Solving Traffic Problems using Autonomous Vehicles

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High level motivation
Planning the future of mobility: mixed autonomy

Neom, KSA

Jurong district, Singapore

Cartube

The boring company

Hyperloop

E-taxi
Example
Impact of automation on the energy footprint of mobility

Short answer:
it is highly uncertain.
Transportation today:
28% US energy consumption
100% self-driving cars:
-60% to +200% energy

Traffic control, traffic management

Forward simulation models

Variety of tools historically developed at different scales

- Energy-based vehicular models
- Microscopic models
- Mesoscopic models
- Macroscopic models
- Agent based models
- Excel accounting models

Traveler energy consumption model
~1 (individual) agent
LBNL Traveler Energy Consumption Model
LBNL Vehicle Model Library (VML)
ANL Autonomie

Micro/meso simulation
~50,000 – 100,000 agents
Aimsun, VSSIM, SUMO, FLUIDS

Macrosimulation
~500,000-1,000,000 agents
Connected Corridors
Mobile Millennium
TOPL, etc.

Agent based model
~ 5,000,000 agents
MATSim, BEAM, Mobiliti, etc.
The state of the art microsim today
Microscopic simulation models: simulating 100,000s of vehicles

Example
App “problem”
Thru-traffic
20% app users
nextGen DTA
Always in motion the future is
The next battlefield (2-5 years)

Data:
Floating car data (GPS, cell tower, CAV data)
Asset data (signal timing, metering etc.)
Event data (closures, games, special events)
Maps assets (#lanes, speed limits etc.)

Calibration:
Estimation: vehicle-based
ID
Missing data inference
Demand
Routing

Model computation:
Computational time for model forecast
Distribution of the model on AWS EC2

Control / deep-RL:
Model free deep-RL
End2end learning / pixel learning
Sample inefficiency
Curse of dimensionality in the action space
Multi-agent learning training
A call to action

Can we over the next few (2) years demonstrate ML-based microsim?

Framework:
State of the art microsim: SUMO, Aimsun or other
RLLAB, RLLIB, TensorFlow, Caffe, etc.
All in AWS EC2 or similar cloud

(Mixed)-autonomy traffic control:
Every controllable asset (infrastructure or CAV) modeled
Most common scenarios solved: merge, intersections, freeways, arterials, roundabouts, tools, metered bridges, etc.

Can we demonstrate the following within 2 years?
Benchmarks for all, winner algorithms for all
Actual migration on assets (static and vehicles)
Acceleration of history
Deep-RL is about to leapfrog 80 years of model-based research

1935:
First aggregate model of congestion

1955:
First PDE model of traffic
Acceleration of history
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2017:
First controller implemented

Dissipation of stop-and-go traffic waves via control of a single autonomous vehicle

Prof. Daniel Work, Vanderbilt
Prof. Benedetto Piccoli, Rutgers
Prof. Benjamin Seibold, Temple
Prof. Jonathan Sprinkle, UoA
Acceleration of history
Deep-RL solution to the same problem

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2018: Better result with deep-RL
Acceleration of history
Deep-RL solution to the same problem

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2018: Better result with deep-RL (Cathy Wu’s PhD)

AV off

Automated
Observed
Unobserved

Prof. Cathy Wu, MIT
Acceleration of history

Deep-RL solution to the same problem

Setting: 1 AV, 21 human

Experiment:

- **Goal**: maximize average velocity
- **Observation**: relative velocity & headway
- **Action**: acceleration
- **Policy**: multi-layer perceptron (MLP)
- **Learning algorithm**: policy gradient

Results:

- 1 AVs: +49% average velocity
- Stabilization at near-optimal velocity
Acceleration of history
Will deep-RL leapfrog 80 yrs. of model-based research?

