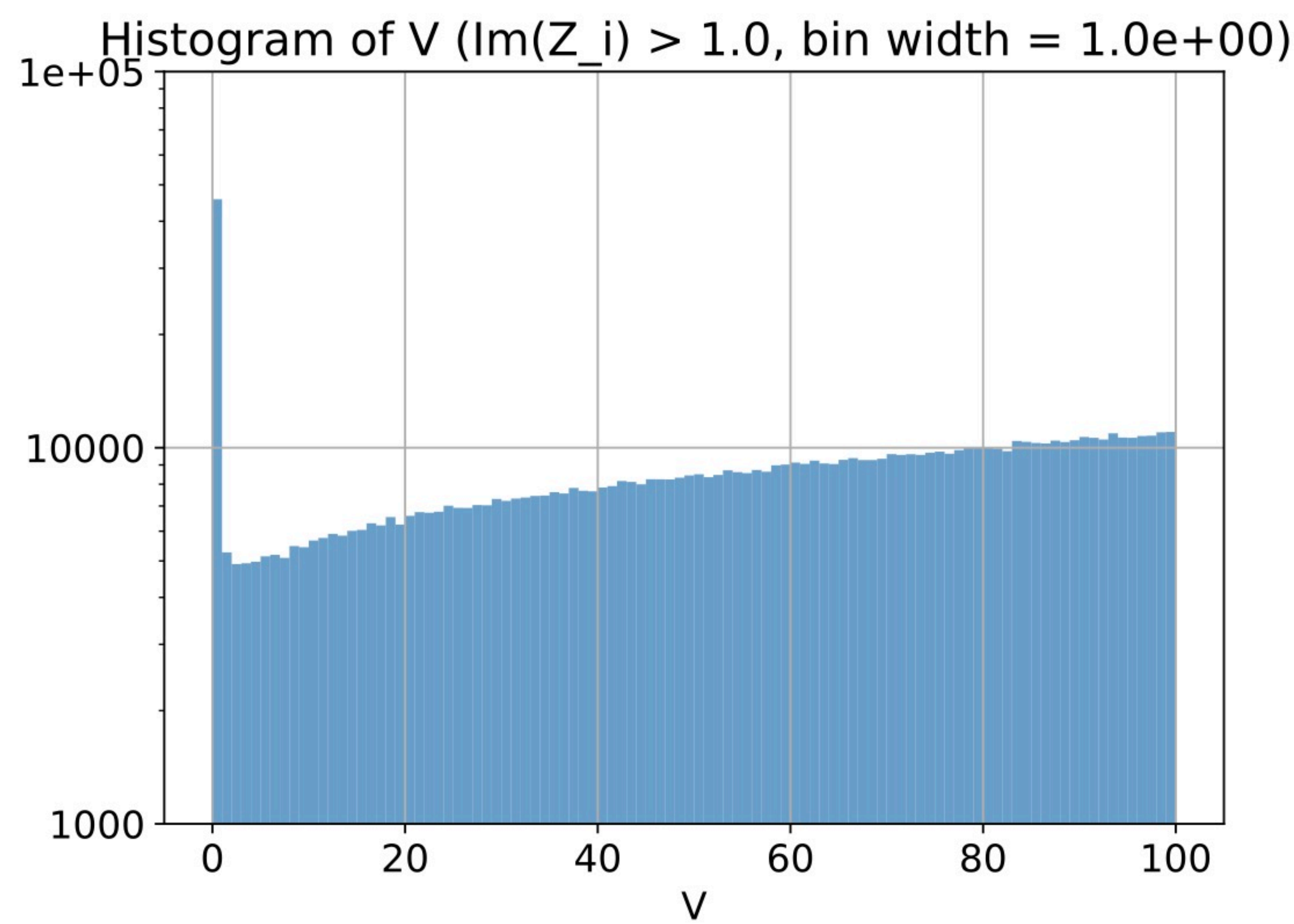
1: Scan of $\mathcal{O}(10^8)$ vacua.

1: We perform minimization by gradient descent method.

