Exploring deep reinforcement learning for real-world autonomous driving systems

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100% Autonomous 100% Driverless 100% Electric
Quick overview of Reinforcement learning
- Taxonomy of autonomous driving tasks
- History & Applications
- Taxonomy of methods in RL today

Autonomous Driving Tasks
- Which tasks require reinforcement learning
- Which tasks require Inverse reinforcement learning
- Role of simulators

Challenges in RL for Autonomous driving
- Designing reward functions, Sparse rewards, scalar reward functions
- Long tail effect, Sample efficient RL/IL
- Moving from Simulation to reality
- Validating, testing and safety

Conclusion
- Current solutions in deployment in industry
- Summary and open questions
Scene interpretation tasks:
- 2D, 3D Object detection & tracking
- Traffic light/traffic sign
- Semantic segmentation
- Free/Drive space estimation
- Lane extraction
- HD Maps: 3D map, Lanes, Road topology
- Crowd sourced Maps

Fusions tasks:
- Multimodal sensor fusion
- Odometry
- Localization
- Landmark extraction
- Relocalization with HD Maps

Reinforcement learning tasks:
- Controller optimization
- Path planning and Trajectory optimization
- Motion and dynamic path planning
- High level driving policy: Highway, intersections, merges
- Actor (pedestrian/vehicles) prediction
- Safety and risk estimation
Learning what to do—how to map situations to actions optimally: an optimal policy*

*Maximization of the expected value of the cumulative sum of a received scalar reward
**Supervised Learning**
Given input examples \((X, Y)\)
Learn implicit function approximation
\[ f: X \rightarrow Y \]
\((X: \text{images}) \text{ to } (Y: \text{class label})\)

\[ R_{\text{emp}}(f) = \frac{1}{N} \sum_i L(f(x_i), y_i) \]

**Empirical risk (loss function):** representing the price paid for inaccurate prediction

Predictions do not affect environment
\((\text{Samples are IID})\)

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**Reinforcement learning**
Given input state space, rewards, transitions
Learn a policy from state-to-actions
\[ \pi: S \rightarrow A \]
\((S: \text{vehicle state, images, A: speed, direction})\)

\[ \max_{\pi} \mathbb{E} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right] \]

**Value function:** long-term reward achieved

Predictions affect both what is observed as well as future rewards

Requires Exploration, learning and interaction
STATE SPACE, ACTIONS AND REWARDS

Vehicle state space
- Geometry (vehicle size, occupancy grid)
- Road topology and curvature
- Traffic Signs and laws
- Vehicle pose and velocity (v)
- Configuration of obstacle (with poses/v)
- Drivable zone

Reward (positive/negative)
- Distances to obstacles (real)
- Lateral error from trajectory (real)
- Longitudinal: Time to collision (real)
- Percentage of car on the road (sim)
- Variation in speed profile (real)
- Actor/Agent intentions in the scene
- Damage to vehicle/other agents (sim)

Actions
- Continuous control: Speed, steering
- Discrete control: up, down, left, right, ...
- High level (temporal abstraction): slow down, follow, exit route, merge
ORIGINS OF REINFORCEMENT LEARNING

1950s
Optimal Control
- Pontryagin
- Bellman

1960s
Dynamic Programming
- stochastic optimal control
- Richard Bellman

1930s-70s
Trial/Error Learning
- Psychology, Woodworth

Credit Assignment
- Minsky

Least Mean Squares (LMS)
- Widrow-Gupta

Learning Automata
- K-armed bandits

1980s
Temporal Difference
- R. Sutton Thesis

1990s
Q-Learning, Neuro-DP
- (DP+ANNs)
- Bertsekas/Tsitsiklis

2000s
Policy Gradient Methods
- Sutton et al.

2006s
Monte-Carlo Tree Search
for RL on Game tree for Go
- Rémi Coulom & others

2015-2019
AlphaGo, AlphaZero
- MCTS+DeepRL
- Go Chess Shogi
- DeepMind

2016
Asynchronous Deep RL
- methods A2C, A3C
- Deepmind Mnih et al.

2015
Playing Atari with Deep
- Reinforcement Learning
- Deepmind Mnih et al.

2014
Deterministic Policy
- Gradient Algorithms
- David Silver et al.

2005s
Neural Fitted Q Iteration
- Martin Riedmiller

Adaptive signal processing
Stochastic approximation theory
Animal Psychology and neuroscience
Robotics and Control theory
**TERMINOLOGIES**

