Improving genetic algorithms applied to hyper-parameter optimization using weight merging

The Team





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fitness function

performance and

accelerate optimum search

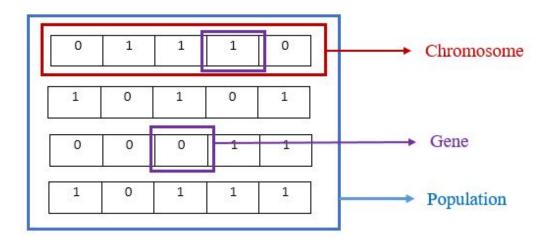
performance of genetic

algorithms applied to HPO?

algorithm's performance

tool that improves this

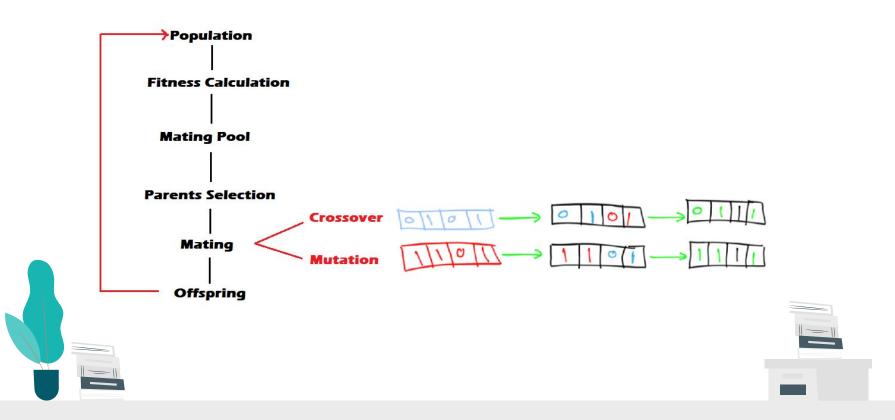
Genetic algorithms







Genetic algorithms



Background

Comparing backpropagation with a GA for NN training

First use of genetic algorithms to train neural networks



NN weight selection using GA

First test of combination of ANN weights (but not merge)

Large-scale evolution of image classifiers

They tried to merge models without success

such choices to others. In a separate experiment, we attempted recombining the trained weights from two parents in the hope that each parent may have learned different concepts from the training data. In a third experiment, we recombined structures so that the child fused the architectures of both parents side-by-side, generating wide models fast. While none of these approaches improved our recombination-free results, further study seems warranted.

Optimizing NN hyper-parameters through an GA

GA successfully applied in HO

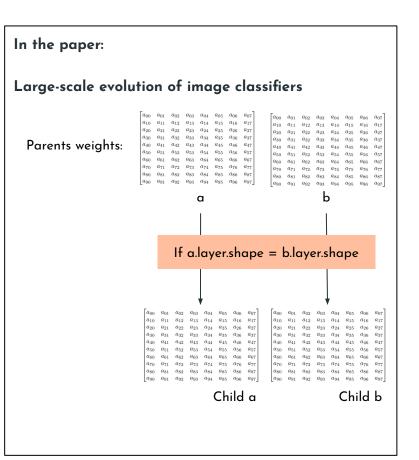


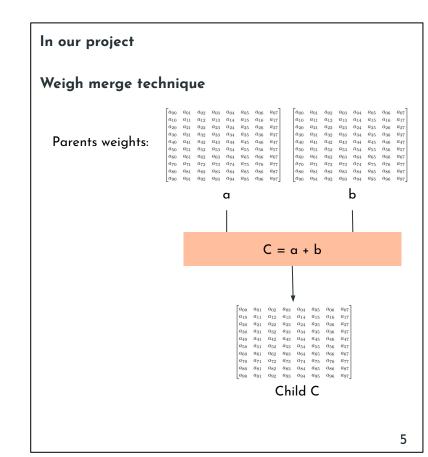
Automatically designing NN using GA for image classification

Efforts should be made to improve fitness functions

several algorithms based on evolutionary computation techniques have been developed. In future, we will place efforts on developing effective evolutionary computation methods to significantly speed up the fitness evaluation of CNNs.

The weight merging technique





Research Methodology

- 2 algorithms per experiment
 - Basic genetic algorithm
 - Genetic algorithm + weight merging
- Collect the duration of each execution of a fitness function
- Compare for each experiment
 - The distribution of the fitness function duration for each algorithm
 - Duration of the entire algorithm
 - Performance of the final model (error/accuracy)



Datasets

volatile citric fixed chlorides acidity acidity acid sugar 7.4 0.70 0.00 1.9 0.076 7.8 0.88 0.00 2.6 0.098 7.8 0.76 0.04 2.3 0.092 3 11.2 0.28 0.56 1.9 0.075 7.4 0.70 0.00 1.9 0.076

MNIST

70,000 handwritten digits

Boston Housing Price

Boston area housing census figures

506 cases, 14 attributes

Wine Quality

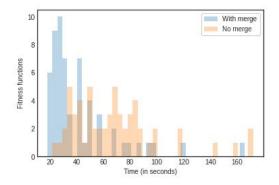
12 attributes of different wines

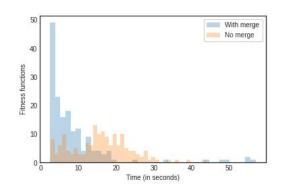
^{*} Y. LeCun, C. Cortes, and C. J. Bruges, "The mnist database of handwritten digits."

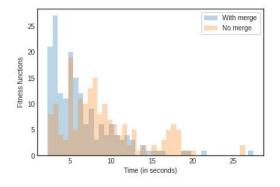
^{**} Harrison, D. and Rubinfeld, D.L. 'Hedonic prices and the demand for clean air', J. Environ. Economics & Management, vol.5, 81-102, 1978.

Results

Dataset	Average time (basic)	Average time (merge)	Time skewness (basic)	Time skewness (merge)	Result (basic)	Result (merge)
Minst	70.7	47.3	1.709575	4.503455	accuracy 0.9641	accuracy 0.9745
The Boston house-price	15.8	7.3	0.231586	1.732404	MAE 3.0085	MAE 3.0086
Wine Quality	9.26	6.65	1.471797	2.675971	MAE 0.4493	MAE 0.4804







MNIST

Boston housing price

Wine Quality

Analysis

Results from weight merging method indicate:



No negative impacts on performance (accuracy and mean errors)



Reduces the average training time by at least 25%*

^{*} With the tested datasets

Conclusion and future work





Weight merge effective in preserving training data in GA

Layer shape is not an obstacle to the implemented technique

Distributed learning. Merge weights trained with different chunks of data

Conv. layers or RNN with weights matrices of different dimensionality

Questions?

