自动驾驶课程大作业介绍

自动驾驶方向题目

基于udacity仿真器实现基于深度强化学习的高速路超车换道功能

状态表征：可以基于图像，也可基于仿真器读取的低维信息(速度，距离等)

动作空间：可以选择高层决策动作(直行，左右换道)，也可以直接控制油门/方向盘

提交形式：demo+可运行代码+大作业报告
（可参考科研论文形式，需要有过程分析）

代码：https://github.com/DRL-CASIA/Autonomous-Driving/tree/master/decision-making-CarND

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要求：

- 尽可能少的发生碰撞；
- 除了换道时，要保持在车道线内平稳行驶；
- 速度不超过50mph（接近50mph最好）；
- 有前车阻挡时，能够尝试安全换道；
- 加速度不超过10m/s2；
- 加加速度（急动度）不超过10m/s3。

性能评估指标：

- 安全率：无碰撞完整跑完赛道次数/6次测试圈数
- 平均行驶速度
- 平均换道次数
- 平均行驶英里数

https://github.com/martonistvan/CarND-Path-Planning-Project-master

自动驾驶课程大作业介绍

环境配置： ubuntu16.04

CarND-test	add files
decision-making-CarND	add files
term3_sim_linux	add files
LICENSE	Initial commit
README.md	add files
environment.yaml	add files

程序环境依赖在environment.yaml

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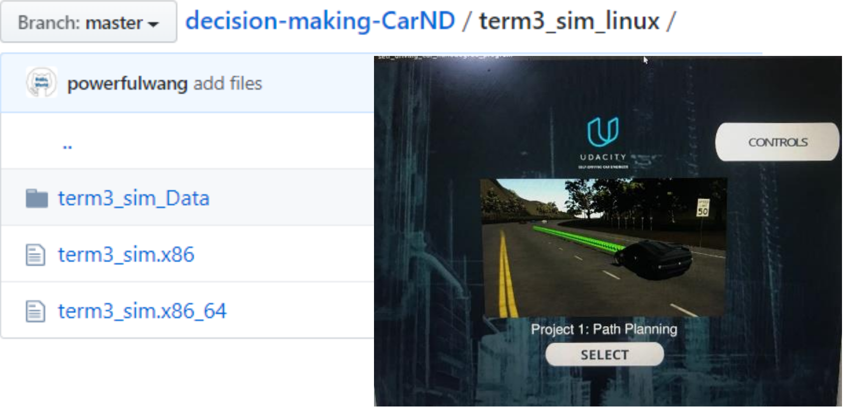
仿真器



在终端界面运行 sudo ./term3_sim.x86_64

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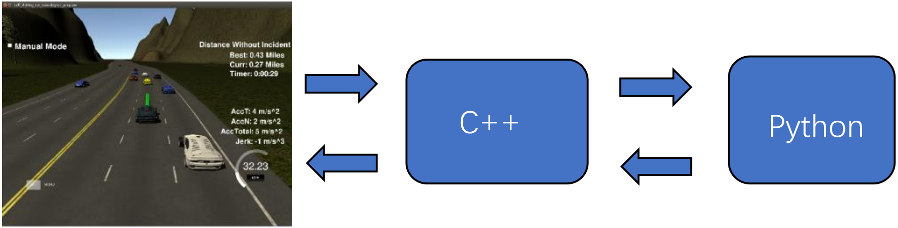
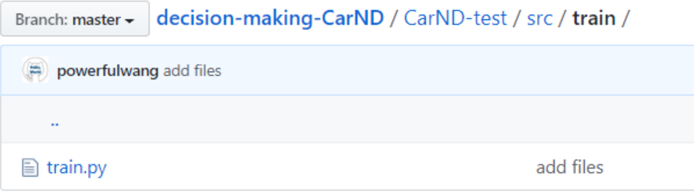


仿真器　　速度控制及路径生成　　DQN换道决策

- 速度控制基于简单的规则
- 换道决策基于DQN
- 仿真器与C++之间的通讯通过uWebSockets(已封装好)

编写程序



在CarND/src/train文件夹下运行补充你的train.py文件

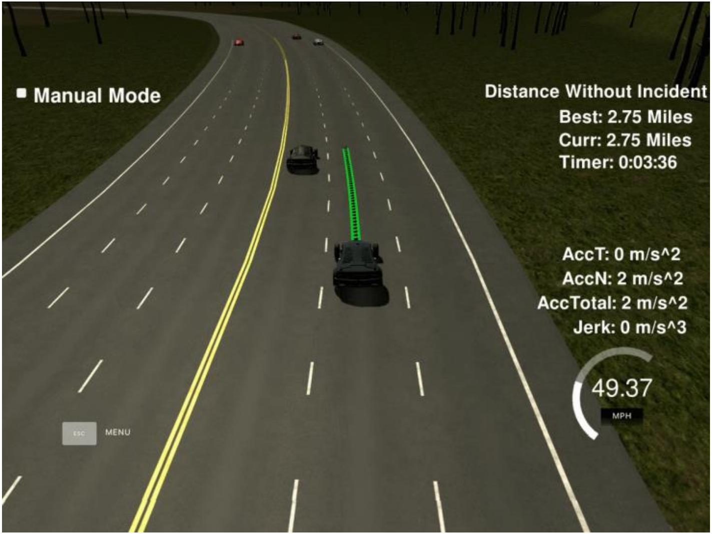
train.py文件使用的是栅格表征为输入，高层决策指令为输出的DQN Agent

