Machine Learning for String Compactifications

PASCOS’25, Durham, 24 July 2025

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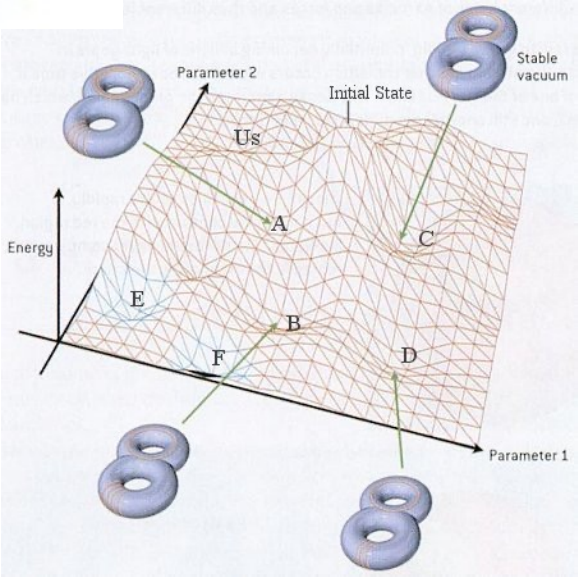
Based on collaborations with
A. Lukas, F. Ruehle, **R. Schneider**; L. Anderson, J. Gray; **Y. Hendi, M. Walden**

String theory and the real world

- **String compactifications**:
  get 4d physics from 10d theory
- The compact **topology and geometry determines physics**
- Many choices:
  - 10d string theory (all dual)
  - Compact geometry
  - Vector bundles, branes, ...

→ Large string theory landscape



String landscape

- But why construct a landscape of physics models?
- Surely, one good model is enough to describe our Universe?

- Needle in a haystack problem/Don’t know what we’ll get
- Constructions are hard –
  build *many* OK models and hope to find *some* really good ones
- Statistics of models: what is typical in string theory?
- Landscape vs swampland: what cannot occur in string theory (or QG)?

compare w Miguel Montero’s talk

Motivation for ML in string theory

- Build string vacuum with {Standard Model, ΛCDM, quintessence, ...}
  - Can ML pick good geometries? Find vacua?
- Computations/Numerics
  - Can ML improve approximations? Speed up hard computations?
- Learn mathematical structures (of relevance for physics)
  - "Pure" data sets exist (or can be created); can ML find new patterns?
- Swampland vs Landscape
  - Can ML help classify UV-complete effective field theories? Test conjectures in classes of models?

… *progress on all of these topics, driven by many researchers*

Reviews: Ruehle:20, Bao, He, Heyes, Hirst:22, Anderson, Gray, ML:23

This talk: ML progress in Calabi-Yau Landscape

1. ML of CY topology -- Learn mathematical structures
2. ML of CY geometry -- Computations/Numerics
3. ML searches in the CY landscape -- Build string vacuum

The Calabi-Yau landscape of string theory

- **String compactifications**: Topology and geometry determine physics

- **Calabi-Yau manifolds** are popular example spaces:
  - Compact, complex, Kähler, with $c_1 = 0$
  - Admit Ricci-flat metric, but this is *not* known analytically
  - Large data bases of examples (algebraic geometry)
  - Topology computed in examples (algebraic geometry)

1. Machine learning Calabi-Yau topology

- CY-related topology computable with AG, but algorithms are often costly

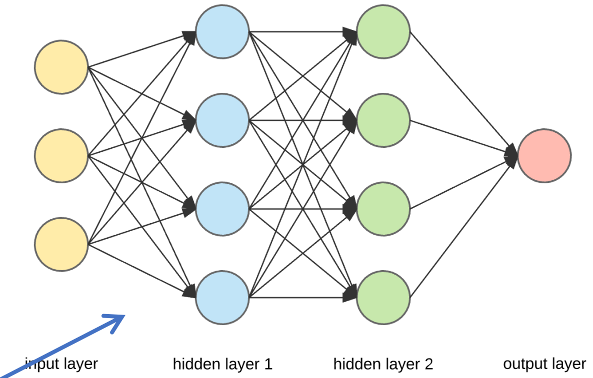
However

- Elements in CY databases are encoded as integer matrix
- CY databases also list integer topological invariants

