

# Blackbox Optimization using LSTMs

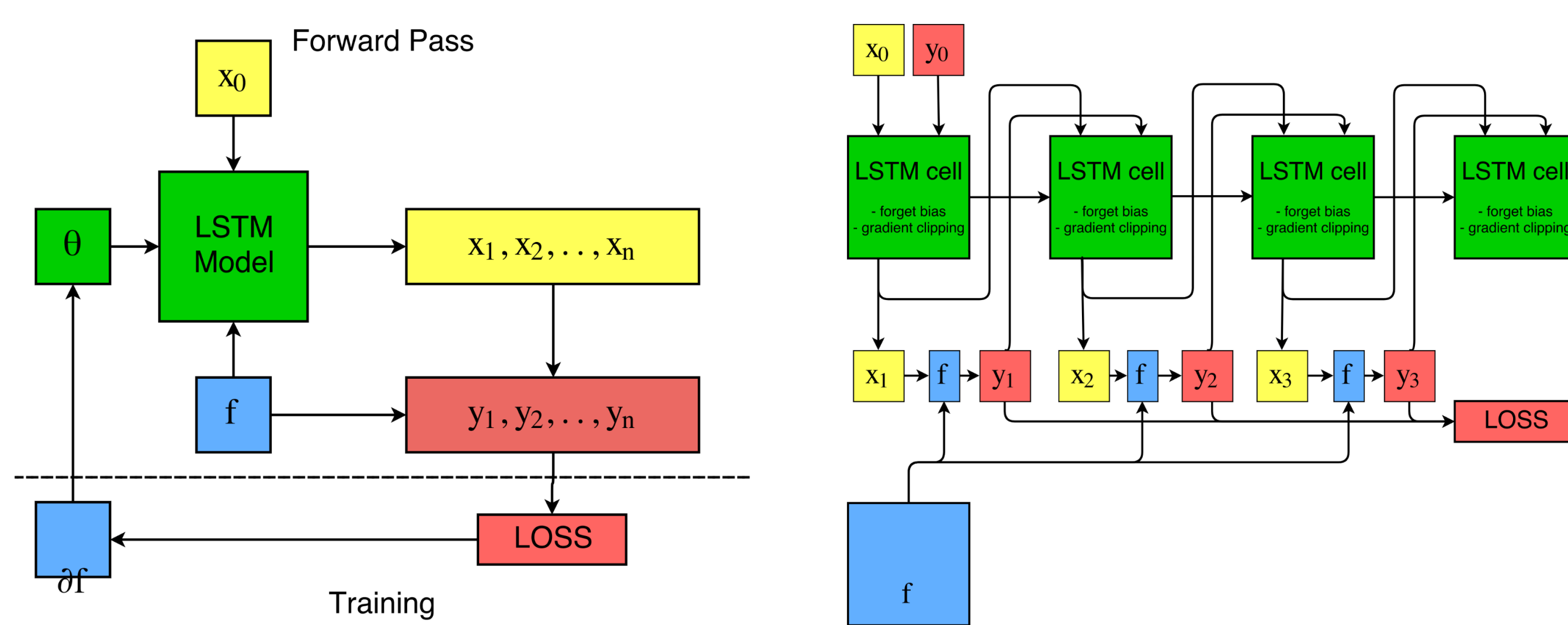
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## Summary

