TRAINING A MULTILAYER PERCEPTRON TO PREDICT A CAR SPEED IN A SIMULATOR

COMPARING RPROP, PSO, BFGS AND A MEMETIC PSO-BFGS HYBRID

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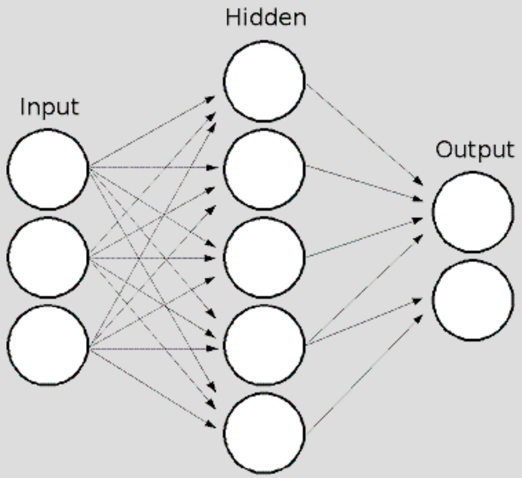
CONTEXT
PREDICTIVE CAR CONTROL IN A RACE

- The Open Racing Car Simulator (TORCS)
- Simulated Car Racing Championship
- Model-based predictive control (MPC)
- State estimation
- Approximation of physical behavior of a simulated car

In-game screenshot

NEURAL NETWORKS
TRAINING METHODS

- Feedforward Multilayer Perceptron (MLP)
- Backpropagation
- RPROP
- Bio-inspired computing
  - Swarm Intelligence



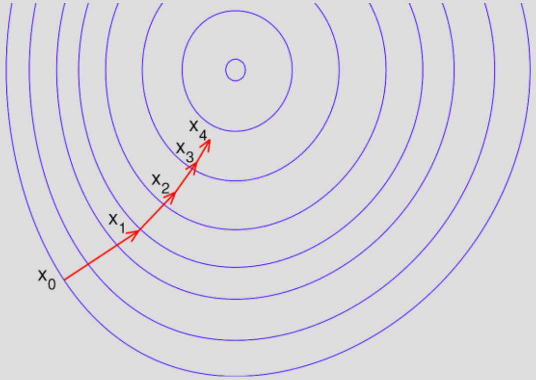
MLP example
(opencv.org)

NEURAL NETWORKS
PARTICLE SWARM OPTIMIZATION

- Flock behavior
- Particles represent sets of synaptic weights
- Particles explore the search space by “flying” over it
  - Velocity determined by personal and populational best positions
- Switches from global to local search
  - Not as effective after approaching local minima

NEURAL NETWORKS
HYBRIDIZATION

- Distinct methods have different pros and cons
- Combination of methods increases complexity
  - Successful hybridizations offer sufficiently increased quality as well
- Memetic approach
  - Population-based global search method combined with a local search method
  - PSO with quasi-Newton method BFGS – two approaches:
    - Full run of PSO followed by full run of BFGS
    - PSO and BFGS alternate after a number of iterations

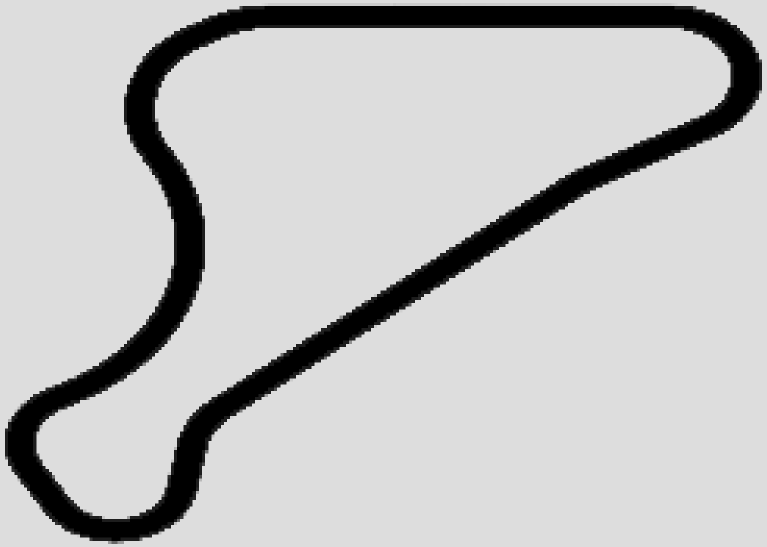


Local search by gradient descent

EXPERIMENT
DATA

- *SnakeOil* framework
- Data abstraction
  - Sensors: current longitudinal and transversal speeds
  - Actuators: throttle, brake, and steering wheel
- Model must predict variation of X and Y speeds for $t + 1$
- Simulator works at 50Hz
  - Data set subsampled to 5Hz to reduce correlation between current and future speeds