1. Machine learning Calabi-Yau topology

- CY-related topology computable, but AG algorithms are often costly
- Elements in CY databases are encoded as integer matrix (input)
- CY databases also list integer topological invariants (labels)
- Nice playground for standard ML techniques

$$\begin{bmatrix} 6 & 1 & 1 & 0 & 6 & 4 \\ 0 & 1 & 2 & 7 & 5 & 2 \\ 0 & 4 & 6 & 6 & 3 & 4 \\ 1 & 1 & 2 & 6 & 7 & 0 \\ 3 & 6 & 6 & 5 & 5 & 3 \end{bmatrix}$$



Label	Prediction
…	…
cat	0.92
…	…
dog	0.06
…	….

Update via gradient descent to minimize loss encoding accuracy of prediction

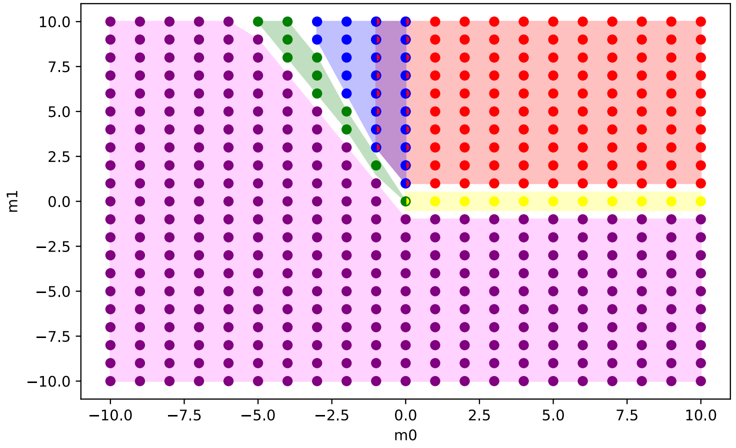
1. Machine learning Calabi-Yau topology

- Hodge numbers
  He:17, Ruehle:17, He–Lukas:20, Erbin-et.al.:20,22, Hirst-et.al.23,...

$$X[8,29] = \left[\begin{array}{c||cccccccccc} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 2 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 2 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 2 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 2 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{array}\right]^{8,29}_{-42}$$

Label	Prediction
h^11=8	0.99
…	…
h^21=29	0.6

- Topology of CY vector bundles
  Klaewer–Schlechter:18, Constantin–Lukas:18, Brodie-et.al.:19,20, Bull-et.al.:18,19, ML–Schneider:19, …
  → **new analytical formulae** for line bundle sum topology



h^0 for $O(m_0, m_1)$ on CICY

- Or CY orientifolds Gao-Zou:21, 7D G_2 topology Aggarwal-et.al:23
  …

2. ML for CY geometry: Ricci flat metrics

- Let X be an n-dimensional compact, complex, Kähler manifold with vanishing first Chern class ($c_1 = 0$).
  Then in any Kähler class $[J]$, X admits a unique Ricci flat metric g_{CY}.

Calabi:54, Yau:78

- Physics care about g_{CY} but there is *no analytical expression* (for d>1).
- Solve $R_{ij}(g) = 0$ — 2^{nd} order, non-linear PDE for g in 6D
- Equivalent to — 2^{nd} order PDE for function ϕ.
  Hard, but may solve numerically on examples

2. ML for CY geometry: Ricci flat metrics

Kähler form J_{CY} satisfies

- $J_{CY} = J + \ i\,\partial\bar{\partial}\phi$ same Kähler class; ϕ is a function
- $J_{CY} \wedge J_{CY} \wedge J_{CY} = \kappa\, \Omega \wedge \bar{\Omega}$ Monge-Ampere equation (κ constant)

Numerical method:

- Sample large set of random points on CY (at fixed moduli)
- Compute Ω and reference J at all points
- Solve MA eq. numerically for J_{CY} (or ϕ)
- Check approximation: does MA eq hold and is Ricci tensor 0?