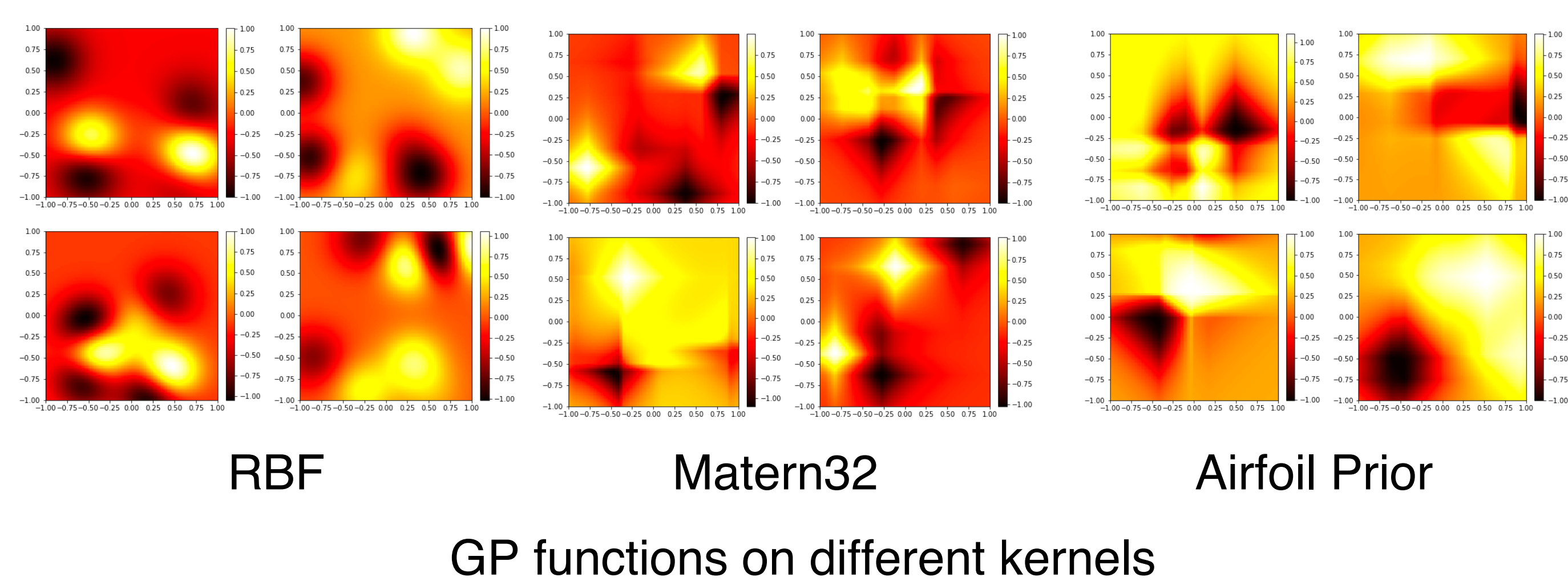
We present a new, learning-based, approach to global Black Box optimization. We train a LSTM to output a sequence of sample points that seek to minimize a given objective function.

