# VEOS by Data Driven Planning

## 测试条件:

- 固定测试场景
- 固定工况
- 不开空调(减少空调能耗干扰)
- 往返路线(减少地形差异干扰)
- 观测噪声: 地形,压缩机,电池SOC,(大灯,tbox,...)
- 测量驾驶风格:纵向控制问题中,特定工况下油门踏板(和刹车踏板)的使用情况
- 通过独立的UDP数据记录交叉验证测量和性能

### 驾驶风格

- 无AI和带AI的基准驾驶风格比较

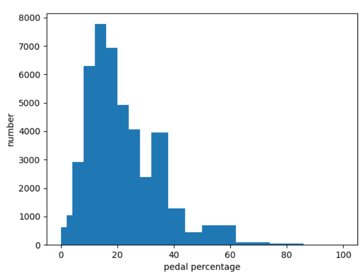



图1.1 无AI的基准风格分布

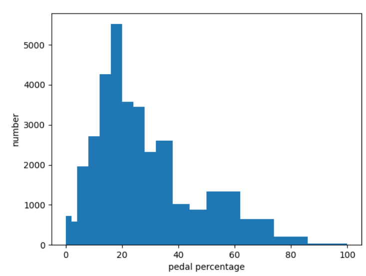



图1.2 带AI的基准风格总平均分布

- 驾驶风格按周期变化: 驾驶风格相对同一个司机是固定的

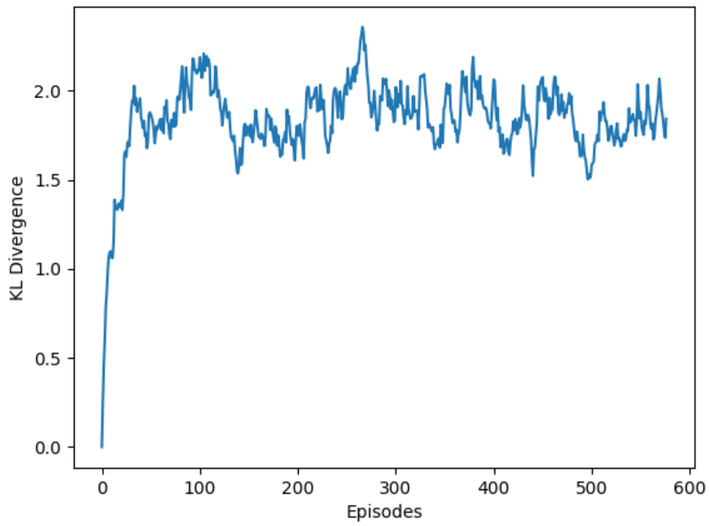
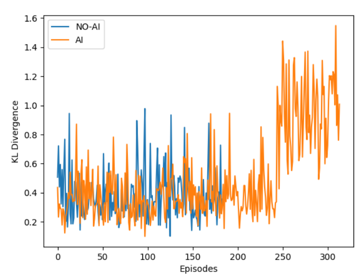



图2 驾驶风格变化按KL散度评估, 风格相对固定

- 驾驶风格有AI和无AI比较



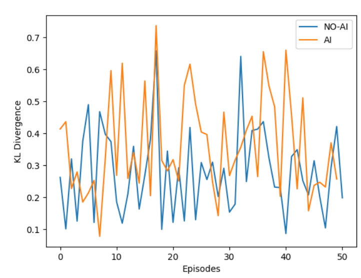
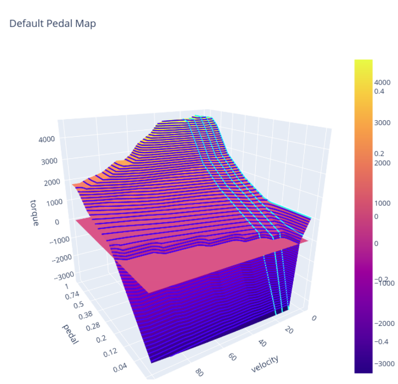
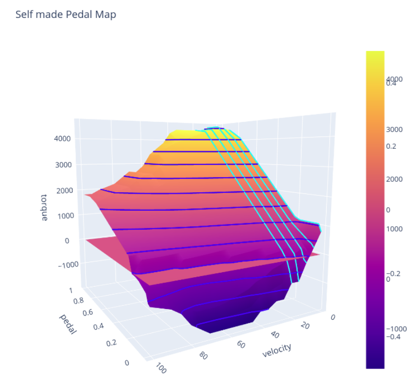