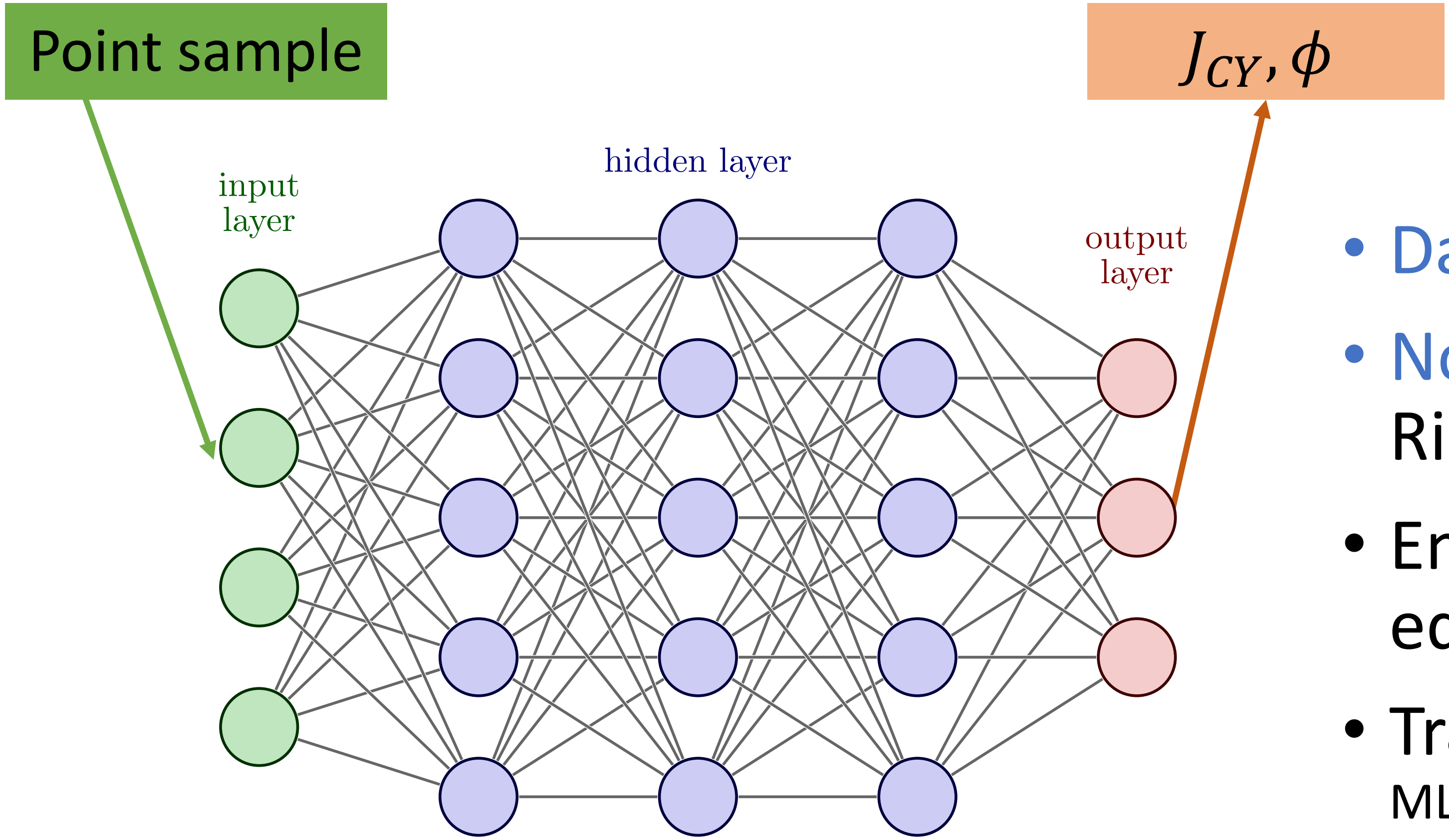
Numerical CY metrics – a longstanding quest

- Donaldson algorithm
  Donaldson:05, Douglas-et.al:06, Douglas-et.al:08, Braun-et.al:08, Anderson-et.al:10, ...