**Reinforcement Learning**

- **Prediction**
  - Evaluation of Policy

- **Control**
  - Infer optimal policy
    - (policy/value iteration)

- **Model Based** (P & R known)
  - Control: Policy/Value Iteration
  - Prediction: Policy Optimization

- **Model Free** (P and R unknown)
  - Prediction: MonteCarlo(MC), TimeDifference(TD)
  - Control: MC control step
  - Q Learning

- **MDP**
  - $S$: Set of States (discrete/continuous)
  - $A$: Set of Actions
  - $P(s, s')$: Transition probabilities
  - $r(s, a)$: Reward at state given an action

  **Assumption** $s_{t+1}$ is conditionally independent of the past states/actions given $s_t, a_t$

**On policy methods**
- Learning using current policy

**Off policy methods**
- Learn from observations

**Exploration**
- Learning (P, R, Policy) using current policy

**Exploitation**
- Learn Policy given (P, R, Value function)

**Action spaces**
- Continuous (vehicle controller)
- Discrete (Go, Chess)

**Markovian Decisions Processes**
- (MDP, POMPD)
State-action map as supervised learning
- Directly map (Inputs/states) TO (Outputs/Actions) control and ignore IID assumption, no more a sequential decision process.
- Also known as end-to-end learning since sensor streams are directly mapped to control

Issues:
- Agent mimics expert behavior at the danger of not recovering from unseen scenarios such as unseen driver behavior, vehicle orientations, adversarial behavior of agents (overfits expert)
- Poorly defined reward functions cause poor exploration
- Requires huge No. (>30M samples) of human expert samples

Improvements:
- Heuristics to improve data collection in corner cases (Dagger)
- Imitation is efficient in practice and still an alternative

DAGGER: A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning
Hierarchical Imitation and Reinforcement Learning
SIMULATORS: ENVIRONMENT FOR RL

Perception Stream Simulators for End-to-End Learning

- CARLA
- Zoox Simulator
- NVIDIA Autosim
- DEEPDRIVE

Vehicle state, reward, damage

- TORCS
- SUMO

Audi partners with Israel’s autonomous vehicle simulation startup Cognata
Learning vehicle controllers
- For well defined tasks: Lane following, ACC classical solutions (MPC) are good
- Tuning/choosing better controllers based on vehicle and state dynamics is where RL can be impactful
- ACC and braking assistance

Path planning and trajectory optimization
- Choose path that minimizes certain cost function
  - Lane following, Jerk minimizer
- Actor (pedestrian/vehicle) behavior prediction

Decision making in complex scenarios:
- Highways driving: Large space of obstacle configurations, translation/orientations/velocity, Rule based methods fail
- Negotiating intersections: Dynamic Path Planning
- Merge into traffic, Split out from traffic

Planning algorithms, Steven Lavalle
Real-time motion planning
Inverse RL or Inverse Optical control

- **Given**: States, Action space and Roll-outs from Expert policy, Mode of the environment (State dynamics)
- **Goal**: Learn reward function, Then learn a new policy
- **Challenges**: not well defined, tough to evaluate optimal reward
- **Applications**: Predicting pedestrian, vehicles behavior on road, Basic Lane following and obstacle avoidance

It is commonly assumed that the purpose of observation is to learn policy, i.e. a direct representation of mapping from states to actions. We propose instead to recover the experts reward function and use this to generate desirable behavior. We suggest that the **reward function offers much more parsimonious description of behavior**. After all the entire field of RL is founded on the presupposition that the reward function, rather than the policy is the most succint, robust and transferable definition of the task.

*Algorithms for Inverse Reinforcement Learning*, Ng Russel 2000

**DESIRE: Distant Future Prediction in Dynamic Scenes with Interacting Agents**
CHALLENGES IN REWARD FUNCTION DESIGN

Where do rewards come from?

