Brain-Inspired Deep Neural Layers for Low-Dimensional Inputs

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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

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

\[
h_k(x) = \sum_{d=1}^{D} \sum_{k=1}^{K_d} w_{d,k} \varphi(x_d - c_{d,k}, \sigma_{d,k})
\]

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