- Functional minimization
  Headrick–Nassar:13,
  Cui–Gray:20,
  Ashmore–Calmon–He–Ovrut:21, ...

- ML methods
  Ashmore–He–Ovrut:19,
  Douglas–Lakshminarasimhan–Qi:20,
  Anderson–Gerdes–Gray–Krippendorf–Raghuram–Ruehle:20,
  Jejjala–Mayorga–Pena:20 ,
  Larfors-Lukas-Ruehle-Schneider:21, 22
  Ashmore–Calmon–He–Ovrut:21,22,
  Berglund-etal:22,24 ,
  Gerdes–Krippendorf:22,
  Constantin-etal:24,25,
  Hendi-Larfors-Walden:24,
  Butbaia-etal:24, Ek-etal:24 ...

2. ML for CY geometry: model setup & train

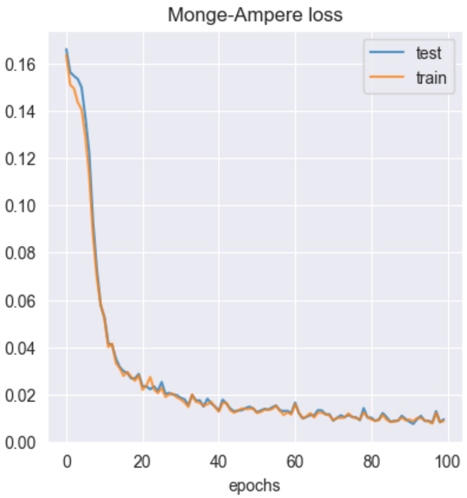


- Data: Sample of points
- No labels: Know Ω and ref. J but Ricci flat metric unknown
- Encode constraints (e.g. MA equation)as loss function
- Train: Stochastic gradient descent
  ML libraries TensorFlow, JAX, PyTorch
- When trained: NN is J_{CY} or ϕ

