Deep Autoencoders in the Heterotic Orbifold Landscape

Andreas Mütter

Technical University of Munich

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in collaboration with

Erik Parr and Patrick Vaudrevange

arxiv:1811.05993

SFB 1258 Neutrinos Dark Matter Messengers

Motivation

The search for MSSMs in String Theory has a long history

- Type IIA/B with D-branes
- F-Theory
- Heterotic orbifolds

MSSM searches in heterotic orbifolds

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Goals of this talk

- Have a careful look at the parameter space of heterotic orbifold models
- Understand the connection between choices of parameters and "good" models
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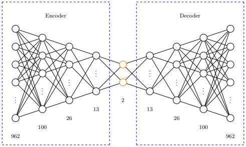
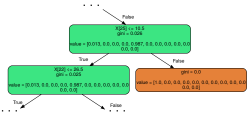
in order to achieve this: **Machine learning**

ORBIFOLDER

Data generation
Data preparation

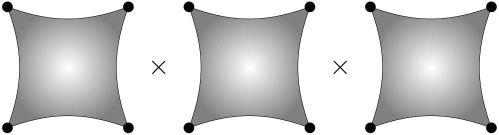


Neural Network
(find fertile patches)



Decision tree
(extract conditions)

Parameter Space of (Heterotic) Orbifolds

$\mathbb{R}^{1,3} \times$ 

Orbifolds are characterized by the *space group*

$$g \;=\; (\theta \,|\, n_\alpha \, e_\alpha)$$

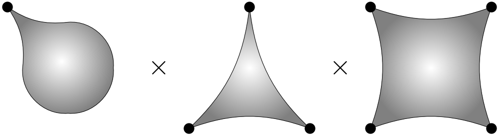
For the heterotic string: Embed into $\mathrm{E}_8 \times \mathrm{E}_8$
(e.g. using the `orbifolder` [1110.5229])

$$\left.\begin{array}{cccc} v_\theta & \to & V_\theta & \textbf{Shift} \\ e_\alpha & \to & W_\alpha & \textbf{Wilson lines} \end{array}\right\} \in \mathbb{Q}^{16}$$

subject to *modular invariance conditions*

$\to$ spectrum, local gauge groups (local GUTs) fully determined

Compactification Parameters in $\mathbb{Z}_6$-II



- Geometric twist fixed as $v_\theta = \left(\frac{1}{6}, \frac{1}{3}, -\frac{1}{2}\right)$
- Gauge embeddings:
  - 1 shift of up to order 6
  - 1 order 3 Wilson line, 2 order 2 Wilson lines
- Local shifts: $V_g = kV_\theta + (n_3 + n_4)W_3 + n_5 W_5 + n_6 W_6$

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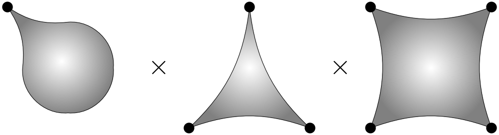

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"Sweet spots" in the landscape,
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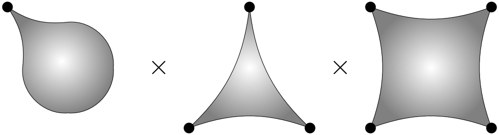

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Machine Learning

reproduce and extend the idea of the Mini-Landscape in an automated fashion

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addition of lattice vectors	$V \mapsto V + \lambda$

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Solution: use *breaking patterns* (= number of invariant roots)

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For each gauge embedding V count the number of roots p that fulfill

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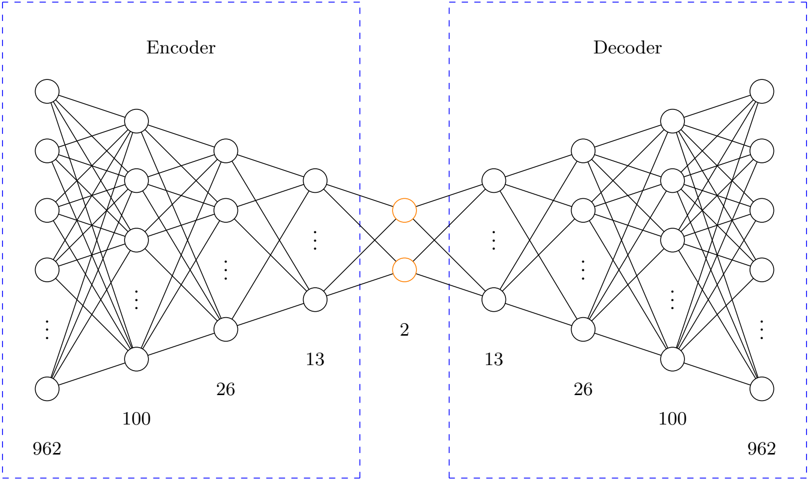
- Amend local breaking patterns by global gauge group $\rightarrow$ $2 \times 12 \;+\; 2 \;=\; 26$ parameters
- For later purposes: one-hot encoding $\rightarrow$ $26 \times 37 = 962$ input dimensions

The Dataset(s)

