

# Selfish vs. Global Behavior Promotion in Car Controller Evolution

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MACHINE  
LEARNING  
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- 1 Scenario and motivation
- 2 Problem and approach
- 3 Experiments

# Cooperation and goals

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Should the fitness award **selfish** or **global** behavior?

# Global vs. selfish behavior

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Global behavior

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## Global behavior

- + captures the actual degree of achievement
- long to compute: simulate the full system with many agents

## Selfish behavior

- + “fast” to compute: simulate just one agent
- a proxy for the actual degree of achievement: how to choose?

# An example

Road traffic system:

- Agents: car drivers
- System goal (two-fold):
  - reaching targets (efficiency)
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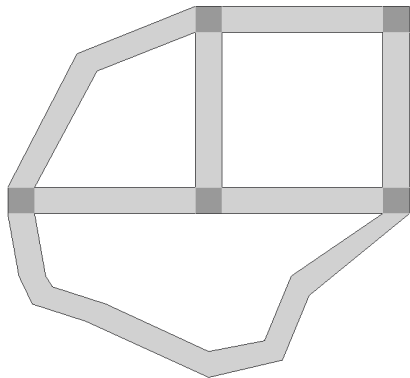
Global or selfish fitness while evolving a cooperative driver?

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# World

- 2D continuous space, discrete time world
- road (section, intersection), off-road
  - cars move on road only
  - cars collide with other cars and with road side

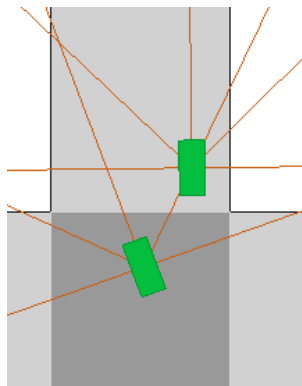




# Car and agents

Car:

- each w/  $5 \times 3$  distance sensors
  - to roadside
  - to intersection
  - to other cars



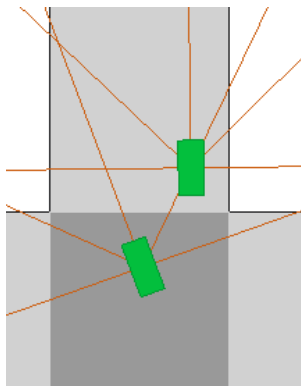
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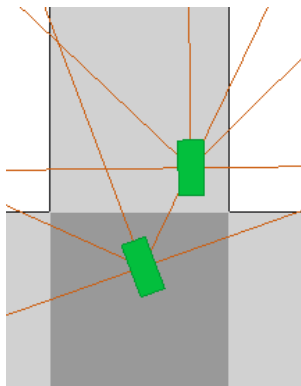
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## Agent (car driver/controller):

- assigned to sequence of targets
  - subsequent targets on adjacent road sections
- neural network
  - input:  $5 \times 3$  distance sensors, car speed, distance to target, direction of target
  - output: steering angle, acceleration/brake



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Maximize traffic **efficiency** and **safety**

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- Efficiency: the global number of reached targets in the unit of time

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- Safety: (opposite of) the global number of collisions in the unit of time

$$S = -\frac{1}{n_{\text{car}}} \sum_{j=1}^{n_{\text{car}}} \frac{c_j}{\tau}$$

# Neuroevolution of the agents

Goal: evolve a the driver which maximizes, on average, traffic efficiency and safety

We used NEAT

# Neuroevolution: global

- individual: controller
- fitness:
  - $f_{\text{glob}} = 100E + 0.1S$
  - $n_{\text{sim}}$  simulations with  $n_{\text{car}}$  each, **all with the same controller** under evaluation



# Neuroevolution: selfish

- individual: controller
- fitness:
  - $f_{\text{self}} = 100E_{\text{self}} + 0.1S_{\text{self}}$

$$E_{\text{self}} = \frac{1}{\tau} \left( t + 1 - \frac{I^f}{I^i} \right) \qquad S_{\text{self}} = -\frac{C}{\tau}$$