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



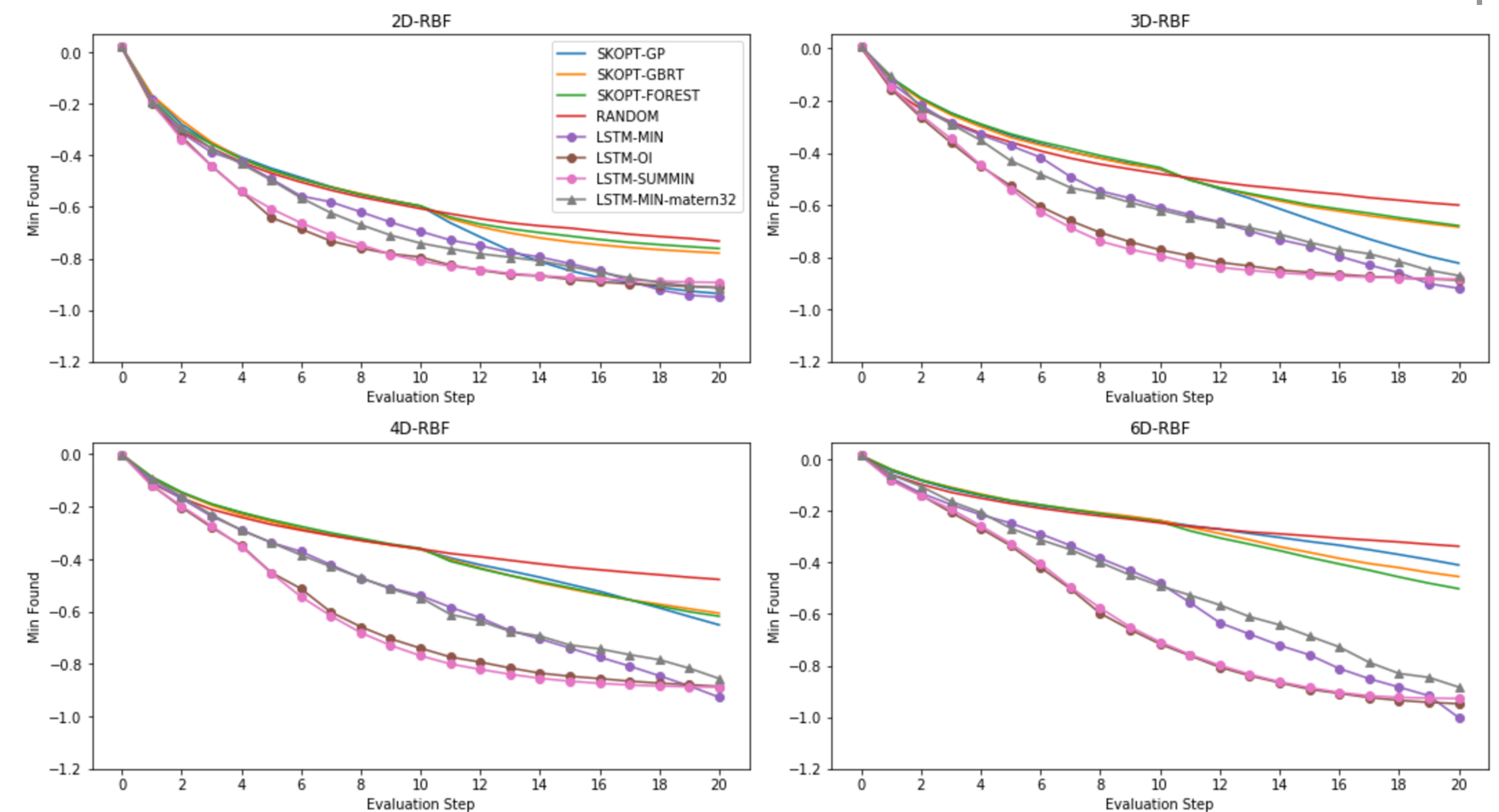
## Comparison of Loss Functions

$$L_{\text{SUM}}(\theta) = \sum_{k=1}^n f(x_k), \quad L_{\text{OI}}(\theta) = \sum_{k=1}^n \max(0, f(x_k) - \min_{i < k} f(x_i))$$
$$L_{\text{MIN}}(\theta) = \min_{k=1, \dots, n} f(x_k), \quad L_{\text{WSUM}}(\theta) = \sum_{k=1}^n w_k f(x_k)$$