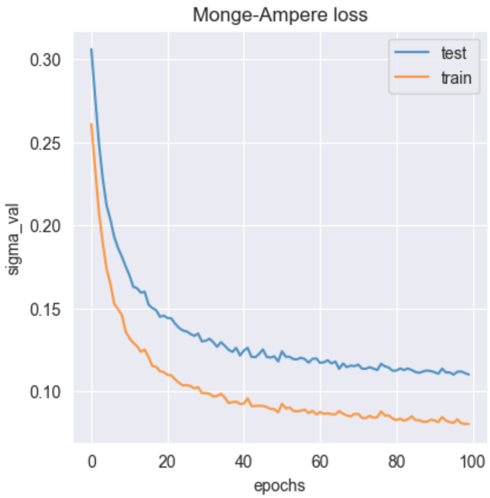
ML works on different CYs

Larfors ,Lukas, Ruehle,Schneider:22
Anderson, Gray, Larfors:23

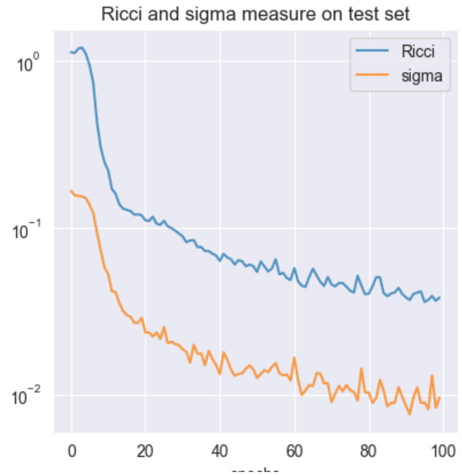
Quintic



Fermat



Generic



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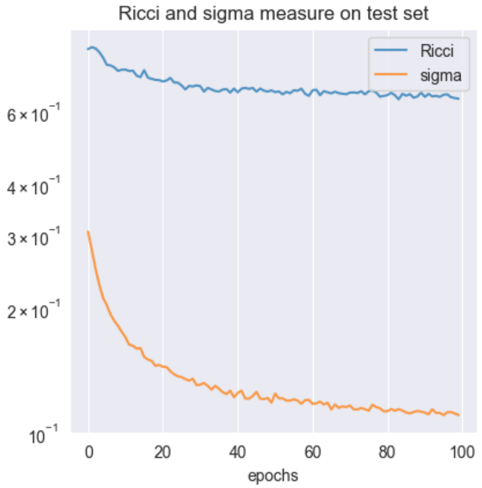
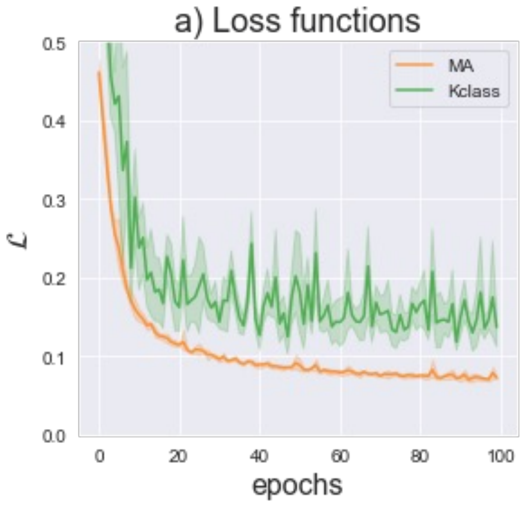
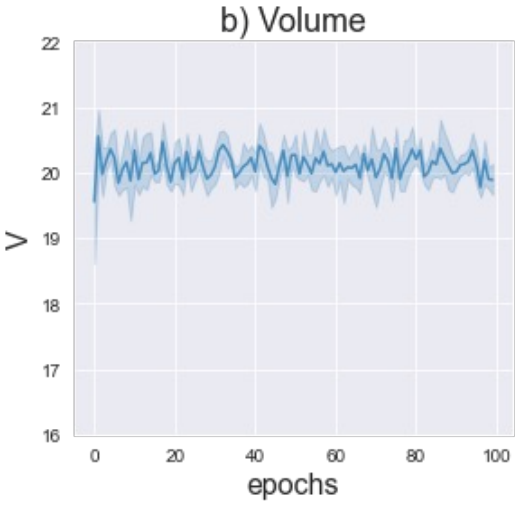
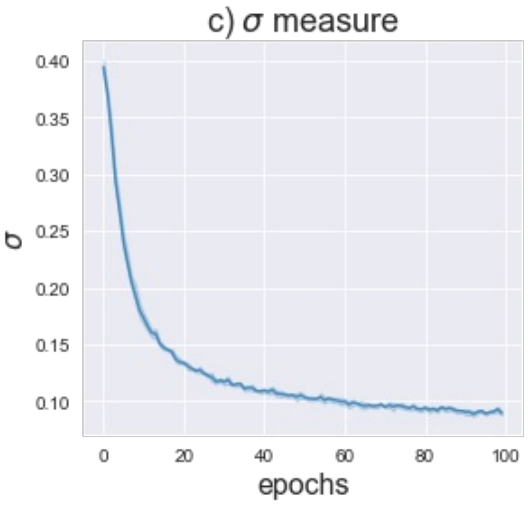


