

## OBJECTIVE

- ▷ Current deep neural architectures are designed for high-dimensional inputs
- ▷ But: Many important datasets consist of low-dimensional inputs for which non-adapted MLPs are used by default
- ▷ Goal: Investigate deep neural layers that are specialized for continuous low-dimensional input data

## BACKGROUND

### Neuroscientific Inspiration

- ▷ **Tuning curve stimulus encoding:** Sensory neurons encode low-dimensional stimuli with bell-shaped tuning curves where their activity peaks at a preferred stimuli value

### Alternative Approach

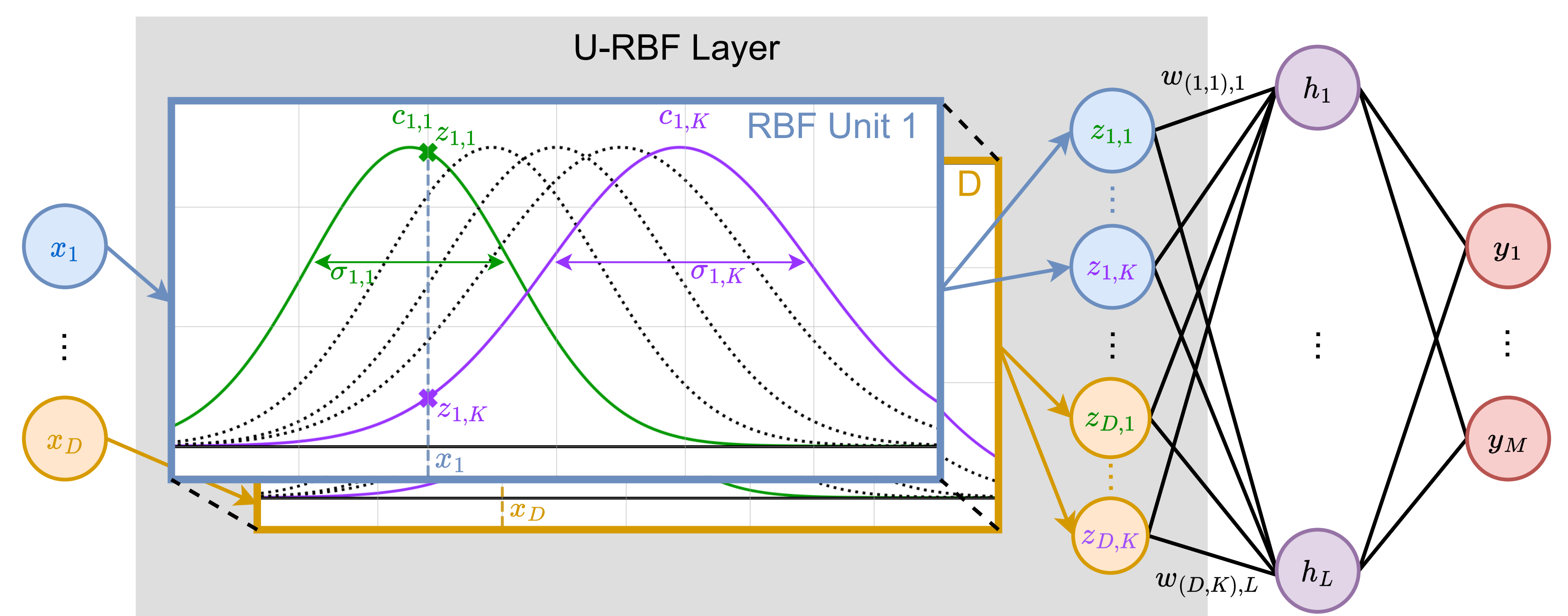
- ▷ **Fourier Features:** Mapping the input to Fourier features before further processing them using a standard MLP enables them to learn high-frequency functions in low-dimensional problem domains

$$\gamma(\mathbf{x}) = [a_1 \cos(2\pi \mathbf{b}_1^T \mathbf{x}), a_1 \sin(2\pi \mathbf{b}_1^T \mathbf{x}), \dots, a_m \cos(2\pi \mathbf{b}_m^T \mathbf{x}), a_m \sin(2\pi \mathbf{b}_m^T \mathbf{x})]$$