- Simulations (low cost to high cost based on dynamics and details required)
- **Large sample complexity**
- Positive rewards without negative rewards can have dangerous consequences
- Real World (very costly, and dangerous when agent requires to explore)

Temporal abstraction

- Credit assignment and Exploration-Exploitation Dilemma
- **Cobra effect**: RL algorithms are blind maximizers of expected reward

Other ways to learn a reward

- Decompose the problem in multiple subproblems which are easier.
- Guide the training of problems with expert supervision using imitation learning as initialization
- Reduce the hype and embrace the inherent problems with RL: Use Domain knowledge

**Cobra effect**: The British government was concerned about the number of venomous cobra snakes in Delhi. They offered a reward for every dead cobra. Initially this was a success as large numbers of snakes were killed for the reward. Eventually, however, enterprising people began to breed cobras for the income. When the government became aware of this, the reward program was scrapped, causing the cobra breeders to set the now-worthless snakes free. As a result, the wild cobra population further increased. The apparent solution for the problem made the situation even worse.

https://www.alexirpan.com/2018/02/14/rl-hard.html
**Hierarchy of tasks**
- Decompose the problem into multiple subproblems which are easier.
- Combining learnt policies

**Guide training for complex problems**
- Train on principle task, then subtasks
- Expert supervision using imitation learning as initialization

https://thegradient.pub/the-promise-of-hierarchical-reinforcement-learning/
Composing Meta-Policies for Autonomous Driving Using Hierarchical Deep Reinforcement Learning
Rare and adversarial scenarios are difficult to learn

- Core issue with safe deployment of autonomous driving systems
- Models perform well for the average case but scale poorly due to low frequency, as well as sparse rewards

Hairpin bends, U-Turns

- Rare with difficult to model state space dynamics

Create simpler small sample based models blended with average case model

- Cures symptom not the disease

Drago Anguelov (Waymo) - MIT Self-Driving Cars
SCENARIO GENERATION FOR DRIVING SCENARIOS

Meta-Sim

Use my trained network on real data!

Need a labeled dataset to train my network!

Real dataset!

Generated synthetic dataset!

https://nv-tlabs.github.io/meta-sim/

Carla Challenge 2019
CHALLENGES SIMULATION-REALITY GAP

Handling domain transfer

• How to create a simulated environment which both faithfully emulates the real world and allows the agent in the simulation to gain valuable real-world experience?
• Can we map Real world images to Simulation?
World models enable agents to construct latent space representations of the dynamics of the world, while building/learning a robust control/actuator module over this representation.

https://worldmodels.github.io/
Safe policies for autonomous agent

- **SafeDagger**: safety policy that learns to predict the error made by a primary policy w.r.t reference policy.
- Define a feasible set of core safe state spaces that can be incrementally grown with explorations

Reproducible (code) on benchmark

- Variance intrinsic to the methods hyperparameters init.
- Cross-validation for RL is not well defined as opposed to supervised learning problems

Future standardized benchmarks

- Evaluating autonomous vehicle control algorithms even before agent leaves for real world testing.
- NHTSA-inspired pre-crash scenarios: Control loss without previous action, Longitudinal control after leading vehicle’s brake, Crossing traffic running a red light at an intersection, and many others
- Inspiration from the Aeronautics community on risk

**Carla Challenge 2019**
Agent maximizes the reward of distance travelled before intervention by a safety driver.

Robust Imitation learning using perturbations and simulated expert variations and augmented imitation loss function

https://sites.google.com/view/waymo-learn-to-drive/
CONCLUSION

How to design rewards?
How should the problem be decomposed to simplify learning an policy?
How to train in different levels of simulations (efficiently)?
How to handle long tail cases, especially risk intensive cases
How to intelligently perform domain change from simulation to reality?
Can we use imitation to solve the problem before switching to Reinforcement Learning?
How can we learning in a multi-agent setup to scale up learning?
WHERE IS THE HYPE ON DEEP RL

Gartner Hype Cycle for Emerging Technologies, 2017

As of July 2017
Hypes are highly non-stationary.
LECTURES AND SOURCES

- David Silver’s RL Course 2015 [link]
- Berkeley Deep Reinforcement Learning [Course]
- Deep RL Bootcamp lectures Berkeley [Course]
- Reinforcement learning and optimal control : D P Bertsekas 2019 [book]
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- StreetLearn, Deepmind google
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DEEP Q LEARNING

Autonomous driving agent in TORCS
$s_{t+1}$ is conditionally independent of the past states/actions given $s_t, a_t$

**MDP**

- $S$: Set of States (discrete/continuous)
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Learning from Demonstrations (LfD)/Imitation/Behavioral Cloning demonstrations are hard to collect

- Measure the divergence between your expert and the current policy
- Give priority in a replay buffer
- Iteratively collect samples (DAgger)
- Hierarchical Imitation reduce sample complexity by data aggregation by organizing the action spaces in a hierarchy

Source: improving diversity of steering angle