Exception Handling in Autonomous Vehicles via Human Language Communication

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11/19/2020

Intro: Autonomous Driving Scenario

Intro: Outline

Background

- Autonomous Driving (AD) systems
- Exceptions

Challenges

Inspirations

- Learning from Demonstrations (LfD)
- Intelligent User Interface (IUI)

Environment

- Perception Simulators

Future work

- Benchmarks
- Voice API

Background: Autonomous Driving Systems

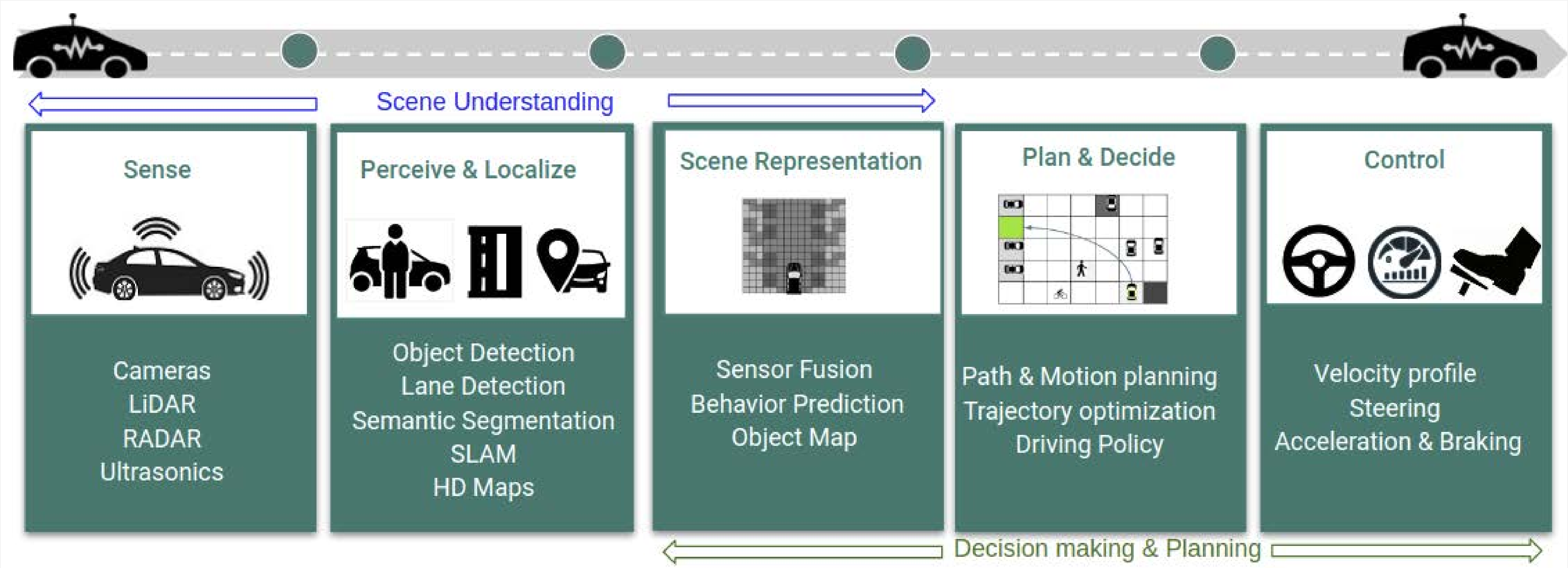

Figure 1: Standard components in a modern autonomous driving systems pipeline listing the various tasks.

[1] Kiran, B. R., Sobh, I., Talpaert, V., Mannion, P., Sallab, A. A. A., Yogamani, S., & Pérez, P. (2020). Deep reinforcement learning for autonomous driving: A survey. *arXiv preprint arXiv:2002.00444*.

Background: Exceptions

- Exceptions are undesired and low frequent events [2].

- Typical Examples:
  - Unfavorable Natural Settings
  - Bad Road Condition
  - Traffic Rule Breaking
  - Pedestrian Hazards
  - Failover Missions

Figure 2: Trajectory detection failure due to sunlight and shadow.