	#(non-SUSY vacua)	#(SUSY vacua)
[Martinez-Pedrera+ ’12]		500,865(including unphysical ones)
[Dubey+ ’23]		$\mathcal{O}(30,000)$
[Krippendorf+ '23]	33,619	
[Chauhan ’25]		179,445,394
This work	12,636,619	32,273

Potential Value



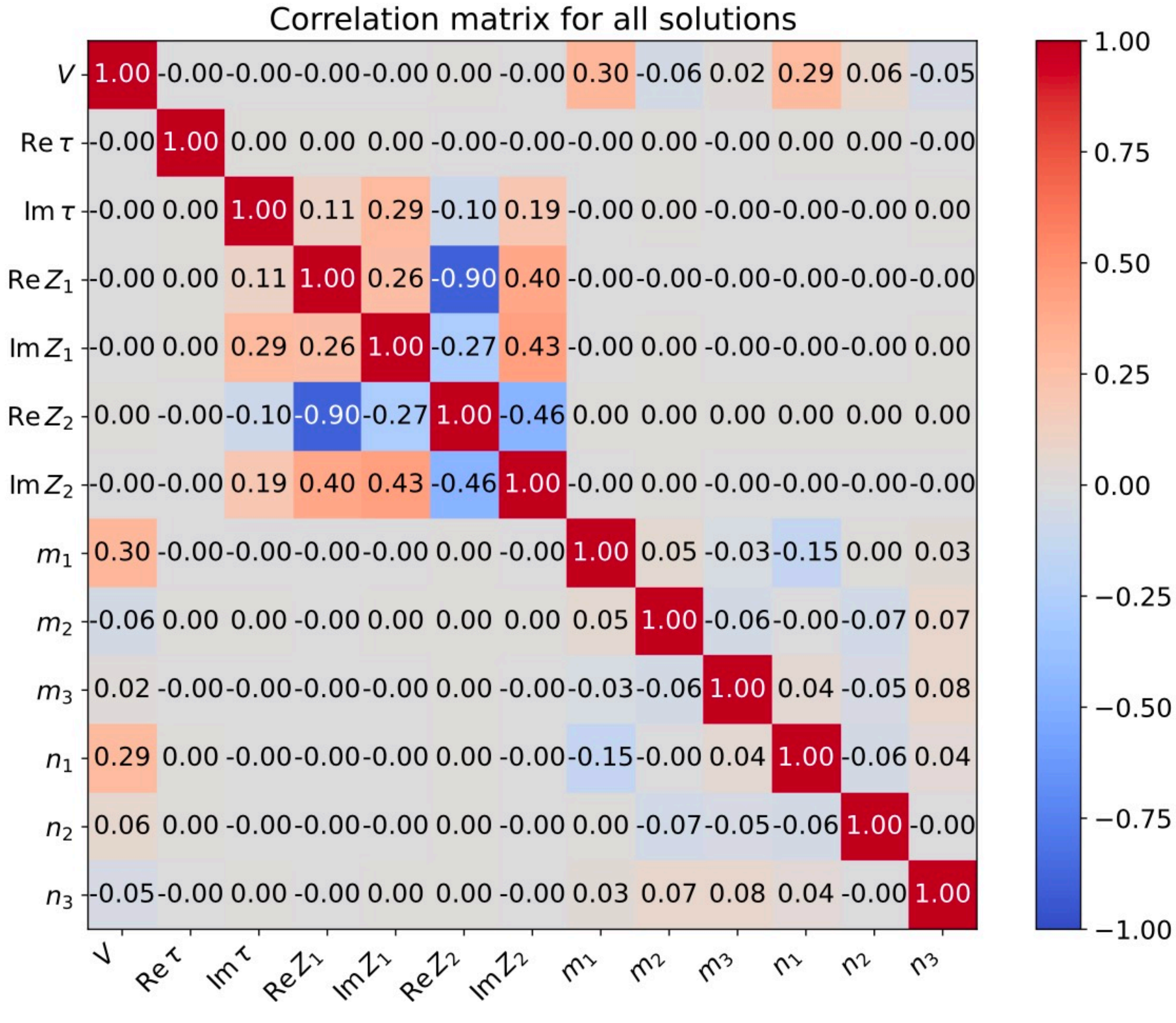


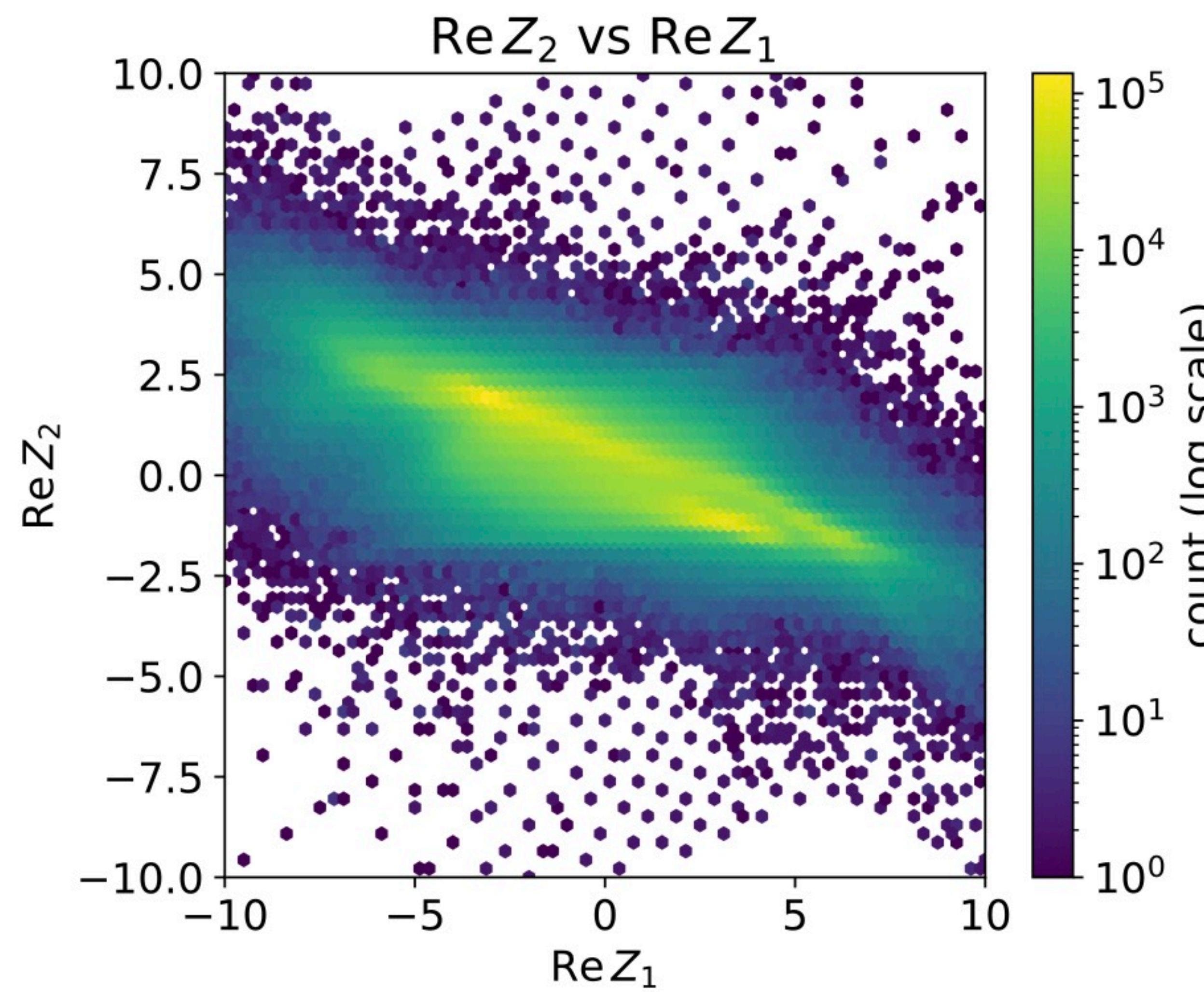
Starting from these, dS vacua could be realized

based on KKLT[Kachru+ '03]/LVS[Balasubramanian+ '05] ($V = 0$ case)

based on [Saltman, Silverstein '04] ($0 < V \ll 1$ case)

Correlations





2: Machine-learning regression task

Input features:

$X = \{V, \tau, Z_1, Z_2, m_i, n_i\}$.

$y \in \{V, \mathrm{Re}\,\tau, \mathrm{Im}\,\tau, \mathrm{Re}\,Z_1, \mathrm{Im}\,Z_1, \mathrm{Re}\,Z_2, \mathrm{Im}\,Z_2, m_i, n_i\}$

We remove y from X and train a regression model to predict y from the remaining features in X.

A non-linear map $f : X \backslash \{y\} \mapsto y$ is a target for learning.

Test of effectiveness

Data set is randomly split into training set (80%) + test set (20%).

We compute coefficient of determination R^2 to assess quality of fit.

true target values $\{y_i\}_{i=1}^n$ v.s. model predictions $\{\hat{y}_i\}_{i=1}^n$.

$$R^2 := 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2},$$

mean value $\bar{y} = \frac{1}{n}\sum_{i=1}^n y_i$

Target	R^2_{train}	R^2_{test}
V	0.77	0.77
m_1	0.88	0.88
m_2	0.55	0.55
m_3	0.61	0.61
n_1	0.85	0.85
n_2	0.55	0.55
n_3	0.62	0.62

$R^2 = 1$: Perfect fit.

$R^2 < 0$: Worse than baseline ($\hat{y}_i = \bar{y}$ for all i).

Summary

Search of flux vacua in string theory.

- $\mathcal{O}(10^8)$ solutions are generated by gradient descent.
- Statistics of solutions are analyzed, and candidates for dS universe are identified.
- Machine-learning for regression tasks.