- the controller under evaluation inserted in  $n_{\text{sim}}$  simulations with other  $n_{\text{car}} - 1$  **different controllers**

# Global vs. selfish

## Global

- one simulation to assess one controller

## Selfish

- one simulation to assess  $n_{\text{car}}$  controllers at once, but on a proxy of their actual goal

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## Two stages

### Evolution:

- $n_{\text{sim}} = 3$ ,  $n_{\text{car}} = 20$ ,  $\tau = 30$  s (simulated)
- 10 runs, same wall time (24 h) per run for both approaches

### Validation of best evolved controllers (10 + 10):

- $n_{\text{sim}} = 10$ ,  $n_{\text{car}} = \{5, \dots, 50\}$ ,  $\tau = 60$  s (simulated)

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- homogeneous vs. heterogeneous
  - homogeneous: all cars driven by the same evolved controller
  - heterogeneous: 50% of cars driven by random (unskilled) controllers

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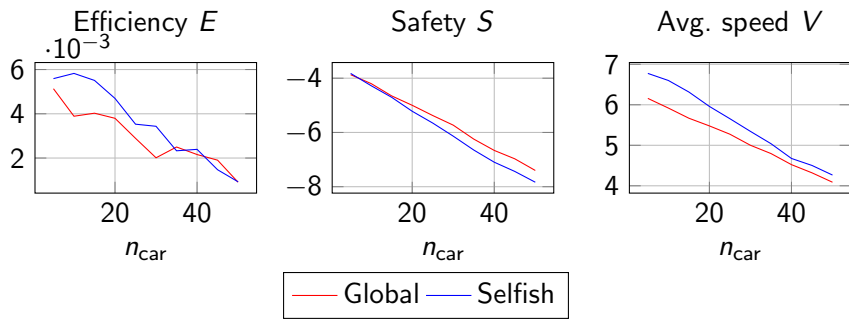
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  - range of  $n_{\text{car}}$   $\rightarrow$  “robustness” of evolved controllers to traffic conditions
- homogeneous vs. heterogeneous
  - homogeneous: all cars driven by the same evolved controller
  - heterogeneous: 50% of cars driven by random (unskilled) controllers
  - “robustness” of evolved controllers to other driving behaviors

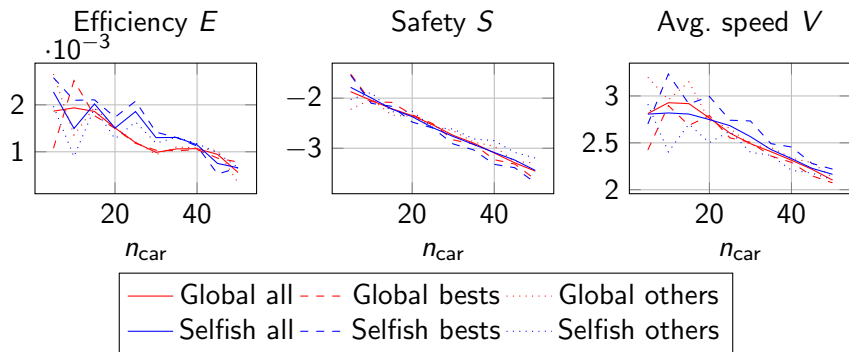
# Homogeneous validation



- In general: the heavier the traffic, the lower efficiency and safety
- Trade-off between efficiency and safety: selfish are more efficient, less safe (reasonable)
- Selfish better with light traffic: more capable of “driving alone”
- Selfish always drive faster



# Heterogeneous validation



- Fuzzier difference
- With medium traffic: selfish more efficient, equally safe  $\rightarrow$  robust to presence of unskilled drivers?

# Conclusions

In cooperative tasks tackled with neuroevolution:

- selfish-based fitness may replace global-based fitness
- opportunity for robustness
- how to choose a proper selfish-based fitness?

Thanks!