## U-RBF LAYER

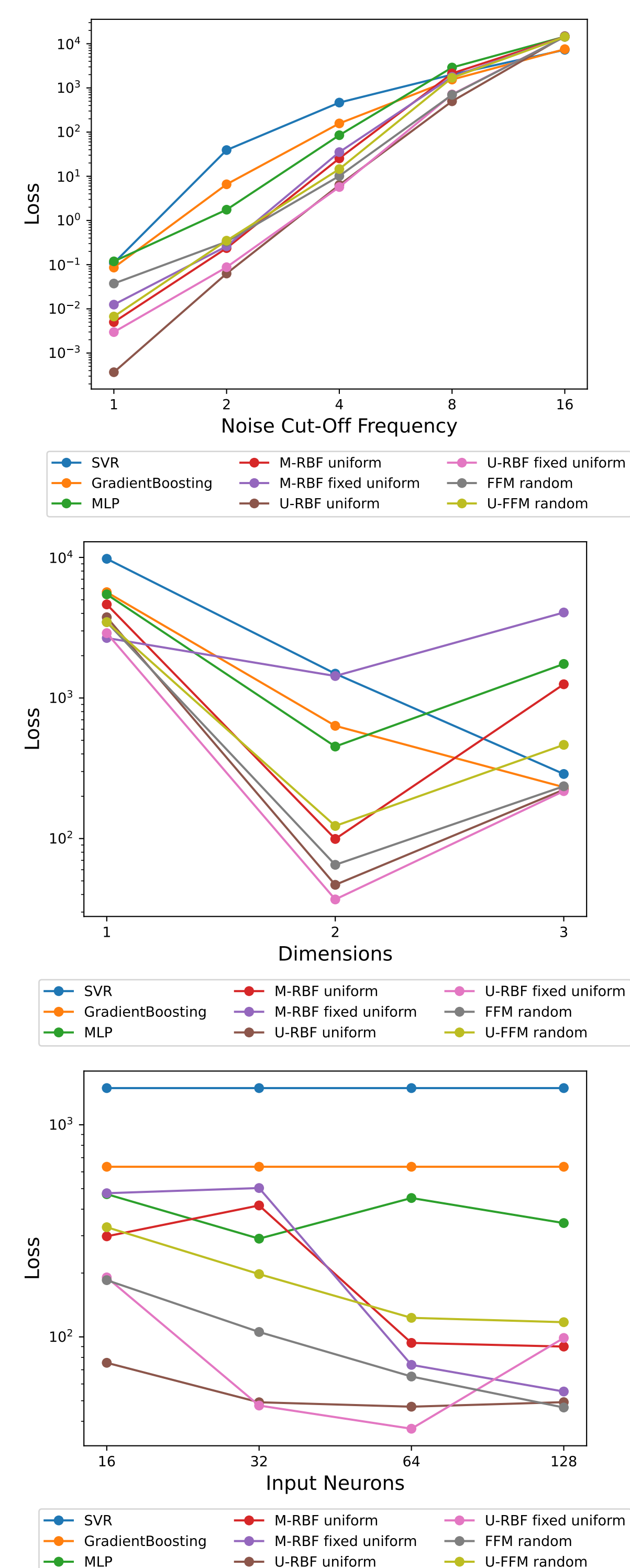
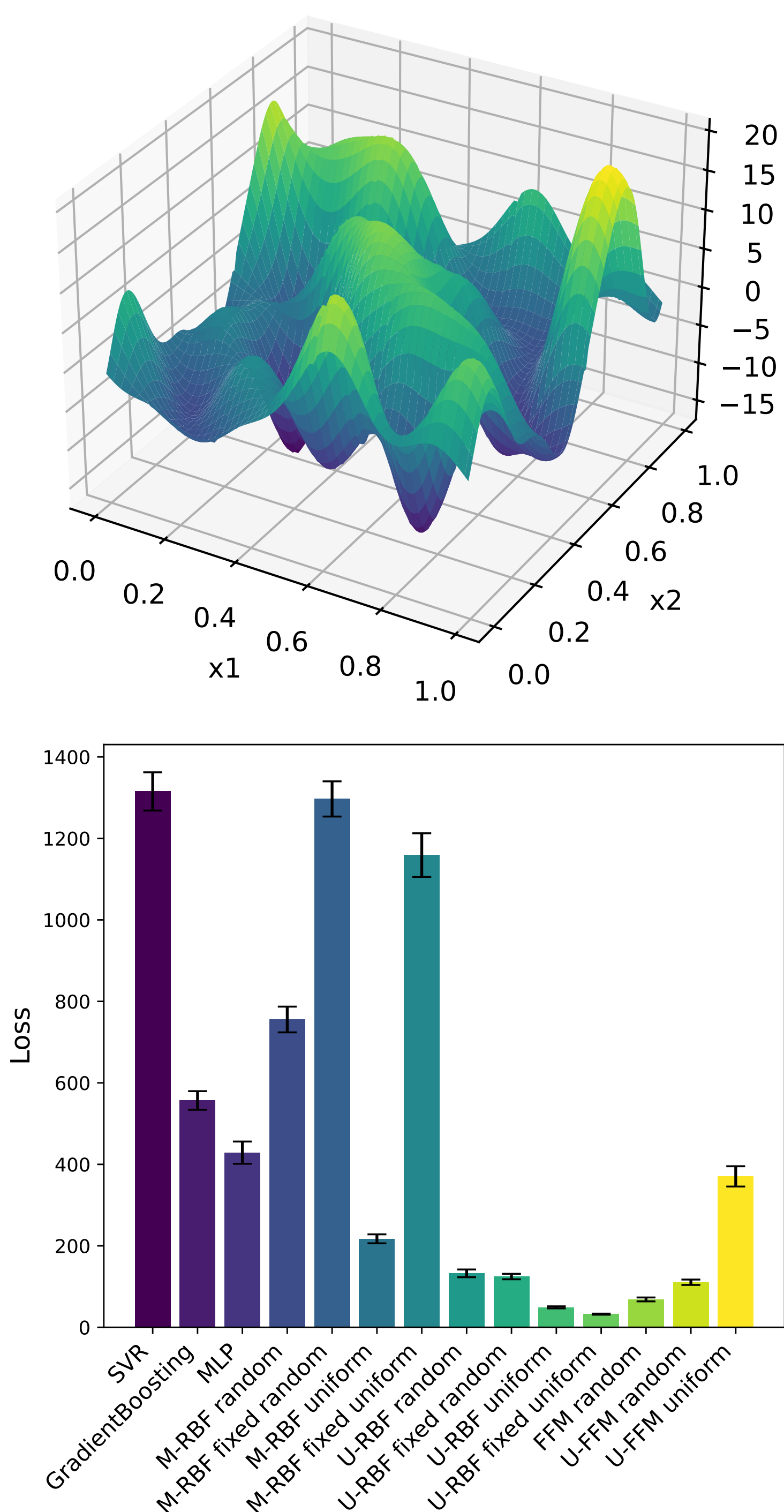
### Univariate Radial Basis Function (U-RBF) Networks