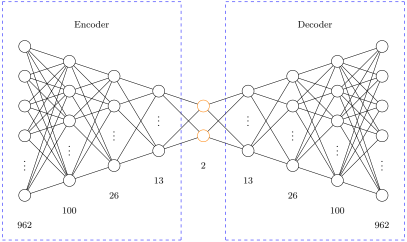
- **Training:** 700k from random search, by chance including some MSSMs
  $\rightarrow$ we will use this dataset in order to identify fertile patches
- **Evaluation:** 6.3M from random search
  $\rightarrow$ are our fertile patches chosen correctly?
- 30k from the **Mini-Landscape**
  $\rightarrow$ compare our approach to physics-motivated considerations

Autoencoders



Autoencoders

- Feed inputs through network
- Train on `output=input`
- Information bottleneck in the latent layer



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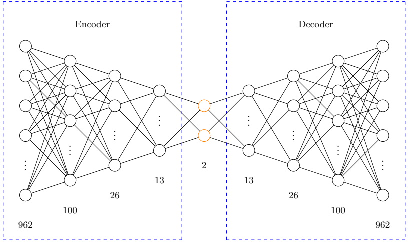
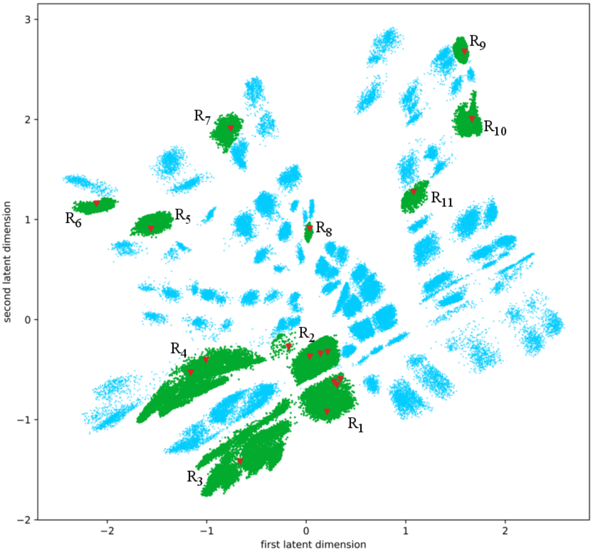


Because of the information bottleneck, the network is forced to learn a compressed representation of the input by exploiting (nonlinear) redundancies

Draw a map: after training, use the first half of the network (=the encoder) to draw a 2-d map of the landscape

Results



Training set: MSSMs in red, random models in blue, fertile islands in green

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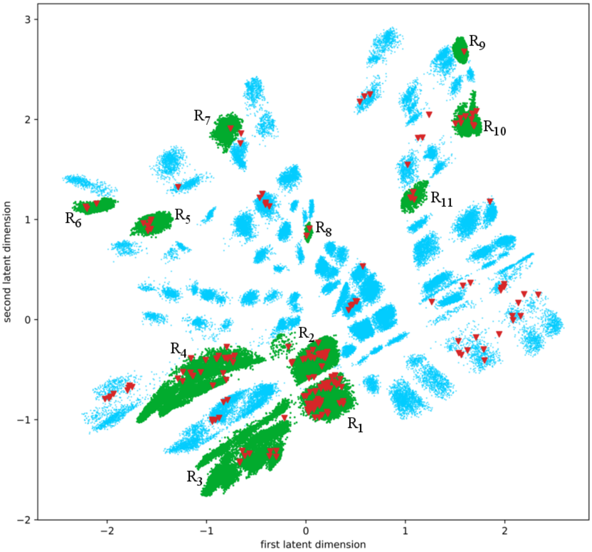

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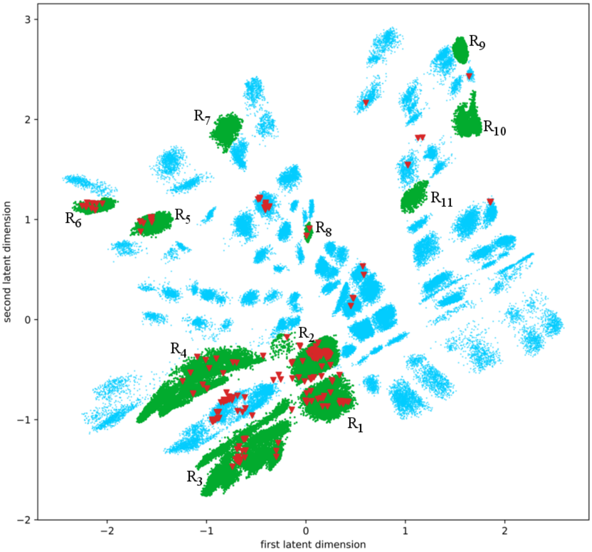

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Main advantages:

- Almost trivial to feed information gathered in this way to a computer
- A first step to an interpretation in terms of physical quantities

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Shortcuts during random search
The `orbifolder` works as follows

(i) Generate random, modular invariant gauge embedding
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Generation of fertile models
Possible algorithm

(i) Generate random shift
(ii) Check whether it has the chance to be in a fertile patch:
    - if no, scrap the model
    - if yes, create random Wilson line
(iii) Repeat until one has a complete model

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Thank You!