图3.1 驾驶风格有AI和无AI比较,从250步开始打开　图3.2 另一位驾驶员有AI与无AI比较

**能耗**

- 电动力默认Pedal Map (PM) vs 自建 Pedal Map
  - 默认PM:高速时请求力矩会降低
  - 自建PM:分段线性,请求力矩分段线性单调




| 图4.1 EP默认PM | 图4.2 自建PM |
| --- | --- |

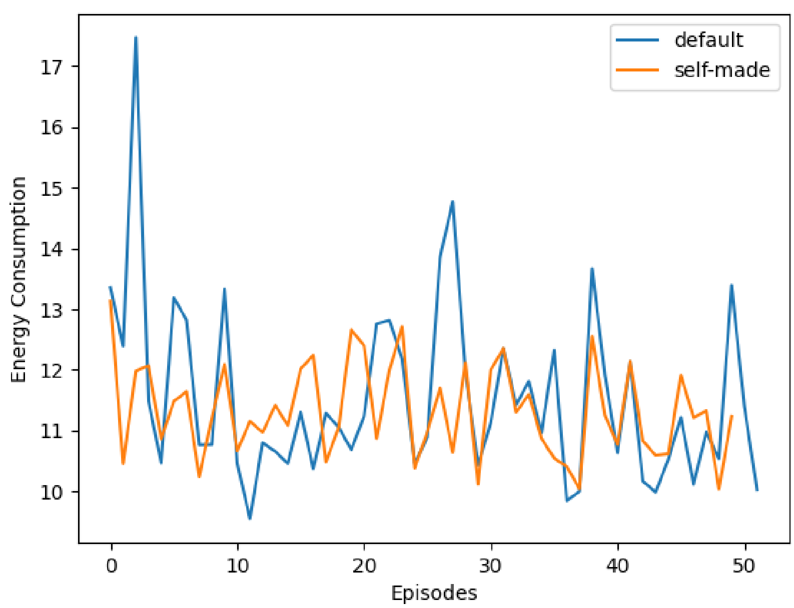



图6 EP默认PM与自建PM能耗比较,

- 具备较强能量回收的pedal map

## 实验结果

### 驾驶风格比较:

- 总分布和KL散度定量比较

1.无AI基准: 默认表 vs 手工表

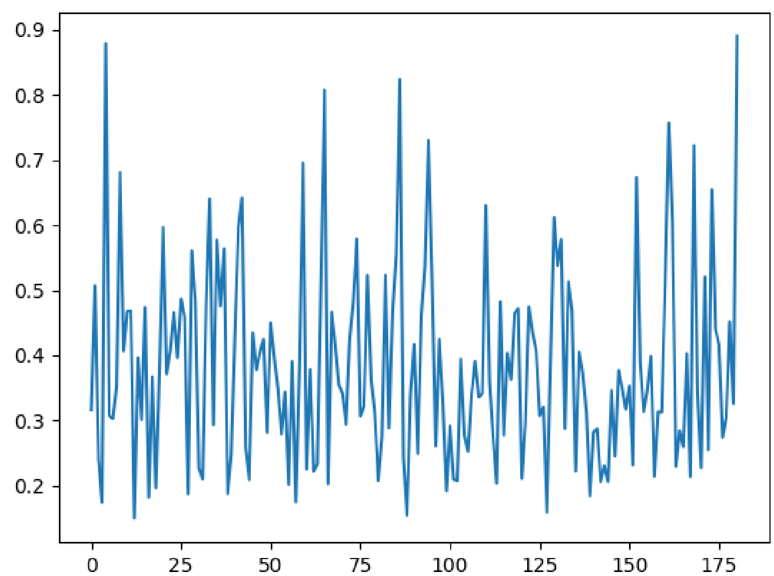
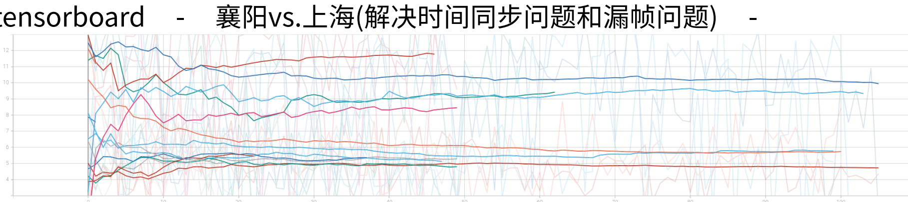



Figure 1: No AI

2.不同驾驶员: 驾驶员 1 vs. 2. vs 3.

3.不同初始表

4.历次带AI tensorboard - 襄阳vs.上海(解决时间同步问题和漏帧问题) -



确认收敛过程

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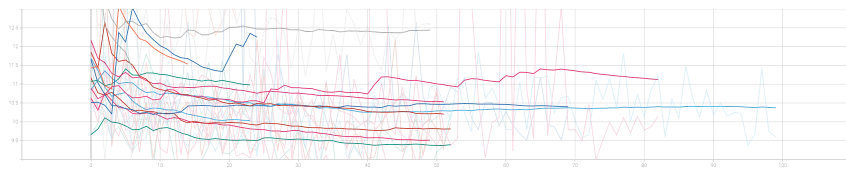
## 上海优化改进过程