1935:
First aggregate model of congestion
1955:
First PDE model of traffic
2008:
First experiment showing instability
2017:
First controller implemented
2018:
Better result with deep-RL (Cathy Wu’s PhD)

Prof. Cathy Wu, MIT
Problem statement
Traffic flow control by CAV (and static assets if needed)

CAV: Autonomous, Onboard policy (learned) Connected to other CAVs

Sensed vehicle: Sensed by CAV proximity Or other [C]onnected vehicle

Other vehicle: Following human dynamics (car following model)
Building lego blocks
Deep-RL lego blocks = science fiction of model based approaches

Setup: 1 AV, 41 human

Experiment
• **Goal**: Maximize average velocity
• **Observation**: following headways, velocity
• **Action**: acceleration and lane change

Results
• **Insight**: A single AV can stabilize multiple lanes of traffic
• **Emergent traffic break**
Building lego blocks
Deep-RL lego blocks = science fiction of model based approaches

Setup: 1 AV, 41 human

Experiment

• **Goal**: Maximize average velocity
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Results

• **Insight**: A single AV can stabilize multiple lanes of traffic
• **Emergent traffic break**
Intersection control
Moving towards automated intersections

- Queuing theory
- Reservation systems
- Model predictive control

A multiagent approach to autonomous intersection management.

Polling-systems-based control of high-performance provably-safe autonomous intersections.
Miculescu, Karaman. CDC, 2014.

What if even one of these vehicles is not automated?
Intersection control
Moving towards automated intersections

Setting: 0 AV, 14 human

Dynamics: cascaded nonlinear systems with right-of-way dynamics model

No autonomy
Intersection control
Moving towards automated intersections

**Setting:** 1 AV, 13 human

**Experiment:**
- Goal: maximize average velocity
- Observation: fully observed
- Action: acceleration

**Results**
- Emergent mixed-autonomy platoon
- **Insight:** A single AV can slow or stop ALL vehicles behind it
- 1 AV: +60% average velocity
Intersection control
For time space diagram afficionados

Setting: 1 AV, 13 human

Experiment:
• Goal: maximize average velocity
• Observation: fully observed
• Action: acceleration

Results
• Emergent mixed-autonomy platoon
• Insight: A single AV can slow or stop ALL vehicles behind it
• 1 AV: +60% average velocity
• 14 AVs: +170% average velocity
Merge control
Moving towards automated merges

Impacts: 40% of highway congestion

Setting: 0 AV, 17 human

Dynamics:
cascaded nonlinear systems with right-of-way dynamics model

Longitudinal control algorithm for automated vehicle merging.

The impacts of a communication based merging assistant on traffic flows of manual and equipped vehicles at an on-ramp using traffic flow simulation.
Merge control
Moving towards automated merges

Setting: 1 AV, 16 human

Experiment:
- **Goal**: maximize average velocity
- **Observation**: Local and merging vehicles, statistics, e.g. queue length
- **Action**: acceleration

Results
- **Emergent mixed-autonomy cooperative merge**
- 1 AV: +142% average velocity (6.3 m/s)
- 0 AV: 2.6 m/s
Transfer learning
Moving towards automated merges

Setting: \( p\% \) CAV penetration

Experiment:
- **Goal**: maximize average velocity
- **Observations**: 1 vehicle ahead/behind
- **Actions**: acceleration

Transfer Learning
- Initial training on ring road with periodically induced perturbations
- Resultant policy extracted and tested on straight highway with merge.
Transfer learning
Moving towards automated merges

**Transfer Learning Results:**
- Ring road policy initially outperforms human-driven dynamics
- **Significance:** Control strategies derived from simplified closed network geometries are somewhat transferable to open network problems.
Transfer learning
Moving towards automated merges

Setting: 0% CAV Penetration
Dynamics: Cascaded nonlin. sms with right-of-way dyn. model, convective instability, and fluctuating densities
Transfer learning
Moving towards automated merges

Setting: 5% CAV Penetration
Dynamics: Cascaded nonlin. sms with right-of-way dyn. model, convective instability, and fluctuating densities
Transfer learning
This slide is also dedicated to the time-space diagram aficionados

6.7% improvement in throughput
Short story: deep-RL just learned to create gaps with forward waves
Penetration studies
How many CAVs does it take to smooth traffic?