[2] Koopman, P., & Wagner, M. (2016). Challenges in Autonomous Vehicle Testing and Validation. SAE International Journal of Transportation Safety, 4(1), 15-24. Retrieved November 19, 2020.

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Figure 3: A snow covered uneven road.

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Figure 4: A traffic rule violation case.

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[3] Tabitha S. Combs, Laura S. Sandt, Michael P. Clamann, Noreen C. McDonald, Automated Vehicles and Pedestrian Safety: Exploring the Promise and Limits of Pedestrian Detection, American Journal of Preventive Medicine, Volume 56, Issue 1, 2019, Pages 1-7, ISSN 0749-3797, https://doi.org/10.1016/j.amepre.2018.06.024.

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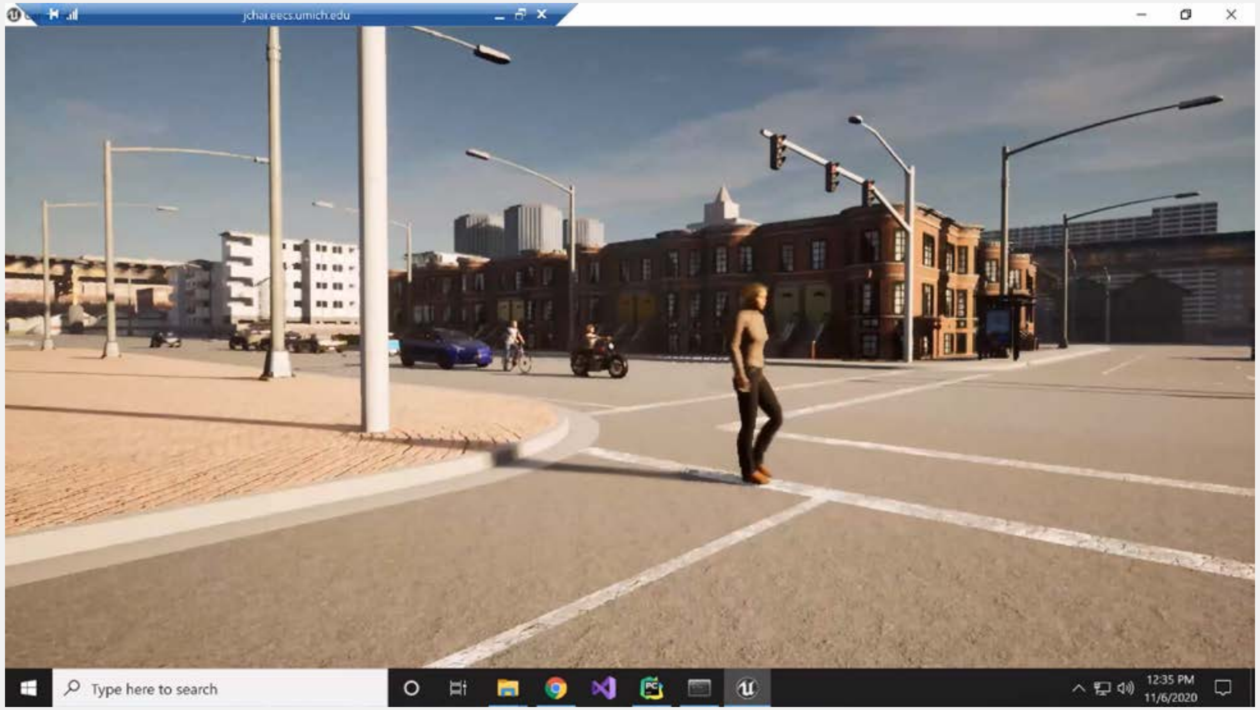

Figure 5: A jaywalking pedestrian.

[2] Koopman, P., & Wagner, M. (2016). Challenges in Autonomous Vehicle Testing and Validation. SAE International Journal of Transportation Safety, 4(1), 15-24. Retrieved November 19, 2020.

