

# HACKATHON: LECTURE

## Optimization and Machine Learning for Automated Cars

Prof. Dr. habil. Vadim Azhmyakov

**DOCET TI**  
and  
**National Research University Higher School of Economics**  
**Moscow, Russia**

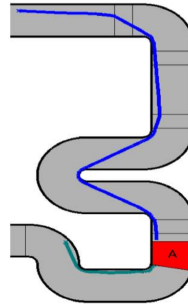
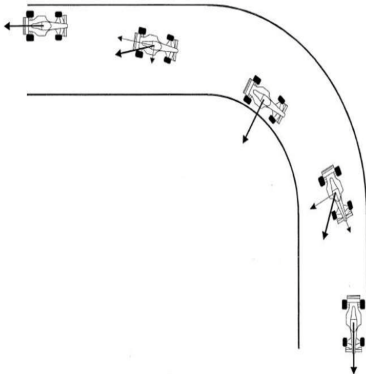
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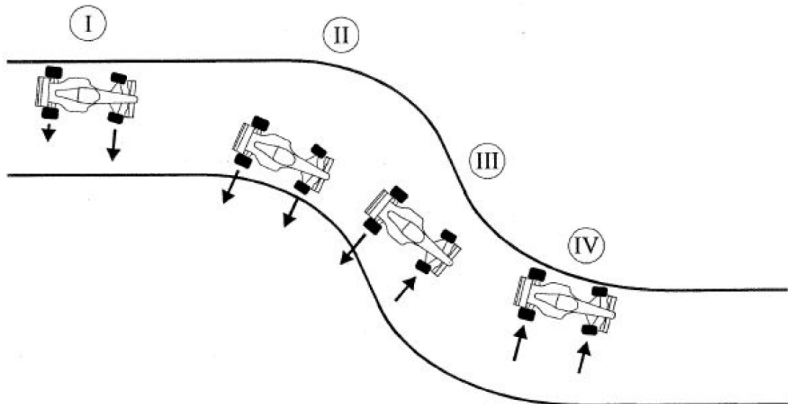
# Introduction: Optimization and Automated Automotive Industry

how to follow the given track as fast as possible?



# Introduction: Optimization and Automated Automotive Industry

a closer tracking during a curvy maneuver  $\Rightarrow$  loss of the velocity



# Introduction: Optimization and Automated Automotive Industry

## two main challenges in automotive development

- Modern automated (intelligent) cars;
- Machine Learning (ML) algorithms for the trajectory optimization (smart driving).

## types of the optimization approaches

- A priori - an optimal path finding = classic optimization;
- Real-time feedback-based optimization = Reinforcement Learning (RL).

Obstacle avoidance! Best reference trajectory tracking! Minimum driving time (maximum average speed)!

# RL as an Optimization Algorithm

## mathematical model of a racing car

**State** :  $\xi := (x, y, \psi, v)^T$ , Euclidean coordinates  $(x, y)$ ,  
 car orientation  $\psi$ , velocity  $v$ ,

**Action** (control) :  $u := (\delta, d)^T$  steering angle  $\delta$ , duty cycle of the motor  $d$ ,

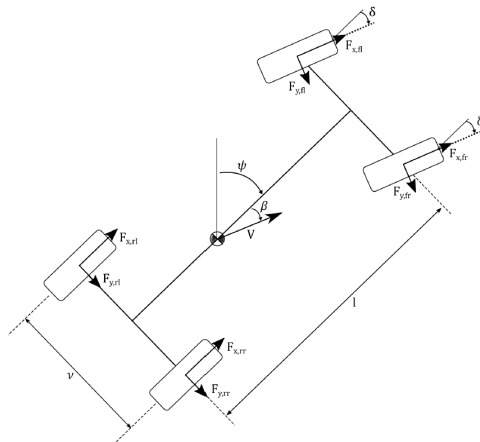
**Environment** (dynamic system) :  $\dot{\xi}(t) = f(\xi(t), u(\cdot))$ ,  $\xi(0) = \xi_0 \in \mathbb{R}^4$ ,  
 (1)

where

$$f(\xi, u) := \begin{pmatrix} v \cos \psi \\ v \sin \psi \\ \frac{1}{L} \delta v \\ (C_1 - v C_2) d - C_d v^2 - C_r - C_\delta \delta^2 v^2 \end{pmatrix}$$