- ▷ U-RBF units consist of several neurons encoding each input dimension individually while having a Gaussian activation function peaking at its preferred value  $\mu$  with spread  $\sigma$
- ▷ The U-RBF units and the subsequent MLP are trained using standard Gradient Descent
- ▷  $h_l(\mathbf{x}) = \sum_{d=1}^D \sum_{k=1}^{K_d} w_{(d,k),l} \mathcal{G}(x_d - c_{d,k}, \sigma_{d,k})$

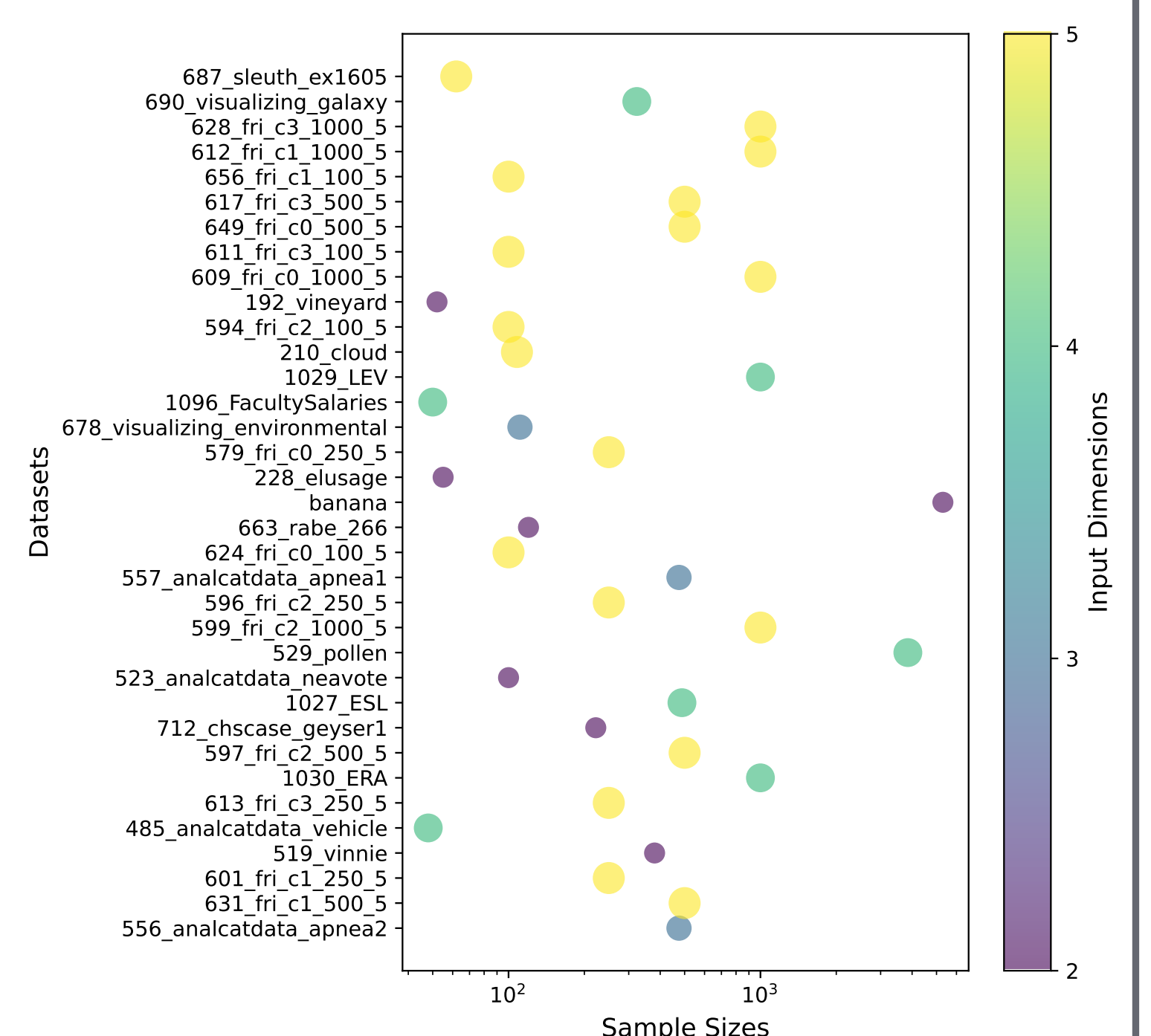
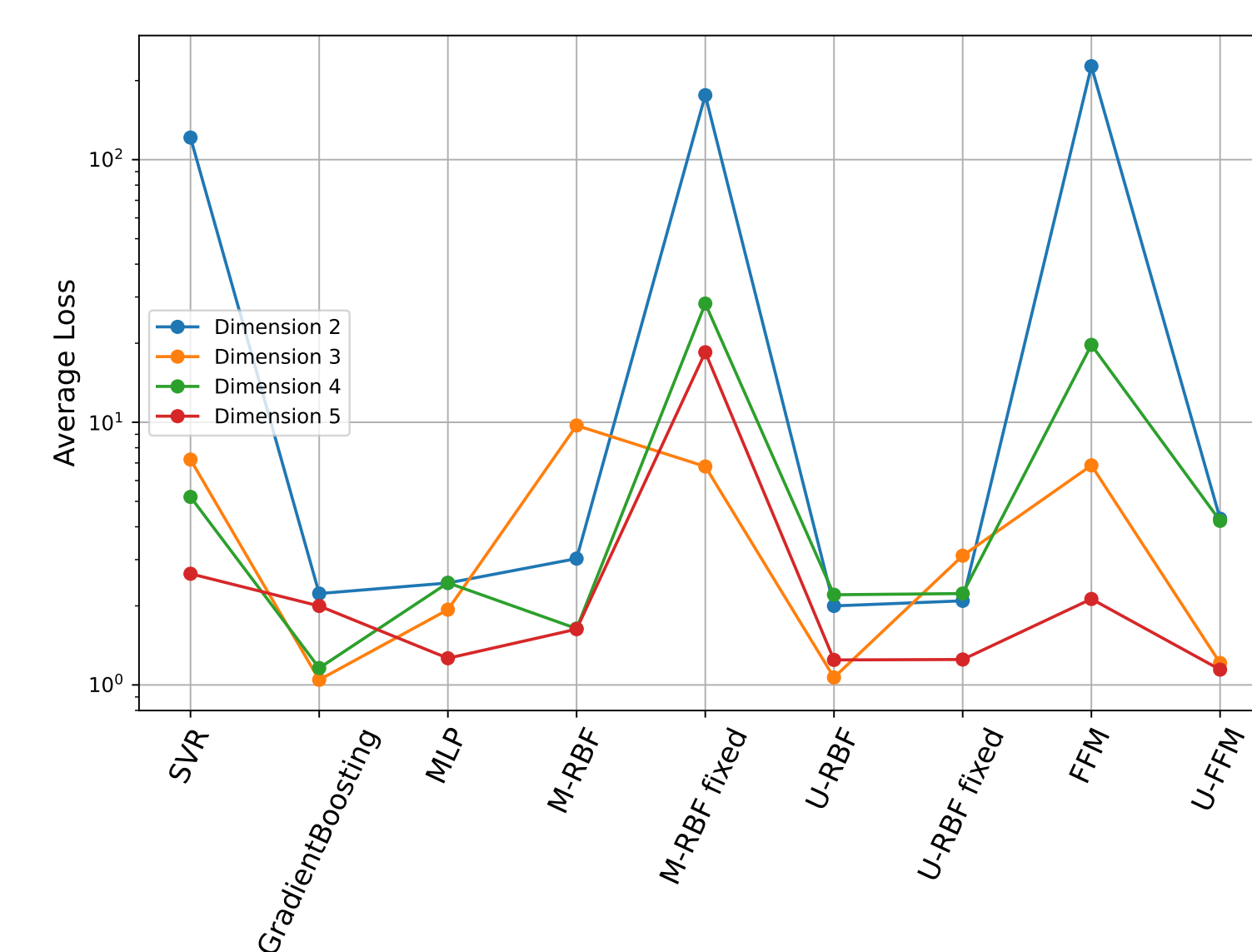


