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Comparing Deep Recurrent Networks Based on the MAE Random Sampling, a First Approach

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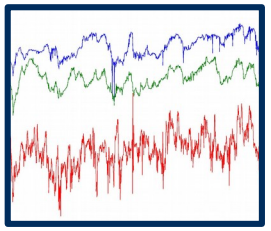
There is no silver bullet



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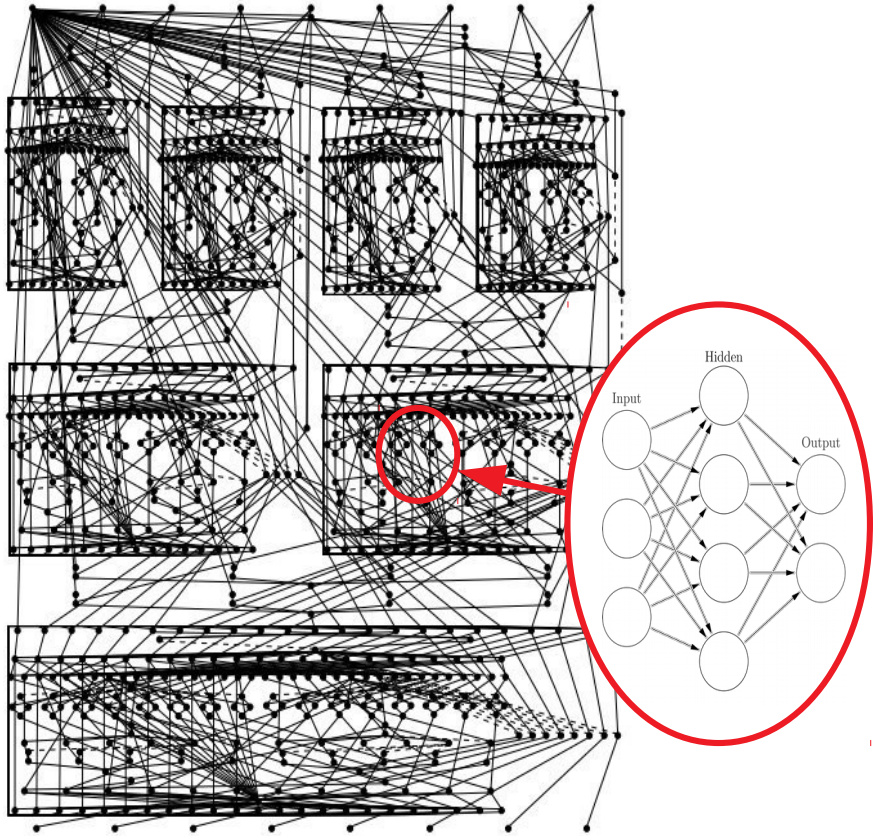
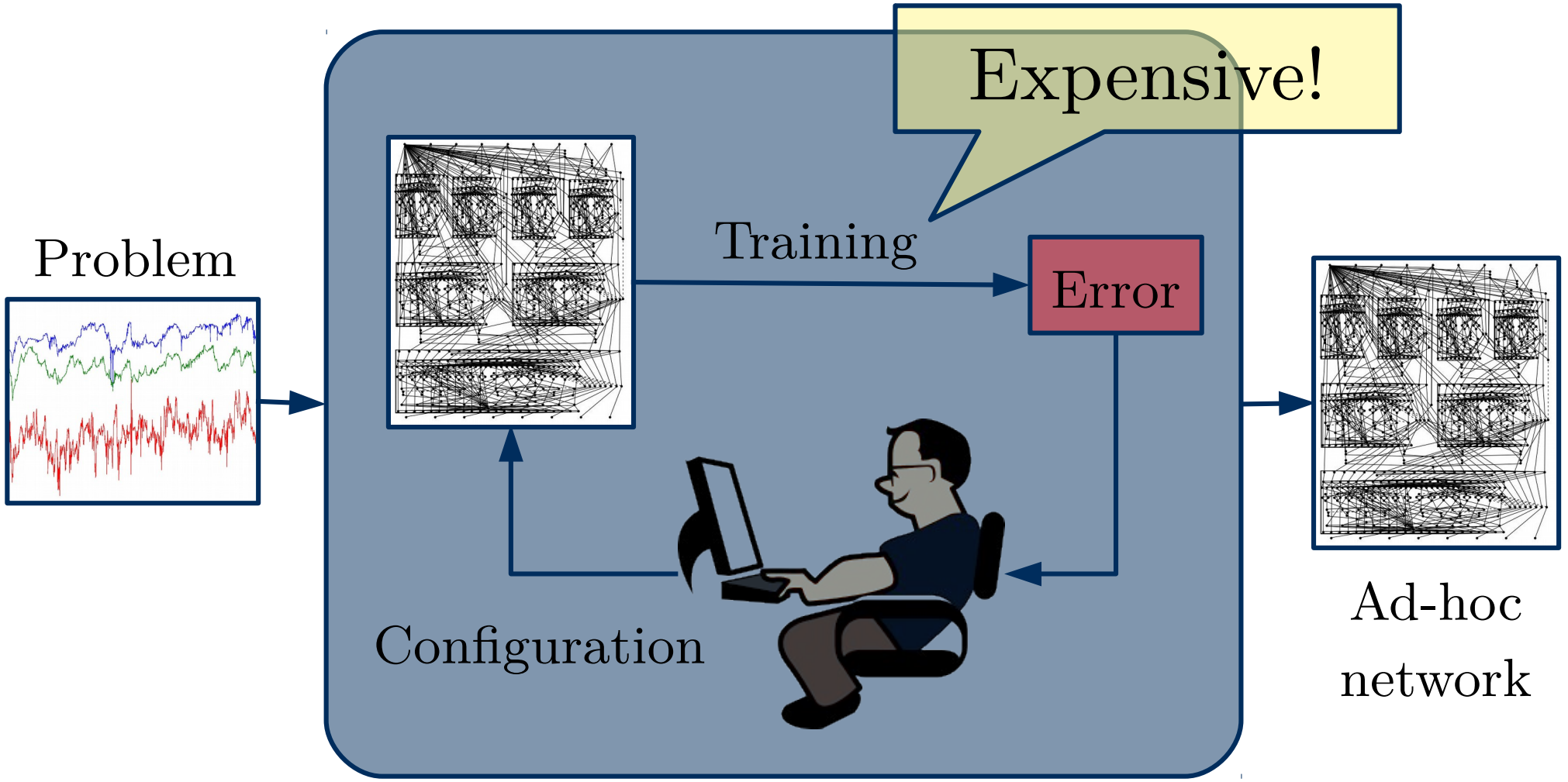
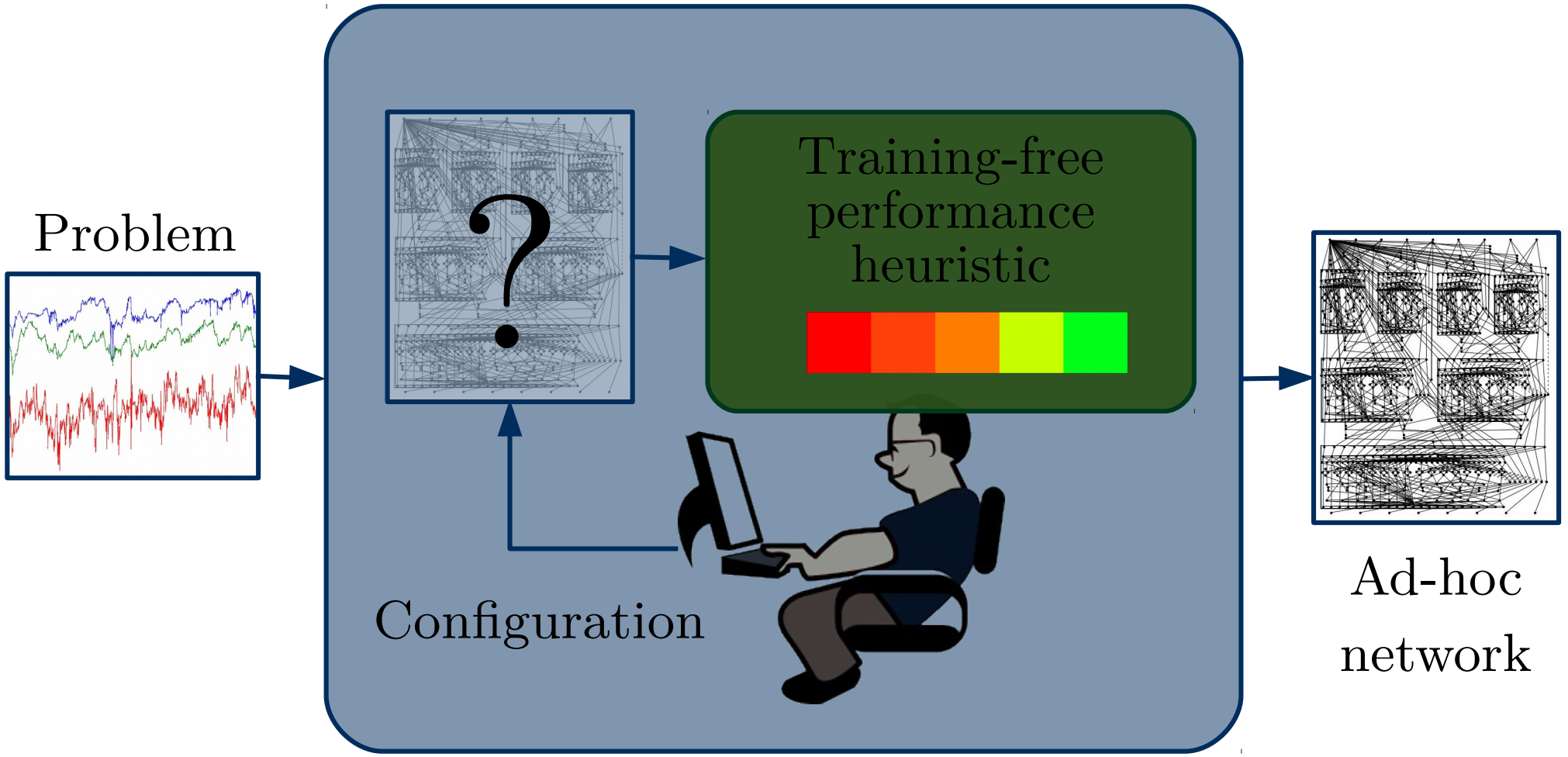