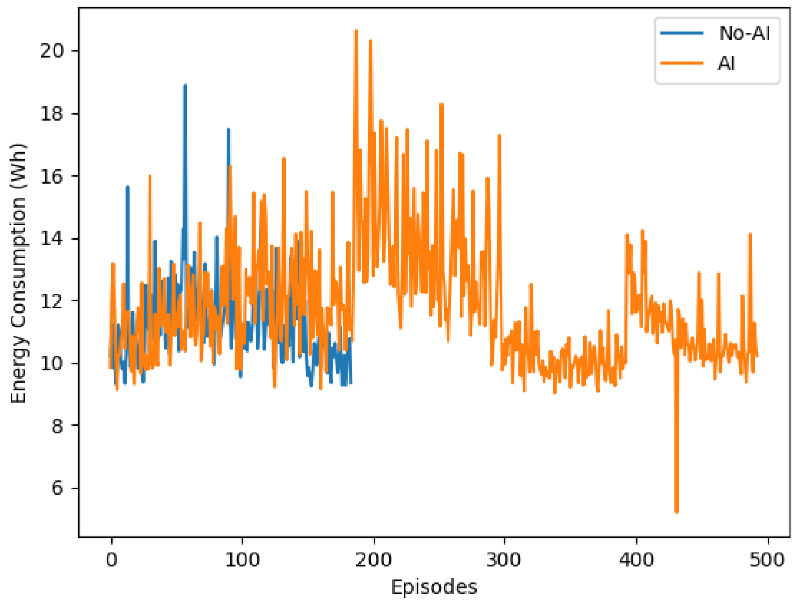



Figure 2: AI-comp

5.(无AI vs.有AI)各50次 6.有AI持续模式 7.不同驾驶员带AI优化过程 8.怠速表关闭/打开 9.熵变小/策略趋向确定性 10.DDPG vs. SAC

- baselines
  - driver styles analysis (analysis)
  - pedal map comparison
  - A2C
  - different initial map
- Declining in each epoch
  - RL agent cooperative / Human driver adapting?
  - Epoch tendcy
  - declining in total loss / inclining in total reward

  - entropy declining / becoming more and more deterministic
  - expected wh declining
  - seems cooperative, at least no conflict
  - baseline: strong regen –> higher efficiency
  - methods
  - achievements
  - status
- long-term in resume mode (model and table resumed)
- weak regen (fix coastdown / constrained action space)
- strong regen (exploit coastdown / relax action space)

## Analysis

weaker regen: not stronger regen, but better motion control for the test case

- possible models

debug

- tools
  - **driving style analysis (quantitative)**
    * vehicle interfaces and systems (stable and reliable)
    * synchronization
  - data logging (for analysis and offline algo)
  - udp episodic analysis (cross check)
  - energy consumpt cross-check by UDP messages
  - model resume tool
  - different driver storage with resume and from scratch
  - debug (latency analysis)
  - verifying DL algo with cpu only resources
  - analysis
  - optimal motion planning
  - limiting action space,
  - exploit regen, activate coastdown part
  - better assistance for manual motion control for eco
  - reward shaping (penalize braking could be cooperative)
  - need recurrency to encode system dynamics
  - observing, acting rate, BP rate

## 方法

强化学习方法, 以大数据为基础的奖励驱动优化方法 - **没有模型** - 车辆动力学的模型和知识 - 电机模型 - 电源管理系统模型 - 符合学习直觉: - 利用大数据建立内部模型 -

自适应动态过程 -

## 理论分析

- not like this: big data –> NN –> label ==> good result
- learn from data (distribution) not label (label is supervision)
  - distribution, law of large number n>30, (multiplicity with samples)
  - dynamic environment –> drifting distribution
  - **advantages**: previously impossible cases can be solved elegantly by big data.
- basic observability/controllability
  - observation enough? fully observable –> which should I observe?
  - control signal sufficient/efficient?
  - long-term dependency
- Model
  - Complete observable model (MDP)
  - human driver model $Th = Th(\mathbf{O_h})$
  - pedal map $\tilde{PM}(Th) = Trq$
  - $Trq = \tilde{PM} \circ Th = \tilde{PM}(Th(O_h))$
  - $\mathbf{O_h} = (vel, road, objects)$
  - Objective: Optimal Motion Planning
    * $\min_{Trq}(\Sigma_i(u \cdot i) \cdot dt)$
      - follow the optimal motion planning (follow the optimal speed curve)
      - reduce unnecessary large torque
      - maintain a speed when regenerative brake occurs (exploit regenerative brake)
  - Implementation, POMDP
    * $\mathbf{O_{rl}} = (vel, Th)$
    * $\mathbf{O_{rlx}} = (vel, Th, MotionPlan)$

## Outlook

### fully autonomous

1. optimal motion control/prediction
2. exploit regen

#### assistance system

1. fix driving style and analysis
2. different reward

#### Challenge

动态过程未知，奖励不完全知道，并非简单将数据灌入神经网络,需要考虑几个因素。

- sample efficiency
- offline data utilization
- reward shaping
- memory

#### Counter measures