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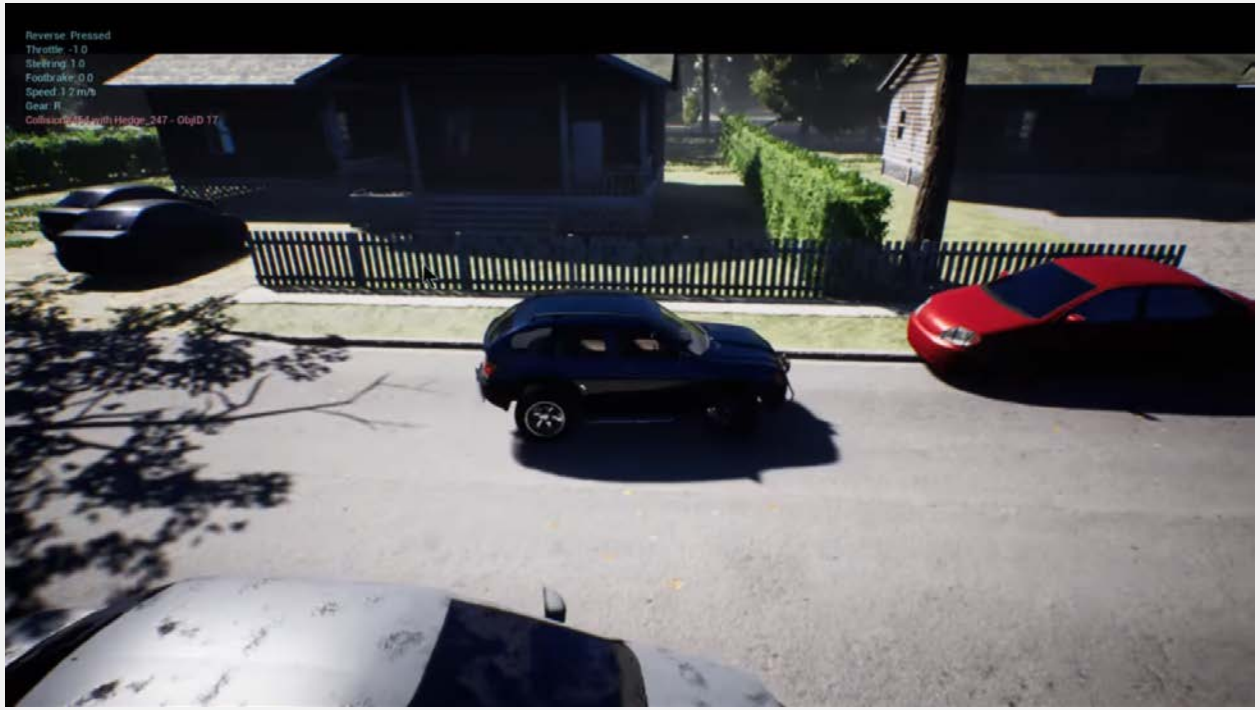


Figure 6: A failover case in the parking task.

[2] Koopman, P., & Wagner, M. (2016). Challenges in Autonomous Vehicle Testing and Validation. SAE International Journal of Transportation Safety, 4(1), 15-24. Retrieved November 19, 2020.

Challenges: Learning to Handle Exceptions

- Complex surrounding make exceptions hard to represent [4];
- Infrequent exceptions require unrealistic sample efficiency [1];
- Learned policy:
  - Requires data for reasonable performance [5];
  - Intrinsic Reward functions are hard to design [1];
- Manually designed policy:
  - Reward optimal policy is sub-optimal from ground truth [4].