基本要求是在train.py中补充完整各组的DQN Agent

在一个新的终端界面运行train.py文件进行训练，训练完成后固定模型测试

课程大作业介绍

Demo片段



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无人驾驶换道超车

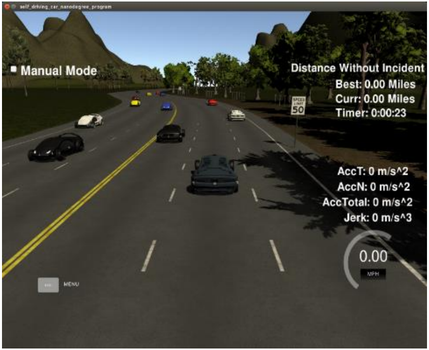
https://github.com/udacity/self-driving-car-sim/releases/tag/T3_v1.2

自动驾驶课程大作业介绍

端到端方案的状态输入：

以当前驾驶员视角的图像作为网络输入

或者以连续历史帧图像作为输入



端到端方案的动作输出：

方向盘转角 （离散/连续）
油门刹车控制量
（离散/连续，纵向速度控制不做要求）

- 需要有较强的算力
- 对算法设计能力要求比较高

自动驾驶课程大作业介绍

模块化方案1的状态输入：

低维状态

s_1		Agent1	
s_2	a_1	Stay in current lane	
	a_2	Change lanes to the left	
s_3	a_3	Change lanes to the right	
s_{3i+1}		Agent2	κ
s_{3i+2}	a_1	Stay in current lane, keep current speed	
	a_2	Stay in current lane, accelerate with -2 m/s^2	ego vehicle
	a_3	Stay in current lane, accelerate with -9 m/s^2	go vehicle
s_{3i+3}	a_4	Stay in current lane, accelerate with 2 m/s^2	ehicle
	a_5	Change lanes to the left, keep current speed	vehicle
	a_6	Change lanes to the right, keep current speed	go vehicle

模块化方案1的动作空间：

行为决策指令：-1(向左换道)，0 (保持当前车道)，1(向右换道)

Hoel et al, Automated Speed and Lane Change Decision Making using Deep Reinforcement Learning, 2018.

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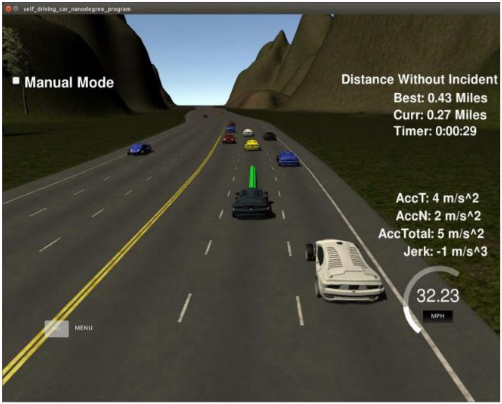
模块化方案2的状态输入：

栅格化地图



−0.35724575	1.0	1.0
1.0	1.0	1.0
1.0	−0.32895369	1.0
1.0	−0.32895369	1.0
1.0	−0.32895369	1.0
1.0	−0.32895369	1.0
1.0	1.0	1.0
1.0	1.0	−0.33921215
1.0	1.0	−0.33921215
1.0	1.0	−0.33921215
−0.33914119	1.0	−0.33921215
−0.33914119	1.0	1.0
−0.33914119	1.0	1.0
−0.33914119	−0.35665066	1.0
1.0	−0.35665066	1.0
1.0	−0.35665066	1.0
1.0	−0.35665066	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	−0.38066016
1.0	1.0	−0.38066016
1.0	1.0	−0.38066016
1.0	1.0	−0.38066016
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	0.3306313	1.0
1.0	0.3306313	1.0
1.0	0.3306313	1.0
1.0	0.3306313	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	−0.41660752
1.0	1.0	−0.41660752
1.0	1.0	−0.41660752
1.0	1.0	−0.41660752
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0
1.0	1.0	1.0

模块化方案2的奖赏信号举例:

$r(v) = \lambda(v - v_{ref})$ 车道行驶

$$r_{ch1} = \begin{cases} -0.2 & \text{换道策略} \\ 0 & \text{保持策略} \end{cases}$$

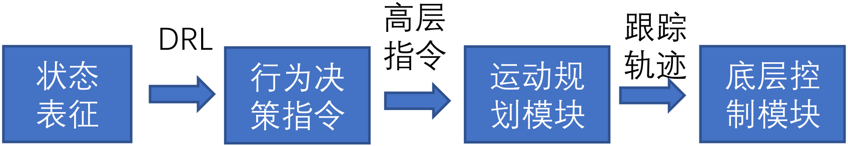
$r_{ch2} = -3$，　非法换道策略

$r_{co} = -10$，　发生碰撞

$$\Rightarrow \quad r = \begin{cases} r(v) + r_{ch1} \\ r_{ch2} \\ r_{co} \end{cases}$$

模块化方案2的动作空间：

行为决策指令：-1(向左换道)，0 (保持当前车道)，1(向右换道)



Wang et al., Lane Change Decision-making through Deep Reinforcement Learning with Rule-based Constraints, 2019.

自动驾驶课程大作业介绍

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自动驾驶汽车 专项课程

Launch Your Career in Self-Driving Cars. Be at the forefront of the autonomous driving industry.

4.7 1,405 个评分

Steven Waslander 另外 +1 位授课教师

Motion Planning for Self-Driving Cars

4.8 140 个评分 • 24 条评论

Welcome to Motion Planning for Self-Driving Cars, the fourth course in University of Toronto's Self-Driving Cars Specialization.

This course will introduce you to the main planning tasks in autonomous driving, including mission planning, behavior planning and local planning. By the end of this course, you will be able to find the shortest path over a graph or road network using Dijkstra's and the A* algorithm, use finite state machines to select safe behaviors to execute, and design optimal, smooth paths and velocity profiles to navigate safely around obstacles while obeying traffic laws. You'll also build occupancy grid maps of static elements in the environment and learn how to use them for efficient collision checking. This course will give you the ability to construct a full self-driving planning solution, to take you from home to work while behaving like a typical driving and keeping the vehicle safe at all times. For the final project in this course, you will implement a hierarchical motion planner to navigate through a sequence of scenarios in the CARLA simulator, including avoiding a vehicle parked in your lane, following a lead vehicle and safely navigating an intersection. You'll face real-world randomness and need to work to ensure your solution is robust to changes in the environment. This is an intermediate course, intended for learners with some background in robotics, and it builds on the models and controllers devised in Course 1 of this specialization. To succeed in this course, you should have programming experience in Python 3.0, and familiarity with Linear Algebra (matrices, vectors, matrix multiplication, rank, Eigenvalues and vectors and inverses) and calculus (ordinary differential equations, integration).

https://www.coursera.org/specializations/self-driving-cars

https://www.coursera.org/learn/motion-planning-self-driving-cars#syllabus

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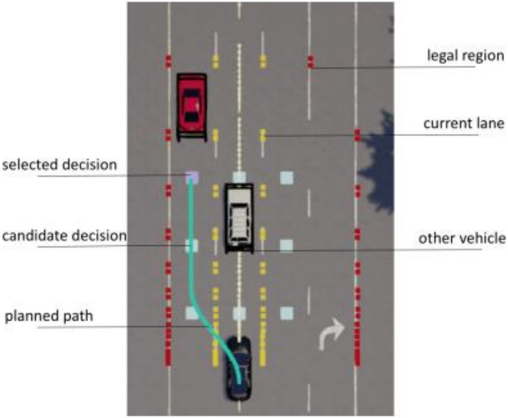
模块化方案3的状态输入:

局部地图



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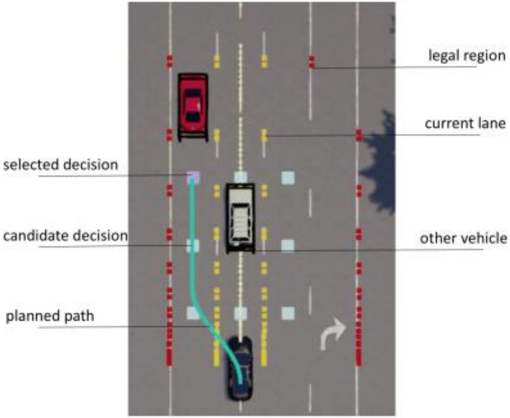
模块化方案3的动作空间:

离散目标点



Huang et al., Learning Driving Decisions by Imitating Drivers' Control Behaviors, 2019

自动驾驶课程大作业介绍

智能驾驶课程作业的提交：

- 以组为单位提交一份大报告
- 代码
- 运行的demo

要求：

- 需要在大报告里体现每个人分工完成的部分
- 必须涉及到强化学习/深度强化学习方法
- 大报告可以以会议论文，或者以PPT汇报的形式

严格禁止抄袭，如有发现，大作业成绩全组计零