Tailored architectures

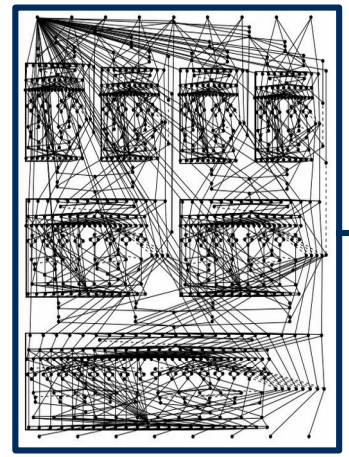


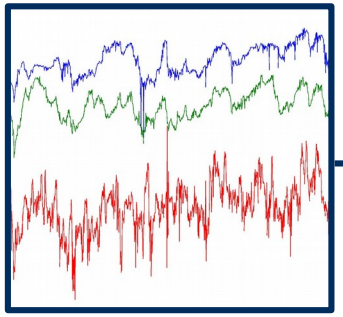
Tailored architectures

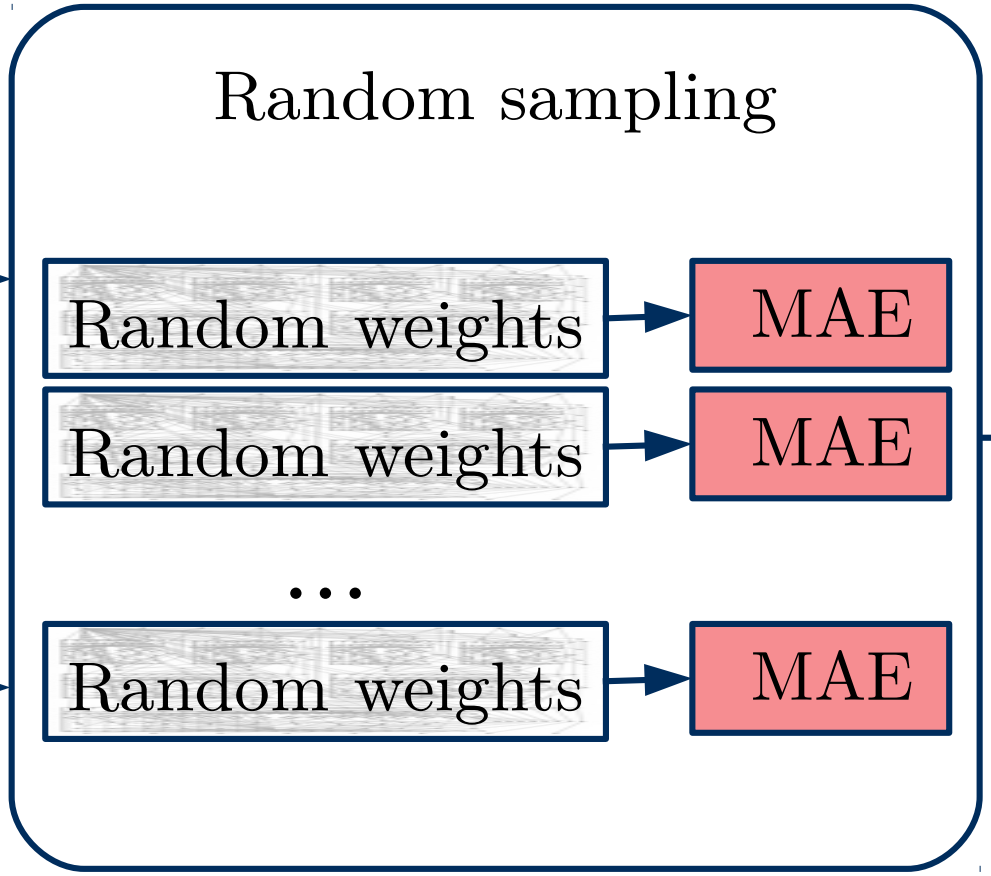


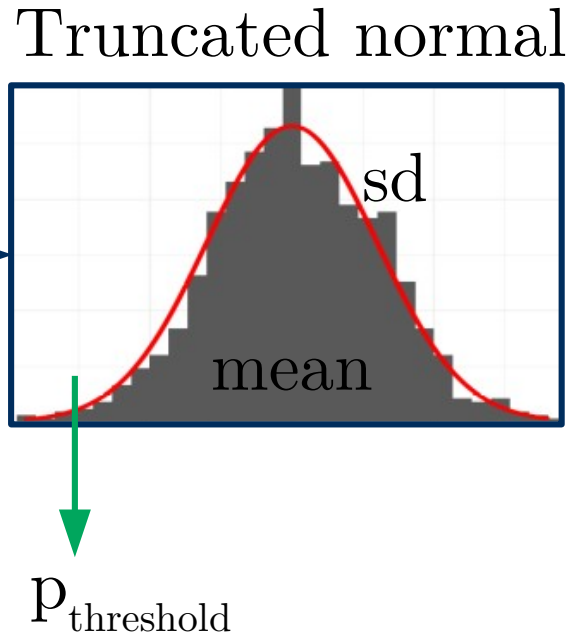
MAE random sampling*

...extended to multiple-hidden-layers





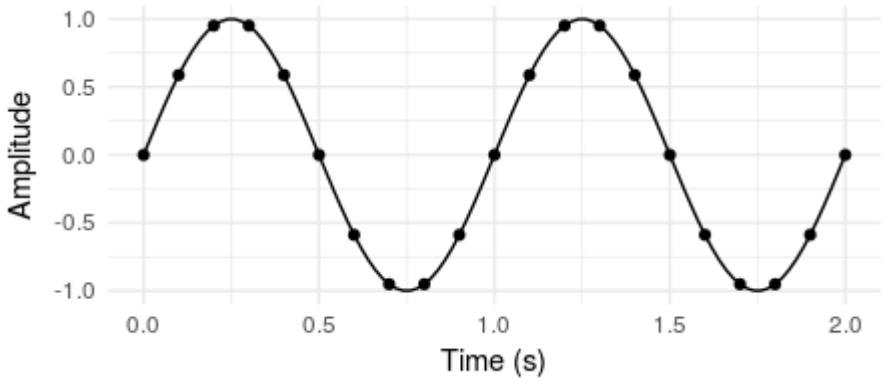




* Camero, A., Toutouh, J., Alba, E.: Low-cost recurrent neural network expected performance evaluation. arXiv preprint arXiv:1805.07159 (may 2018)

The experiment

The problem

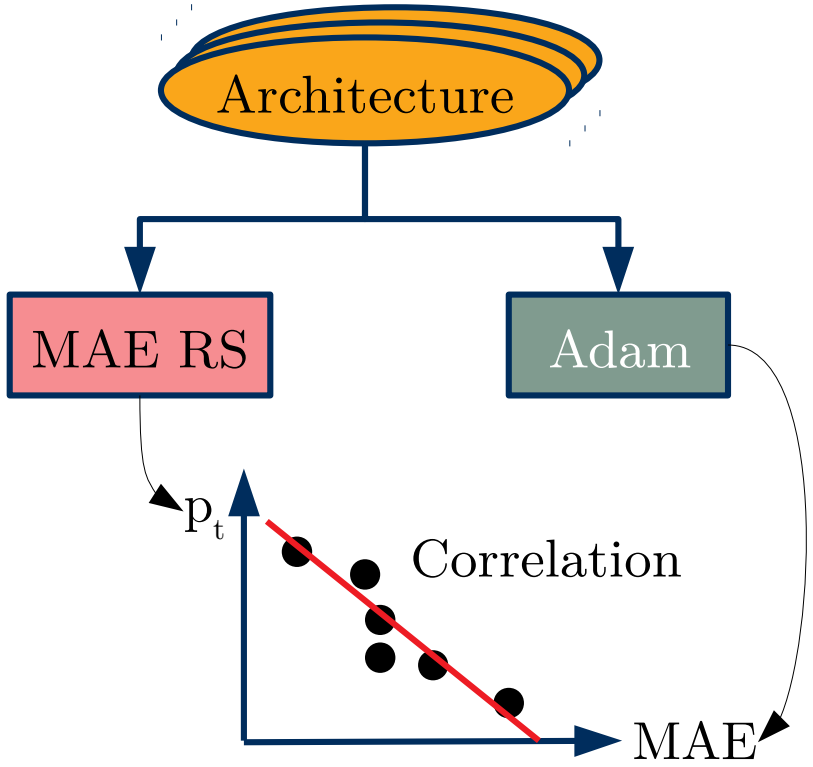


$$y(t) = A \cdot \sin(2\pi \cdot f \cdot t + \phi)$$

The architectures

1, 2 and 3 stacked LSTM layers
+ fully connected *tanh* layer

The comparison



Correlation

	Epochs	Cor Mean	Cor Sd	Cor log $p_{0.01}$
Single stacked LSTM layer	1	-0.447	-0.317	-0.211
	10	-0.726	-0.431	-0.321
	100	-0.790	-0.641	-0.650
	1000	-0.668	-0.458	-0.515
Two stacked LSTM layers	1	-0.086	-0.135	-0.171
	10	-0.450	-0.632	-0.635
	100	-0.709	-0.827	-0.905
	1000	-0.695	-0.843	-0.922
Three stacked LSTM layers	1	-0.334	-0.447	-0.475
	10	-0.546	-0.724	-0.745
	100	-0.720	-0.869	-0.906
	1000	-0.130	-0.873	-0.911

Table 1. Correlation between the MAE (Adam) and the MAE random sampling results.

