Blackbox Optimization using LSTMs

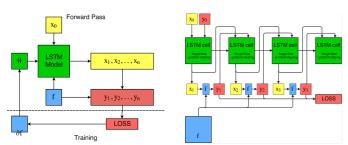
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Summary

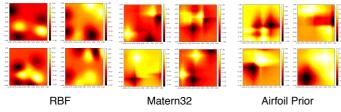
We present a new, learning-based, approach to global Black Box optimization. We train a LSTM to output a sequence of sample points that seek to minimize a given objective function.

Our experiments show that the learned model is able to generalize to a variety of synthetic Black-Box functions, as well as to the real world problem of airfoil optimization. Moreover, our model performs comparable to state-of-the-art Black-Box optimization algorithms w.r.t. the minimum function value found and even outperforms them w.r.t. computation time.

Model

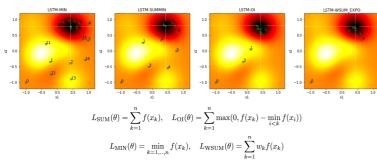


Training Data



GP functions on different kernels

Comparison of Loss Functions

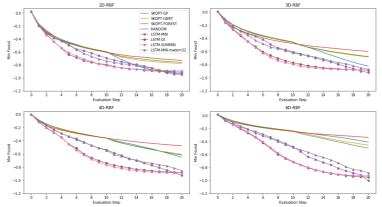


References

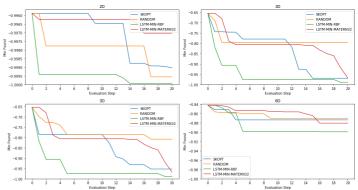
[1] Andrychowicz, Marcin, et al. "Learning to learn by gradient descent by gradient descent." Advances in Neural Information Processing Systems. 2016. [2] Mockus, Jonas. "The Bayesian approach to global optimization." System Modeling and Optimization (1982): 473-481.

[3] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

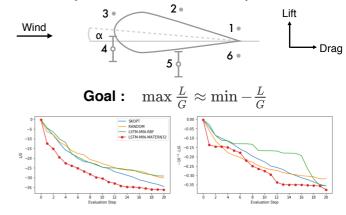
Results on Test Functions



Results on Benchmask Functions



Results (on Airfoil data)



Conclusions

- Our model learns by itself to trade-off exploration and exploitation during sampling; we can guide its behavior by the choice of the loss function we use during training
- Our model performs well also in high dimensions, and inference time scales only linearly with the dimension
- Our approach requires the objective function to be somewhat normalized; this however is no restriction if rough upper and lower bounds

$$y_{2} = i < 6$$
 = [-1,1] $\alpha = [-5,5]$