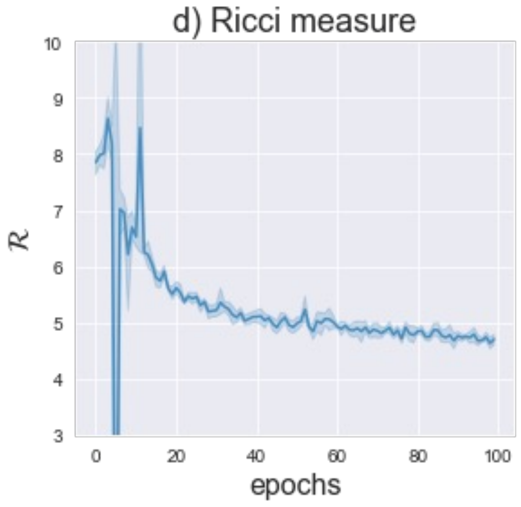
Generic

CY in toric ambient









Experiments using cymetric package

Application: Heterotic Standard-Like Models

Building blocks

- Ricci-flat Calabi Yau manifold X
- Vector bundle V satisfying Hermitian Yang-Mills eq.

$$F \wedge \Omega = 0 = F \wedge J_{CY} \wedge J_{CY}$$

- Discrete symmetry group G (to break GUT to SM)

much more to say; see talk by Luca Nutricati

- Many examples! E.g. 35 000 SLMs found with $V = \oplus L_i$

  Anderson et.al:11,12,13, …

  …. with RL/gen.alg. ML-Schneider:20, Constantin et.al: 21, Abel et al:21,23,…

Application: Heterotic Standard-Like Models

Building blocks

- Ricci-flat Calabi Yau manifold X
- Vector bundle satisfying HYM eq.
- Discrete symmetry $G \rightsquigarrow$ smooth quotient CY X/G
  - allows to break GUT using Wilson lines
  - symmetries: permutations, discrete phase rotations, shifts of input z_i

- Can ML predict Ricci flat metric on quotient CY?

ML G-invariant CY metrics

Hendi, Larfors, Walden:24

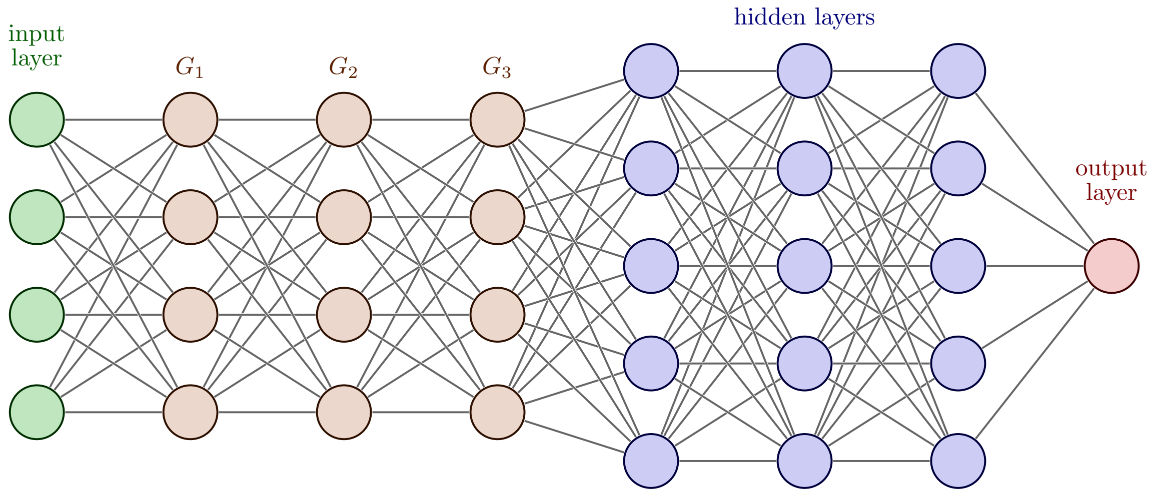
- Let X be smooth CY, G symmetry, $g_{CY} = g_{FS} + \partial\bar{\partial}\phi$
- ML model which approximates $\phi(z)$ is G-invariant if
$$\phi(g \cdot z) = \phi(z)$$
- With enough data, symmetries are learned
- Or, use G-invariant layers to make ML model invariant
  - Invariant NNs are universal approximators for invariant functions Yarotsky:22,..
  - Invariant ML models can be constructed in many ways
  - Geometric Deep Learning: symmetry, performance & interpretability Bronstein et al:17,21,..