Memory and time

	Mean time [s]	Sd time	Mean mem [MB]	Sd mem
Adam 1000 epochs	996	0.006	127	6.338
MAE random sampling	6	0.001	150	98.264

Table 2. Time and memory usage comparison

So far...

- ✔ MAE random sampling seems to be a good low-cost, training-free, rule of thumb method for predicting the performance, but...

- ✔ We need more evidence!

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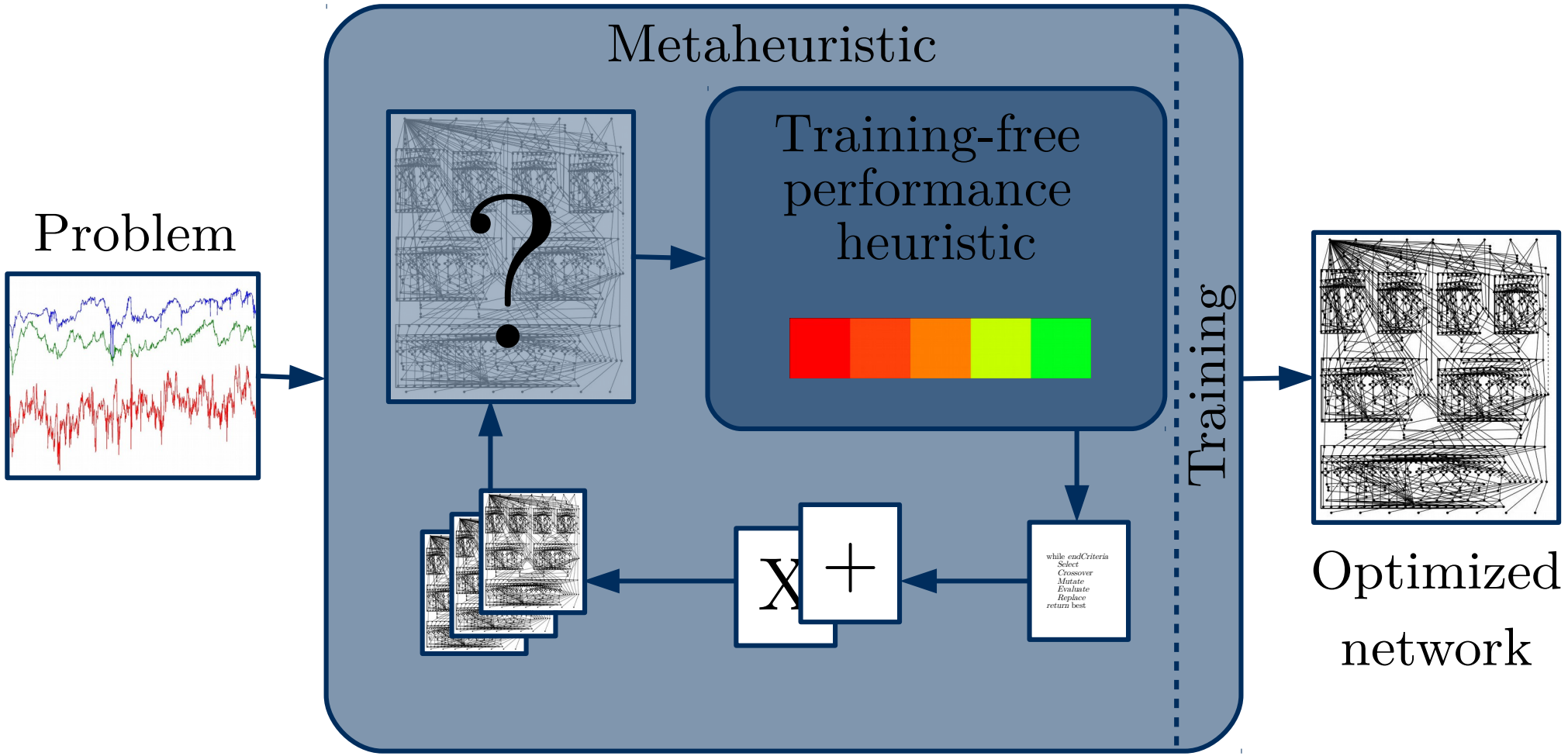
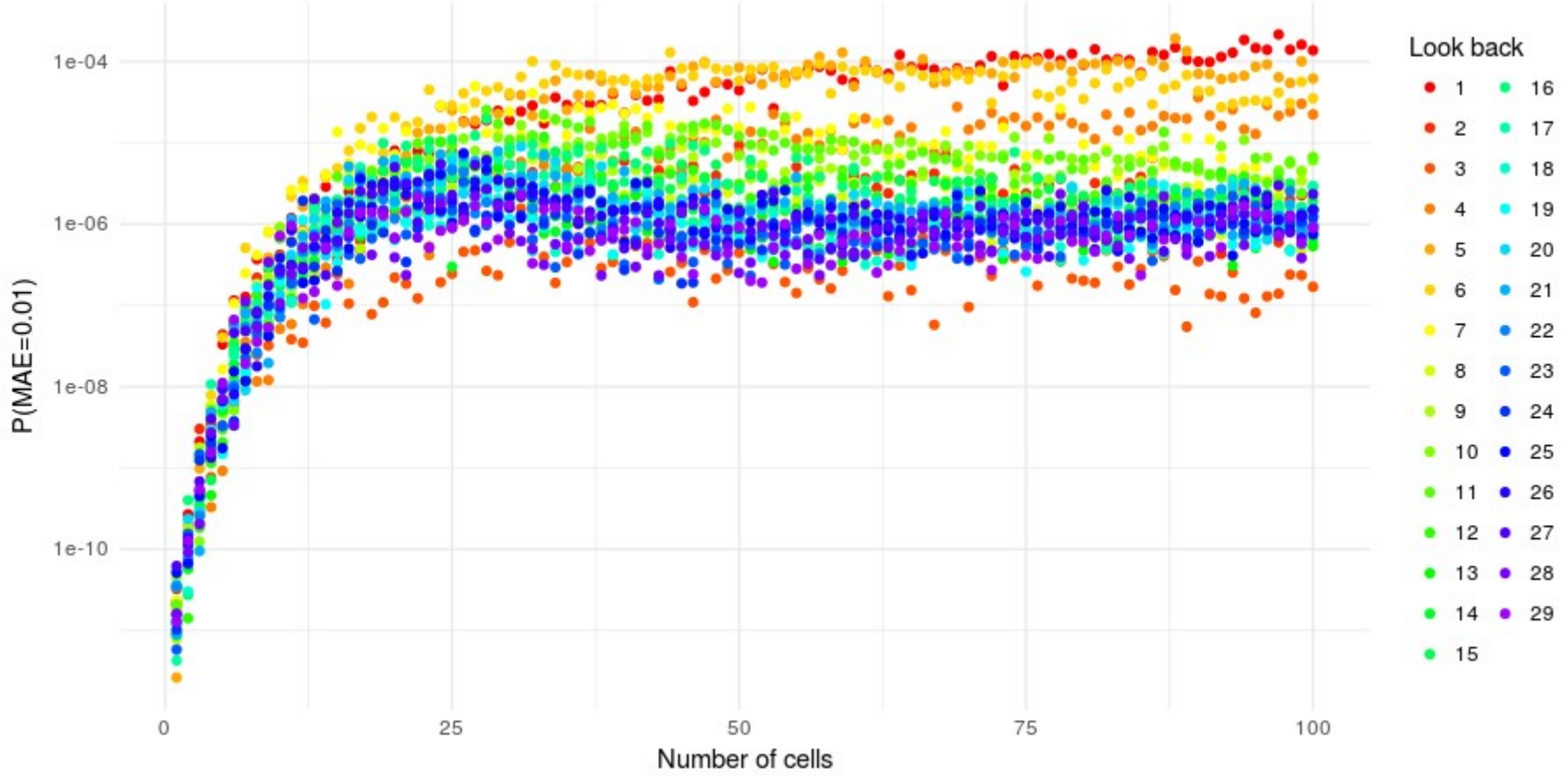
Low cost network optimization



Single stacked LSTM layer



Two stacked LSTM layers