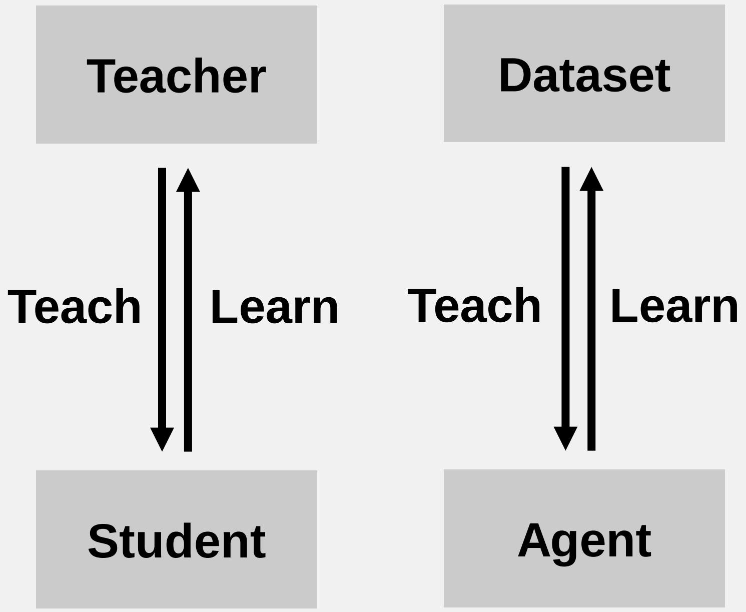
[1] Kiran, B. R., Sobh, I., Talpaert, V., Mannion, P., Sallab, A. A. A., Yogamani, S., & Pérez, P. (2020). Deep reinforcement learning for autonomous driving: A survey. arXiv preprint arXiv:2002.00444.
[4] Chen, J., Yuan, B., & Tomizuka, M. (2019). Deep imitation learning for autonomous driving in generic urban scenarios with enhanced safety. arXiv preprint arXiv:1903.00640.
[5] Hester, T., Vecerik, M., Pietquin, O., Lanctot, M., Schaul, T., Piot, B., ... & Osband, I. (2017). Deep q-learning from demonstrations. *arXiv preprint arXiv:1704.03732*.

Summary: Background and Challenge

- Exceptions are **undesirable** and **infrequent** events;
- Various possibilities and complex environment make them **hard to encode**;
- Traditional **policy learning agents** and **pre-designed agents failed** to address exceptions **efficiently**.

Inspirations: Learning from Demonstrations (LfD)

- Idea
  - Human Learning: Acquire new skills in an expert-to-learner knowledge transmission process;
  - Imitation Learning: A policy is trained to imitate an oracle on ground-truth dataset [6];



[6] Ross, S., & Bagnell, J. A. (2014). Reinforcement and imitation learning via interactive no-regret learning. arXiv preprint arXiv:1406.5979.

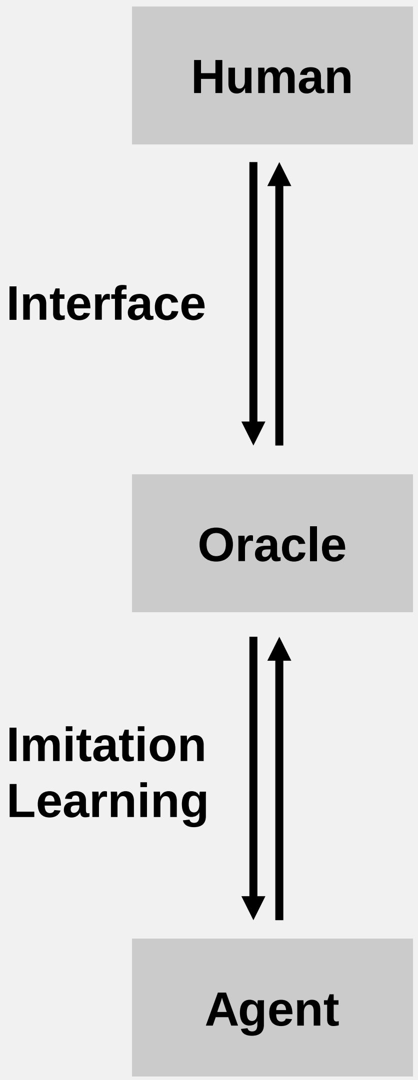
Inspirations: Learning from Demonstrations (LfD)

- Important for initial exploration
  - reward signals are too sparse
  - Input domain is too large to cover.
- No reward
  - In the form of state-action pairs, provided by an expert without any feedback rewards.
- Problem: Bad teacher?
  - Validation models trained on simulated environments often fail to generalize well on real environments [7].

[7] Ross, S., & Bagnell, D. (2010, March). Efficient reductions for imitation learning. In Proceedings of the thirteenth international conference on artificial intelligence and statistics (pp. 661-668).