## EXPERIMENTS

### White Noise Regression



### Real World Datasets



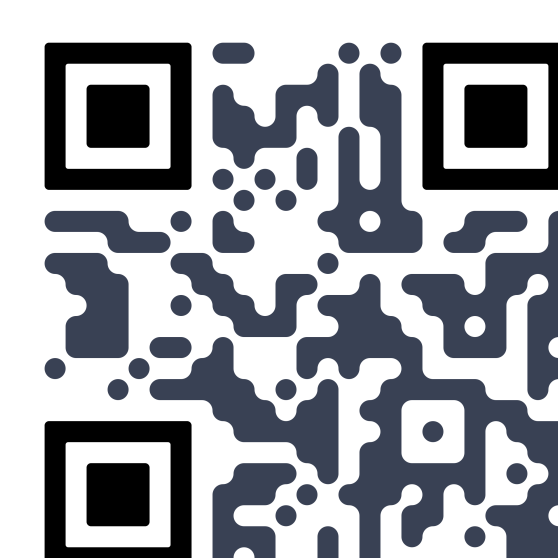
### Results

- ▷ U-RBF shows strongest results for Low-Pass Filtered White Noise Regression
- ▷ U-RBF has the strongest results among the Deep Learning approaches for real-world datasets
- ▷ U-RBF is easier to train than other SOTA approaches (Fourier Feature Mapping), since it does not require complex hyperparameters

## REFERENCES

- ▷ Hornik, Stinchcombe, and White, "Multilayer feedforward networks are universal approximators," Neural Networks, vol. 2, 1989.
- ▷ Romano, J. D., Le, T. T., La Cava, W., Gregg, J. T., Goldberg, D. J., Ray, N. L., Chakraborty, P., Himmelstein, D., Fu, W., and Moore, J. H. PMLB v1.0: An open-source dataset collection for benchmarking machine learning methods, April 2021.
- ▷ Tancik, M., Srinivasan, P., Mildenhall, B., Fridovich-Keil, S., Raghavan, N., Singhal, U., Ramamoorthi, R., Barron, J., and Ng, R. Fourier features let networks learn high frequency functions in low dimensional domains. Advances in Neural Information Processing Systems, 33: 7537–7547, 2020.

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