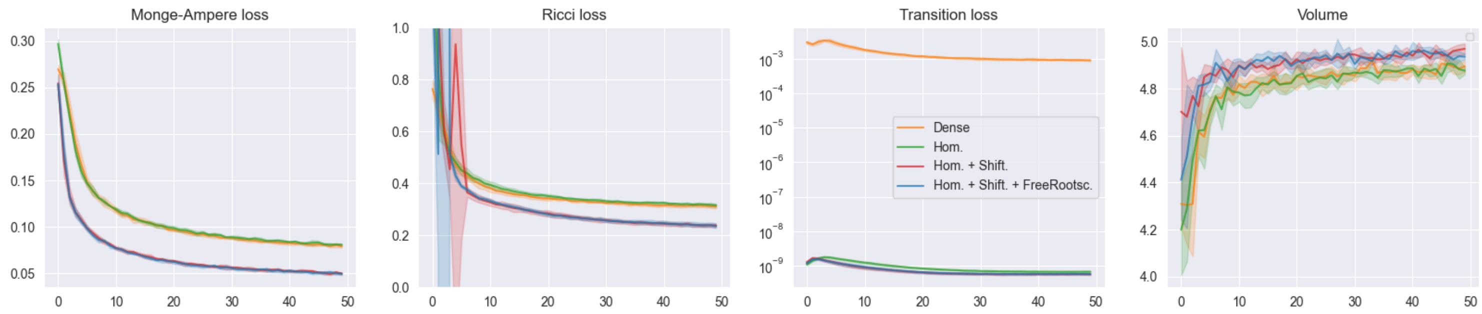
Invariance through non-trainable layers

Hendi, Larfors, Walden:24

G-canonicalization:

- Invariant layers: project data to fund. domain
- Modular and stackable (w. compatibility condition)
- Easily included in ML models for CY metrics





Eg: symmetric Quintic with cymetric package

3. Searching the string landscape

Two well-studied continents:

- Particle physics: heterotic SLMs
  Larfors, Schneider:20,
  Constantin, Harvey, Lukas: 21,
  Abel et al:21, 23
- Cosmology: IIB strings on CY
  Cole et.al:21, Krippendorf et.al: :21
  Krippendorf, Liu 25, ML-Walden:in progress
- ... and many other examples
  F-theory, intersecting branes, heterotic orbifolds,...