Inspirations: Intelligent User Interface (IUI)

- Idea
    - Instead using a dataset for oracle, consider real human collaboration [10].
    - Higher level languages provide more effective communication than machine code. Consider a natural language system [8, 9].



[8] Ross, E. (2000). Intelligent user interfaces: Survey and research directions. Department of Computer Science, University of Bristol
[9] Patrick, E. (2003). Intelligent User Interfaces: Introduction and Survey.
[10] Cellario, M. (2001). Human-centered intelligent vehicles: Toward multimodal interface integration. IEEE intelligent systems, 16(4), 78-81.

Environment: Perception Simulators

- Why Simulators?
  - Physical level testing and validation is infeasible [2];
  - Easier to connect an smart interface to the API [11];
  - Can create and collect flexible exception datasets [11];
  - State-action pairs can be recorded [1].

[1] Kiran, B. R., Sobh, I., Talpaert, V., Mannion, P., Sallab, A. A. A., Yogamani, S., & Pérez, P. (2020). Deep reinforcement learning for autonomous driving: A survey. *arXiv preprint arXiv:2002.00444*.
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[11] Rosique, F., Navarro, P. J., Fernández, C., & Padilla, A. (2019). A systematic review of perception system and simulators for autonomous vehicles research. *Sensors*, *19*(3), 648.

Environment: Perception Simulators

Various high fidelity perception simulators are available [11].

Simulator	Description
CARLA [79]	Urban simulator, Camera & LIDAR streams, with depth & semantic segmentation, Location information
TORCS [103]	Racing Simulator, Camera stream, agent positions, testing control policies for vehicles
AIRSIM [104]	Camera stream with depth and semantic segmentation, support for drones
GAZEBO (ROS) [105]	Multi-robot physics simulator employed for path planning & vehicle control in complex 2D & 3D maps
SUMO [106]	Macro-scale modelling of traffic in cities motion planning simulators are used
DeepDrive [107]	Driving simulator based on unreal, providing multi-camera (eight) stream with depth
Constellation [108]	NVIDIA DRIVE Constellation™ simulates camera, LIDAR and radar for autonomous driving (Proprietary)
MADRaS [109]	Multi-Agent Autonomous Driving Simulator built on top of TORCS
Flow [110]	Multi-Agent Traffic Control Simulator built on top of SUMO
Highway-env [111]	A gym-based environment that provides a simulator for highway based road topologies
Carcraft	Waymo's simulation environment (Proprietary)

Table 2: Frequently used simulators [1].

