Kolmogorov-Arnold Networks with dopant network processing units for interpretable regression

The Kolmogorov-Arnold Network (KAN) was recently introduced as an alternative to multi-layer perceptron networks (MLPs) when requiring both accuracy and interpretability in small-scale AI-assisted science tasks. KANs consist in a combination of tunable activation functions and sums, instead of tunable weights and fixed activation functions found in MLP. The relevant aspect in KANs is that interpretability comes naturally from the tunable features of the activation functions. In-materia computing can benefit from KAN framework if a device analogue to a tunable activation function exists. We identified Dopant Network Process Units (DNPUs) as such device. DNPUs are multi-terminal silicon-based devices with tunable nonlinear characteristics. Their terminals can be distributed between inputs and control electrodes; the later ones tuning nonlinear transformation of the input data. By using a single electrode as input and the rest for tuning, we obtain an activation function with the maximum degrees of tunability, making DNPUs promising candidates to implement physical KANs.

In this work, we present KANs built with DNPUs for small-scale regression tasks. We show that single or grouped DNPU kernels can shape a large variety of functions, and multivariate regression is possible by joining these kernels in KAN structures. Moreover, regularization techniques may be useful for two purposes. Applying regularization at network level may turn DNPU kernels more interpretable, thus enabling symbolic regression tasks. Additionally, regularization at kernel level allows to optimize the number of devices needed to perform regression without incurring in large errors. The results are validated with several examples, by means of simulations using our DNPU surrogated models, and trained with a stochastic gradient descent algorithm. Our findings pave the way to explore efficient networks, in terms of device count, for complex tasks.