0% AV (baseline)

2.5% AV (0% throughput)

5% AV (+6.7% throughput)

10% AV (+13% throughput)

A. Kreidieh  E. Vinitsky
In real life

Oscillations exist naturally in highway traffic
Flow smoothing on I210
How many CAVs does it take to smooth traffic?
Flow smoothing on I210
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Flow smoothing on I210
How many CAVs does it take to smooth traffic?

\[ \text{reward} = -\text{energy consumed} \]

Problem
The agent can optimize that reward by not moving

Need an incentive to move forward:
- Penalty for staying too long in the network
- Additional state (time since entered)
Bridge metering
Lagrangian metering

NextGen infrastructure
Can we remove the metering light and can we replace it with CAVs?
Bridge metering ([not] waiting for Godot)
Lagrangian metering: 33% improvement (throughput)

Setting:
- 10% CAV Penetration
- Four lanes -> Two lanes -> One

Dynamics:
Cascaded nonlinear systems with right-of-way dynamics model, merge conflicts, and excessive, fluctuating inflow
Bridge metering
Lagrangian metering

Multi-lane merge
Toll plaza: 18 lanes
Policy transfer
Left: baseline scenario; right: flow maximization
Policy transfer
Go to our demo booth tomorrow!
End-to-end pixel learning
Deep RL as a Markov decision process

Markov decision process:
End-to-end pixel learning
State space design

Local Observation $S_t$

Agent

Environment

Action $A_t$

Reward $R_t$

$t-4$ $t-3$ $t-2$ $t-1$ $t$

render
End-to-end pixel learning
Action space design

F. Wu
End-to-end pixel learning
Reward function design

\[ r = \frac{1}{v_{\text{max}}} \left( \beta v_{\text{avg}} - (1 - \beta) v_{\text{std}} \right) \]
**End-to-end pixel learning**

*Learning on simple environments*

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**RL augmentation improves human drivers’ skills to the level of an optimized AI.**

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*humans* | *humans+AI* | *AI*
End-to-end pixel learning
What if one could remove the need for state space access?
The vision
Eventually linked to dashcam data

Fully centralized:
Pixel learning

Decentralized:
Pixel learning, multi-agent

Decentralized:
Dashcam segmented data
Who is next?
Traffic management
Deep-RL

Basic optimization framework

Agent

Environment

Goal:

learn policy \( \pi : S \rightarrow A \)
to maximize reward

\[
\max_\theta \mathbb{E} \left[ \sum_{t=0}^{H} r(s_t, a_t) \mid \pi_\theta \right]
\]

Global rewards

Average velocity
Energy consumption
Travel time
Safety, comfort

Cumulative rewards, returns
Policy parameters (deep neural network)
Flow

Brief presentation of FLOW

Computational framework

- Task designer
- Markov Decision Process
- Traffic network
- Traffic dynamics
- Vehicle types
- Noise models
- Inflows
- Routes

Agent

- RL Library
  - RLlib/rllab

Environment

- Custom dynamics
- Traffic microsimulator
  - SUMO / Aimsun

**State s_t** → Reward **r_t** → Action **a_t**
Lego-blocks
Building a library

Single-lane
Multi-lane
Intersection
On/off-ramp
Signalized intersection
Straight road
Bottleneck
Grid network
Benchmarks, launched 2018, CORL
https://flow-project.github.io/
Dashboard CIRCLES
Dashboard CIRCLES

Submission Scores Over Time

- Tacoma-Fit Model
- Prius-Fit Model (with x-axis offset)

Energy Savings (%) vs Date:
- Jun 7 2020
- Jun 21
- Jul 5
- Jul 19
- Aug 2
User community
Classes, workshops, tutorials, events, users...

IEEE CDC, Nice, France
Flow open source library
https://flow-project.github.io/

FLOW is a deep reinforcement learning framework.

Developed by MobileSensing Ltd.
Made in UC Berkeley.
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