[1] Kiran, B. R., Sobh, I., Talpaert, V., Mannion, P., Sallab, A. A. A., Yogamani, S., & Pérez, P. (2020). Deep reinforcement learning for autonomous driving: A survey. *arXiv preprint arXiv:2002.00444*.
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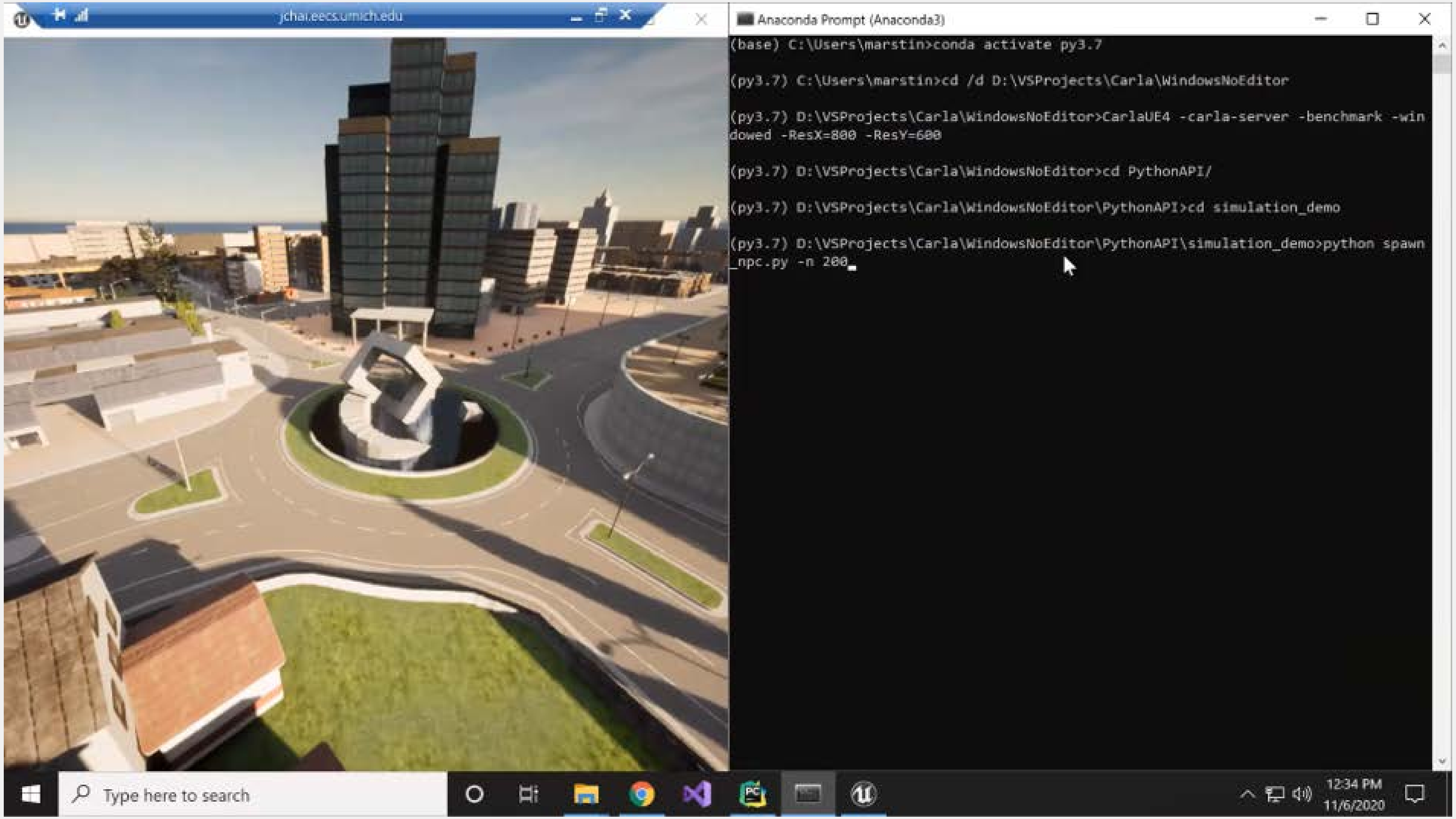
Environment: CARLA [12]

- Why CARLA?
  - Flexible API:
    - multi-agent environment
    - first person view
    - convenient data collector
  - Capability to simulate exceptions:
    - weather/light API
    - pedestrian control
    - traffic markers
  - Robot Operating System (ROS) bridge
  - GPU friendly
  - Well established document and forum
  - …

