

## Notes: Machine learning flat directions

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### Abstract

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## 1 Introduction

## 2 Supergravity setup

- Context: 6d  $\text{AdS}_3 \times S^3$ , truncation to 3d, potential, conformal manifold.
- Choice of truncation from 32 to 13 to 5 variables.

## 3 Numerical analysis

### 3.1 Gradient descent and local analysis

- Gradient descent: implementation, sampling, time needed, loss.
- Local PCA: graphs of number of patches with given local dimension, and with varying size of local patch, discuss optimal patch size (we want at least few points in each direction).
- Clustering: HDBScan (only parameter: minimal number of points in a cluster), and graphs of 3d slices of the 5d space.
- After PCA and clustering we know that the points after the gradient descent sample a three-dimensional manifold.

### 3.2 Annealed Importance Sampling for polynomial symbolic regression

- We can convert the potential to a polynomial by converting the variables that appear in exponentials to logs.
- As the potential is a polynomial, the solutions satisfy polynomial equations. Discuss that fact that we could get polynomials directly by taking the gradient of the potential, but those will be too complicated to express the vacuum in a usable way. We search those using Annealed Importance Sampling.

- Annealed Importance Sampling: first explain general idea (construct density probability, role of temperature, links with Monte-Carlo), discuss  $\beta$  to control exploration and exploitation phases.
- Then more details: discuss hypotheses to compute the weights, choice of transformations, choice of  $\beta$ , choice of loss, prior, initial sampling, choice of representation for the polynomials.
- Discuss the fact that we allow float coefficients even though we know the coefficients will be only integers of square roots of integers?
- Analysis after AIS: select the best polynomials and do exploitation on the coefficients (without MC: we keep only the proposal of it betters the polynomial).
- Results for naive choices of parameters (numbers of iteration and particles, probabilities,  $\beta$ ) and motivate them (we want some exploration and then exploitation, not too long computations): for multiple runs we find multiple polynomials (good polynomial: after exploitation we convert the coefficients to integers and square roots, and recompute loss without regularisation, select with threshold). Quantify it nicely: success rates for each polynomials, and absolute number of success, failing rate. Total time needed, without cluster or fancy computers.

## 4 Supergravity solutions

- For each couple of candidate polynomials, we get the same expression for the solution, and it indeed defines a unique vacuum of the 3d SUGRA.
- Discussion of the vacuum: gauge group, Zham. metric, change of variables, 3d spectrum (and stability), spin 2 spectrum on  $S^3$ , one parameter seems to be a gauge parameter, uplift?

## 5 Conclusion

- Conclusion: good prospects of improvement to be able to access higher dimensional cases. Classify flat directions.
- Appendix with some details on the code?

## References