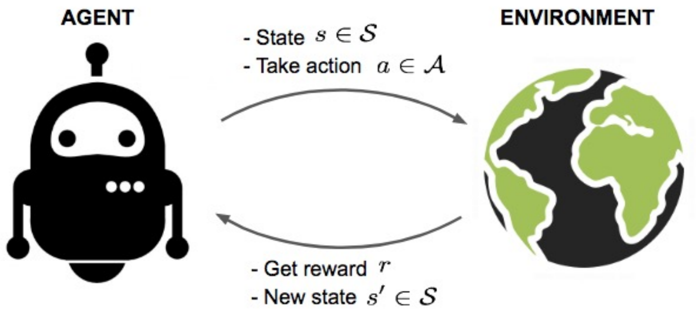
Explored with

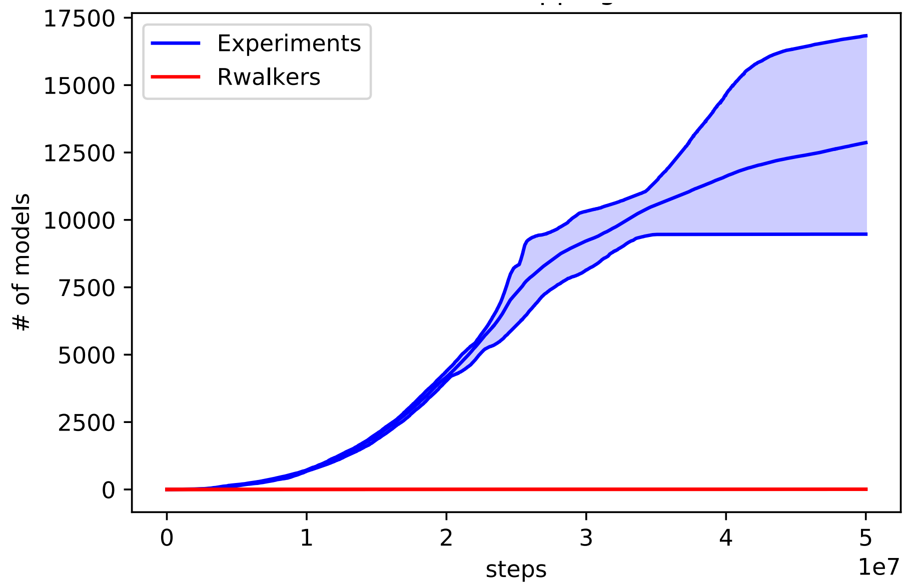
- reinforcement learning (RL)
- genetic algorithms
- generative models

- NB: we want
  - exact solutions
  - clever search strategies

RL Standard-like Models from CYs

Larfors, Schneider:20
Schneider PhD thesis, 2022





5 experiments, mean and variance plotted

- Idea: agent learns to win game
- Set-up: Heterotic SLMs
- Agent solves SLM environment
  - Large number of models
  - New search strategies
- Transfer learning
- Key benefit: go beyond setups probed in systematic scans (here higher h^11)

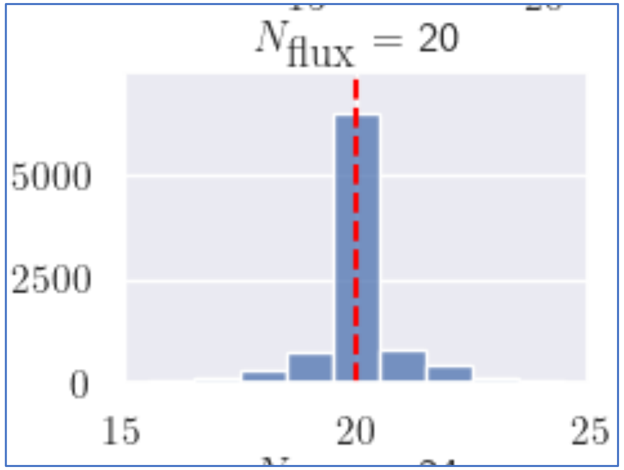
Generative models for IIB flux vacua

ML-Walden:in progress

- IIB flux vacua:
  basis for KKLT and LVS scenarios
- Progress on computational tools
  CYtools, JAXvacua
- Want quantized fluxes solving
  - ISD conditions (F-term vanishing)
  - Tadpole constraint N_{flux}

→ Sample w generative models

- E.g. using Transformer + Int2Int
  Vaswani et al:17, Charton:25



- See also related work using VAE
  Krippendorf, Liu:25

Conclusions

ML methods help string phenomenology:

- Bypass hard computations & detect new patterns --- CY topology
- Improve numerical approximations --- CY metrics
- Search for good vacua in (known) landscapes --- SLMs and flux vacua
- OS ML packages & trained models:
  cymetric, gymCICY, MLgeometry, cyjax, cymyc, AICY, ...

Conclusions and outlook

ML methods help string phenomenology:

- Bypass hard computations & detect new patterns --- CY topology
- Improve numerical approximations --- CY metrics
- Search for good vacua in (known) landscapes --- particle physics/cosmology
- Applications and generalizations
  - Compute quark masses Butbaia-et.al:24, Constantin-et.al:24,25
  - Test Swampland distance conjecture
    Ashmore:20, Ashmore & Ruehle:21 Ahmed & Ruehle:23
  - Geometry beyond CY: e.g. G-structures, G2 holonomy manifolds
    Anderson et al:20, Douglas-Platt-Qi:24
  - Refined searches in string landscape (lots of methods not yet tested)

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Thank you for listening!