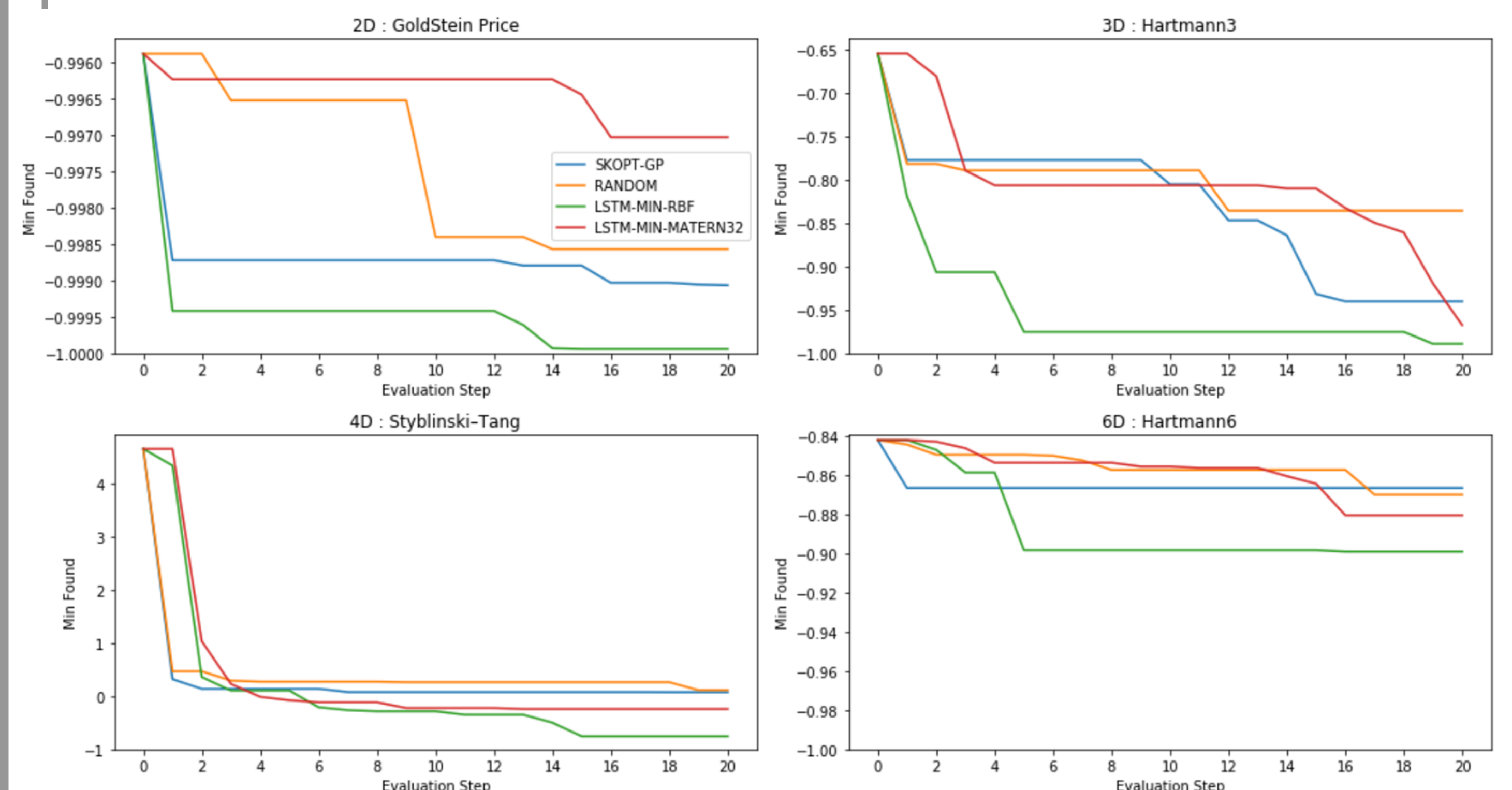
## References

- [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.