# RL as an Optimization Algorithm

## a more sophisticated car model



# RL as an Optimization Algorithm

## a simplified mathematical model (kinematics) for data simulation

$$\begin{aligned} \text{state : } \xi &:= (x, y)^T, \text{ action : } u := (v, \psi)^T, \\ \text{kinematic environment :} & \\ \dot{x}(t) &= v \cos \psi, \quad x(0) = x_0 \in \mathbb{R}, \\ \dot{y}(t) &= v \sin \psi, \quad x(0) = y_0 \in \mathbb{R}. \end{aligned} \tag{2}$$

## the concept **Reward of Stage** (objective)

$$R(\xi(t), u(\xi(t))) := v(t) \cos \psi(t) - w_1 v(t) \sin \psi(t) - w_2 g^2(x(t), y(t)),$$

where  $(\xi, u)^T$  is the state-action pairs,  $w_j, j = 1, 2$  are weights associated with the Reward terms and  $g(x, y) = 0$  is the reference trajectory (set point) for a given smooth function  $g(\cdot)$ . The Reward should not only encourage high speed along the track, but also punish speed vertical to the track as well as deviation from the track.



# RL as an Optimization Algorithm

reward optimization, Q-equation, learning, training, ...

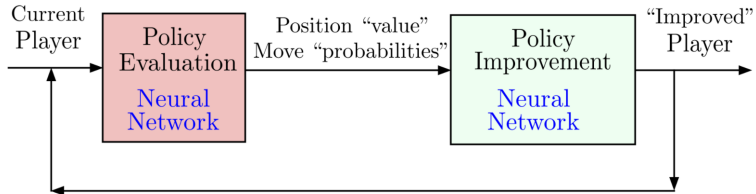
$$\text{minimize } \sum_{t \in [0, t_f]_G} R(\xi(t), u(\xi(t))) \quad (3)$$

$$\begin{aligned} \mathbf{Q} - \mathbf{equation} : \quad & Q(\xi(t), u(\xi(t))) = R(\xi(t), u(\xi(t))) + \\ & \alpha \max_{u_{t+1}(\xi)} Q(\xi(t+1), u(\xi(t+1))). \end{aligned} \quad (4)$$

solution  $Q^{opt}(\cdot)$  of (4)  $\Rightarrow$  policy iteration  $u^{opt}(\xi(t+1))$ .

# Python for Optimization and ML

the ML solution to the Q-equation (4) The essence of Deep Q-Learning is the estimation of  $Q^{opt}(\xi, u)$  using a type of neural network called a Deep Neural Network (also Q-Network) (DNN) parameterized by a specific vector  $\theta$ . A "training" is used for the numerical definition of this parameter vector  $\theta$ .



# Python for Optimization and ML

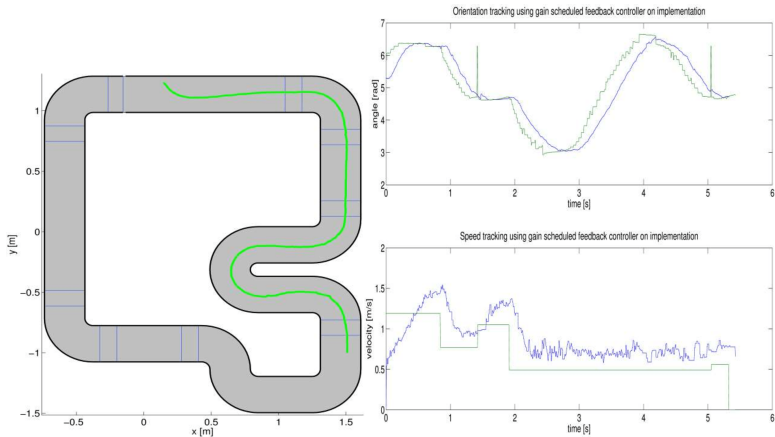
## the Python RL frameworks

OpenAI Gym, Keras (rl.agents, KerasRL), PyTorch, Pyqlearning, TensorFlow (Tensorforce), RLCoach, TFAgents, RLlib and others.

## the Python optimization packages

scipy.optimize (unconstrained and constrained optimization),  
scipy.optimize.minimize and others.

# Some Computational Results



# THANKS!