CARLA

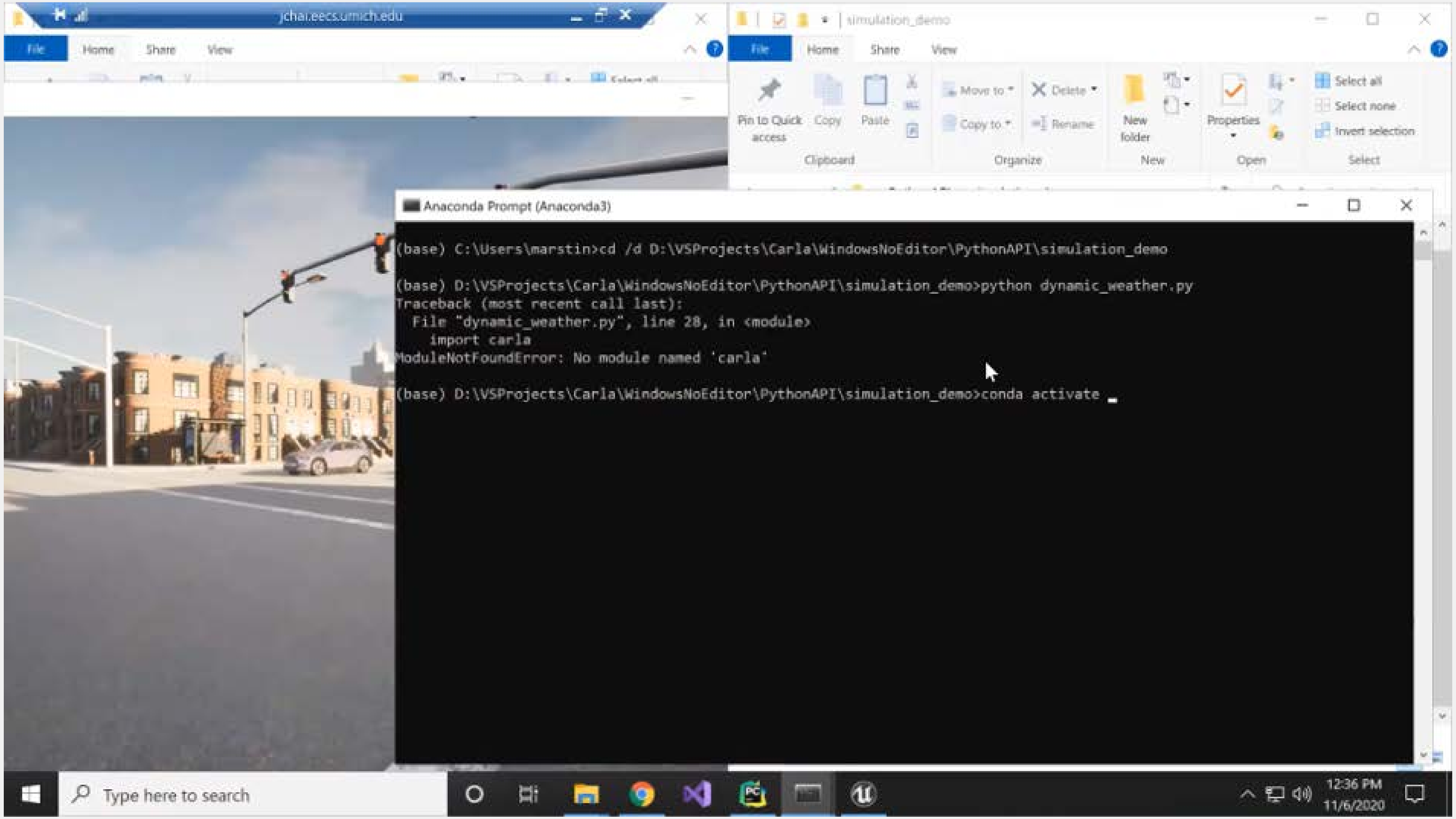
[12] Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). CARLA: An open urban driving simulator. arXiv preprint arXiv:1711.03938.

Demonstration: Multi-agent in CARLA [12]



[12] Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). CARLA: An open urban driving simulator. arXiv preprint arXiv:1711.03938.

Demonstration: Dynamic Weather in CARLA [12]



[12] Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). CARLA: An open urban driving simulator. arXiv preprint arXiv:1711.03938.

Demonstration: Sensors in CARLA [12]

[12] Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). CARLA: An open urban driving simulator. arXiv preprint arXiv:1711.03938.

Summary: Inspirations and Environment

- Instead of using a reward mechanism, imitation learning train a policy that **imitates an oracle** on ground-truth dataset.
- State-of-the-art imitation learning **generalizes badly** from training to testing.
- **Human collaboration** by **natural language system** may be a more reliable input than ground-truth datasets.
- CARLA is a perception simulator with **flexible APIs**, ability to simulate **multiple exceptions**, embedded **Robot Operating System bridge**, thus is suitable for the purpose of this project.

Future Work: Benchmarks

Various autonomous driving tasks were studied. Many involve exception handling.