EXPERIMENT
TRACKS AND TERRAINS



cgspeedway1
Tarmac
No elevations

Dirt 3
Dirt
Various jump sections

EXPERIMENT
CODING

- R programming language
- Neural network and RPROP from *neuralnet* package
  - Uses error derivative threshold as stopping criterion
- BFGS from *optim* function
- PSO and variants from scratch
  - Canonical PSO
  - Canonical PSO with population restart
  - Memetic PSO (MPSO)
  - Memetic PSO with Return (MPSOR)

EXPERIMENT SETTINGS

- Neural network and RPROP configuration
  - RPROP as baseline for best configuration and stopping criterion
    - Stopping criteria for all other methods
      - Best RPROP validation error (with derivative threshold 0.01)
      - Maximum number of iterations
  - Two linear output neurons (X and Y speeds)
  - Two logistic hidden neurons

EXPERIMENT
STEPS

- 30 independent runs of RPROP
  - Best validation error set as stopping criterion for other methods
- 30 independent runs of other methods
  - BFGS (1000 iterations through *optim*)
  - PSO & PSOr (5000 iterations)
  - MPSO (500 PSO + 1000 BFGS iterations)
  - MPSOR (500 PSO with 100 BFGS for each 50 PSO iterations without improvement)

EXPERIMENT RESULTS

- Most differences were significative for the Wilcoxon rank sum test ($\alpha = 5\%$)
- Detailed results are available in the paper

Table 3: Test errors in *cgspeedway1*. PSO with restart (PSOr), Memetic PSO (MPSO), and Memetic PSO with Return (MPSOR).

	RPROP	BFGS	PSO	PSOr	MPSO	MPSOR
Average	0.003996	0.263675	0.110572	0.023097	**0.003845**	0.003951
Std. Dev.	0.000764	0.319624	0.054253	0.021826	0.000823	**0.000662**
Median	0.004071	0.255030	0.094894	0.012584	**0.003704**	0.003856

Table 4: Training times (in seconds) in *cgspeedway1*.

	RPROP	BFGS	PSO	PSOr	MPSO	MPSOR
Average	**32.69**	110.15	310.46	306.75	92.31	90.41
Std. Dev.	7.98	19.69	**3.53**	4.95	16.97	25.66
Median	**33.57**	119.93	311.20	308.1	90.60	94.03

EXPERIMENT RESULTS

- Most differences were significative for the Wilcoxon rank sum test ($\alpha = 5\%$)
- Detailed results are available in the paper

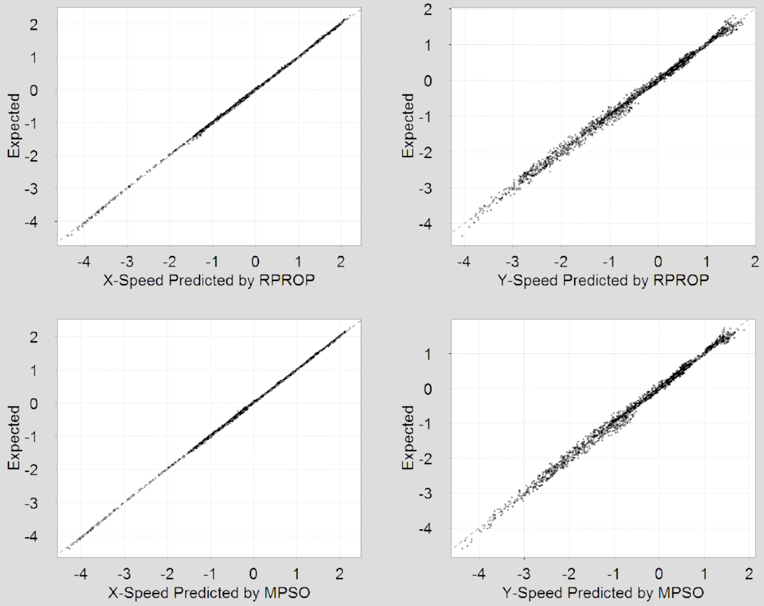
Table 5: Test errors in *Dirt 3*.