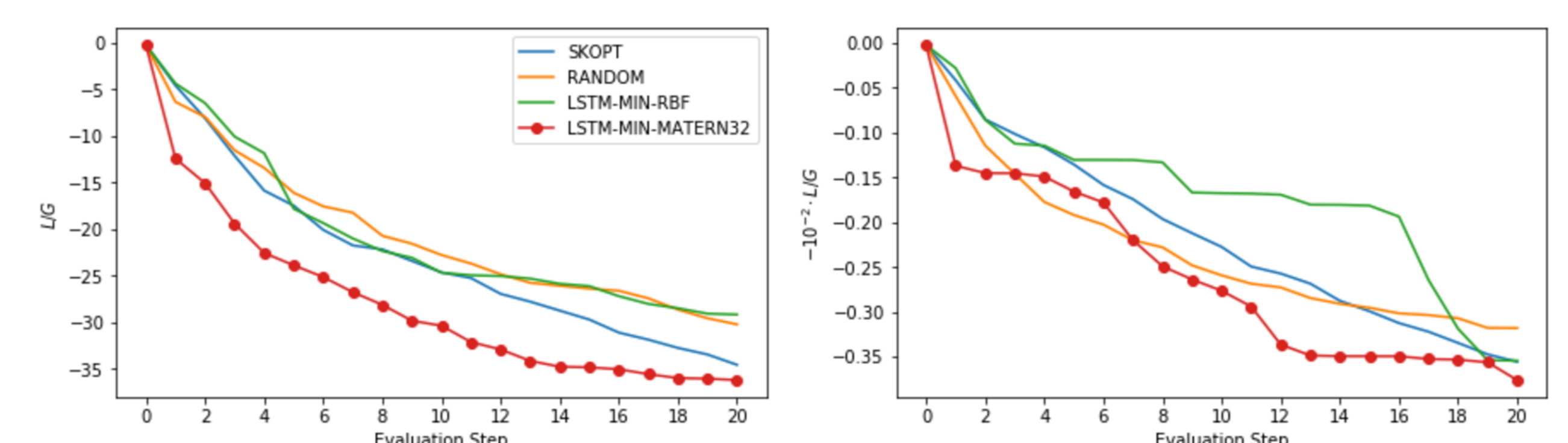
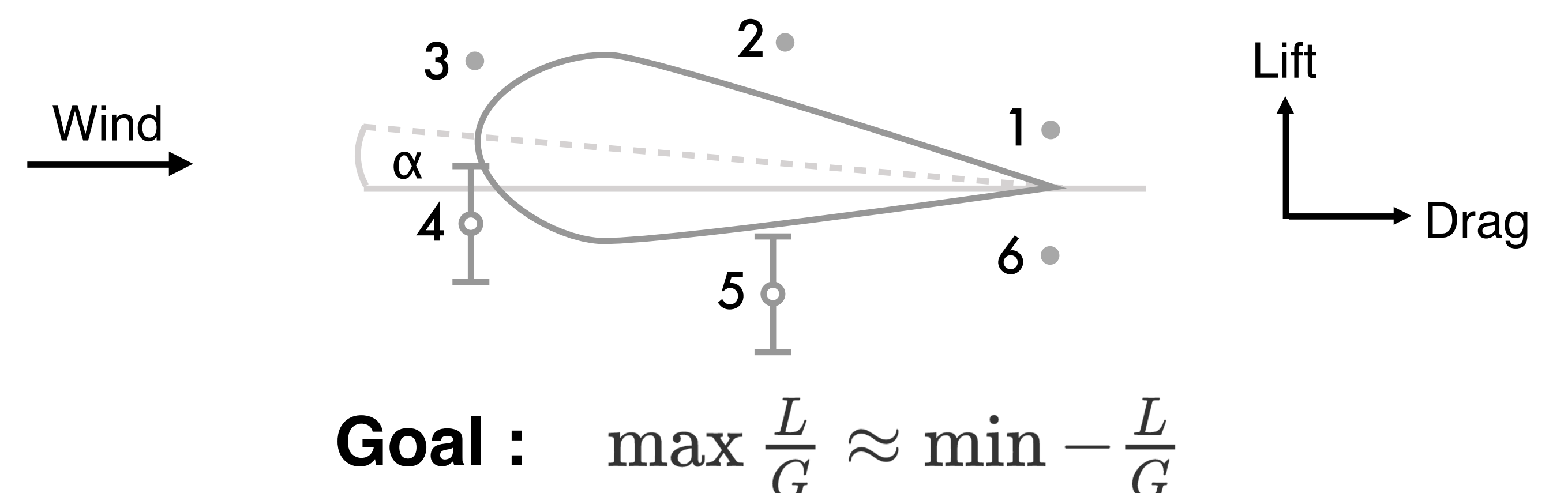
## Results on Test Functions



## Results on Benchmark 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