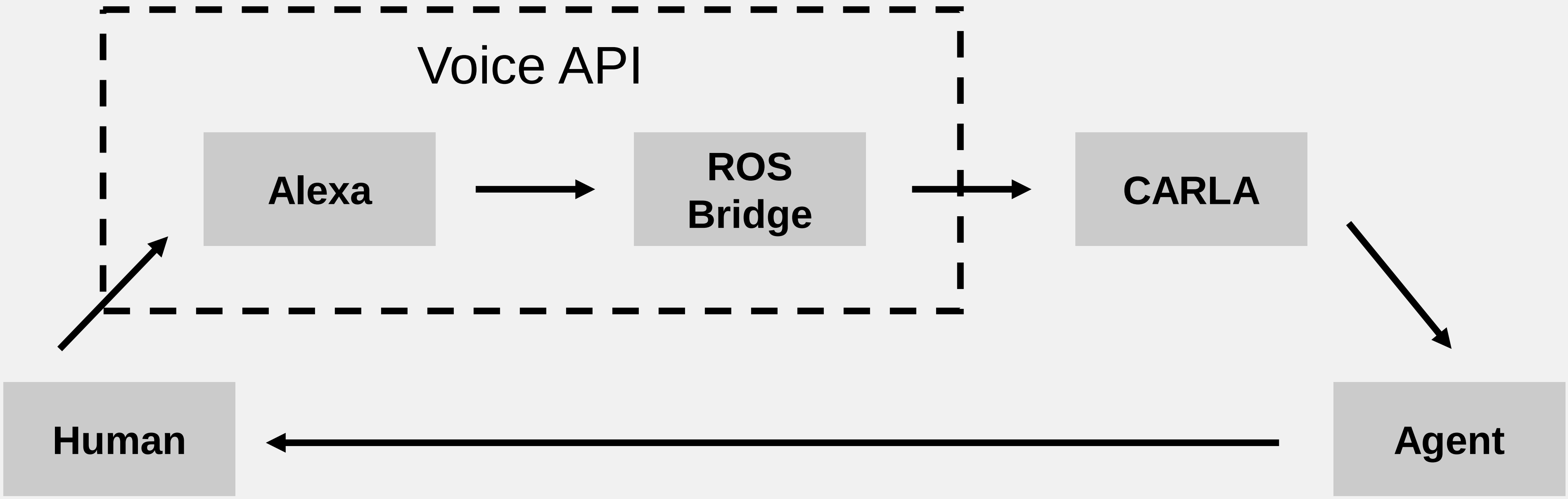
AD Task	Description and Utilization of (D)RL
Motion Planning	Learn to plan trajectories dynamically and optimize cost function to provide smooth control behavior of vehicle. Inverse RL is utilized to learn optimal reward function (or shaping) from experts. Authors propose to learn a heuristic function for the A^* algorithm using a DQN over image-based input obstacle map [84]
Overtaking	Authors [85] propose Multi-goal RL (MGRL) framework to learn overtaking policy while avoiding collisions & maintain steady speed.
Intersections/Merging	Ego-vehicle required to negotiate intersections and merges into highways [86], Ramp merging is tackled in [87], where DRL is applied to find an optimal driving policy using LSTM for producing an internal state containing historical driving information and DQN for Q-function approximation.
Lane Change	Learn a policy that decides whether the vehicle performs no operation, lane change to left/right, accelerate/decelerate. Authors [88] use Q-learning, whereas traditional approaches consist in defining fixed way points, velocity profiles and curvature of path to be followed by the ego vehicle.
Lane Keep	Ego-vehicle follows the lane. Authors [89] propose a DRL system for discrete actions (DQN) and continuous actions (DDAC) using the TORCS simulator (see Table V-C), study concludes that continuous actions provide smoother trajectories, while more restricted termination conditions lead to the slower convergence time to learn.
Automated parking	Learn policies to automatically park the vehicle [90].

Table 3: Existing Benchmarks [1].

[1] Kiran, B. R., Sobh, I., Talpaert, V., Mannion, P., Sallab, A. A. A., Yogamani, S., & Pérez, P. (2020). Deep reinforcement learning for autonomous driving: A survey. *arXiv preprint arXiv:2002.00444*.

Future Work: Voice API

Setting up the voice API connection to the simulator can be tricky.



References

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