	RPROP	BFGS	PSO	PSOr	MPSO	MPSOR
Average	0.004057	0.307323	0.123548	0.027718	**0.003827**	0.100128
Std. Dev.	0.003257	0.329420	0.032478	0.029732	**0.002423**	0.2112
Median	0.002779	0.288398	0.120994	0.017652	0.003061	**0.002431**

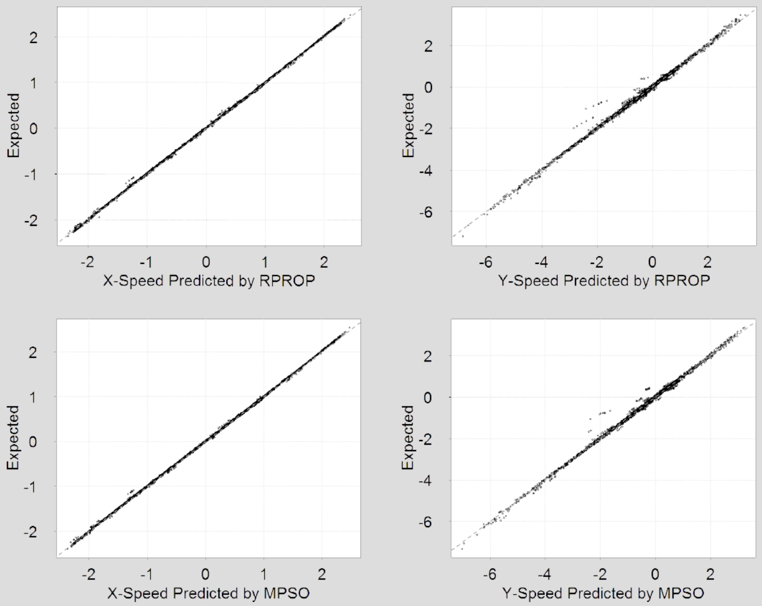
Table 6: Training times (in seconds) in *Dirt 3*.

	RPROP	BFGS	PSO	PSOr	MPSO	MPSOR
Average	**119.68**	180.62	458.54	467.56	152.48	130.55
Std. Dev.	60.72	16.70	**3.07**	4.35	25.42	47.78
Median	**103.08**	186.43	459.12	468.70	150.54	142.72

EXPERIMENT RESULTS



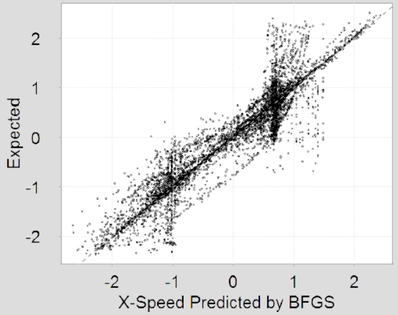
cgspeedway1

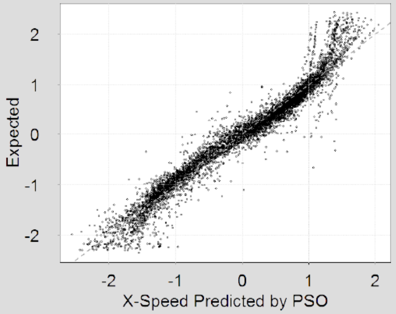


Dirt 3

EXPERIMENT RESULTS

- Prediction issues
  - Vertical lines and clusters in BFGS; may be caused by small weights and a dominance of such values in the data set
  - PSO and PSOr present curvilinear plots; may be limited outputs because of insufficient weights





Dirt 3

EXPERIMENT
CONCLUDING REMARKS

- The hybrid approach is able to compete result-wise with RPROP
  - It’s slower, but this may be improved by using a more efficient implementation in C, for example
  - It’s better and faster than its parts
- PSO never reached the main stopping criterion before reaching its iteration limit
  - Populational purge, which improved its results, was not enough
- Feedforward MLP was able to approximate the behavior of the vehicle
- Future works will focus on improving both global and local search methods and using faster programming languages

THANK YOU!

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