

# Pylot: A Modular Platform for Exploring Latency-Accuracy Tradeoffs in Autonomous Vehicles

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**Abstract**—We present Pylot, a platform for autonomous vehicle (AV) research and development, built with the goal to allow researchers to study the effects of the latency and accuracy of their models and algorithms on the end-to-end driving behavior of an AV. This is achieved through a modular structure enabled by our high-performance dataflow system that represents AV software pipeline components (object detectors, motion planners, etc.) as a dataflow graph of operators which communicate on data streams using timestamped messages. Pylot readily interfaces with popular AV simulators like CARLA, and is easily deployable to real-world vehicles with minimal code changes.

To reduce the burden of developing an entire pipeline for evaluating a single component, Pylot provides several state-of-the-art reference implementations for the various components of an AV pipeline. Using these reference implementations, a Pylot-based AV pipeline is able to drive a real vehicle, and attains a high score on the CARLA Autonomous Driving Challenge. We also present several case studies enabled by Pylot, including evidence of a need for context-dependent components, and per-component time allocation. Pylot is open source, with the code available at <https://github.com/erdos-project/pylot>.

## I. INTRODUCTION

Autonomous vehicles (AVs) have attracted considerable research interest and investment in recent years. Over the past decade, advances in application areas such as object detection and localization [1]–[3], vehicle motion planning and control [4]–[8], and behavior and motion prediction [9]–[11] have enabled rapid advances in AV technology. Reciprocally, the promise of AV technology has motivated many recent advances in emerging technologies like artificial intelligence, with, e.g. driving-based datasets becoming fundamental baselines for modern computer vision [12]–[16].

Various vendors [17]–[21] have chosen to realize the computation that underlies an AV as a pipeline similar to the one shown in Fig. 1. In such a pipeline, the output from sensors such as cameras and LiDARs operating at different frequencies, is used by the perception module to construct a representation of the environment around the AV. Further, the prediction and planning modules utilize this representation to construct a trajectory for the AV to reach its intended destination while preventing collisions with other agents and maximizing the comfort of the AV’s passengers. This modular approach has been the standard for AV systems since at least the DARPA Grand Challenge of the mid-2000s [22].

While this decomposition of the driving task into modules (with multiple components) has enabled researchers to innovate independently on each module, it has also led to the development of problem-specific evaluation metrics that fail

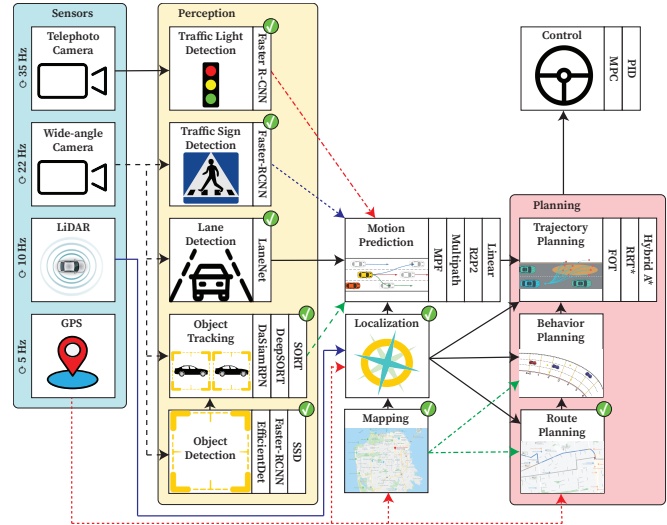


Fig. 1. An AV pipeline consists of several interconnected modules (e.g. perception, planning). For each component in these modules, Pylot provides reference implementations along with “perfect” implementations (for those with a green check mark) that access ground truth data from the simulator.

to account for the end-to-end driving behavior of the AV [23]. For example, even driving-based datasets like KITTI [13] and Cityscapes [14], which are used to develop machine learning (ML) models for the perception module, utilize static evaluation metrics such as average precision [24] that fail to account for the runtime of the model. Exploring the tradeoff between the latency of a module and its accuracy on offline datasets is paramount for safety-critical applications such as AVs where correctness is defined as a function of both the accuracy of the algorithms and their end-to-end runtime [25].

In this paper we introduce Pylot, a modular platform that enables the study of this critical tradeoff between the accuracy of a module and the effects of its runtime on the safety of the AV. Pylot is built on top of our high-performance, deterministic dataflow system [26], and provides: (i) state-of-the-art reference implementations for components allowing researchers to evaluate their algorithms or models in the context of a realistic AV pipeline, (ii) “ground truth” implementations that allow the development of components and their debugging in the context of an idealized AV pipeline, and (iii) a portable interface that enables seamless transition between a simulator and a real vehicle. Finally, Pylot is open source, and is the top submission on the CARLA Autonomous Driving Challenge HD map track <sup>1</sup> [27], thus granting the AV community a platform comparable to proprietary pipelines.

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<sup>1</sup>A demo video of Pylot running on the CARLA Challenge is available at <https://tinyurl.com/y6ozzpwd>.

The remainder of this paper is organized as follows: §II gives an overview of existing open AV platforms, §III presents the critical design goals of Pylot, and §IV discusses how our implementation achieves these goals. Further, §V describes (i) the reference component implementations, (ii) a prototype AV pipeline built with these implementations, and (iii) our experience of porting this pipeline to a real-world AV. Finally, §VI presents several case studies enabled by Pylot that evaluate in-context performance metrics of AV pipeline components, and §VII concludes and discusses future work.

## II. RELATED WORK

Recent work in object detection has emphasized the need to achieve a balance between the latency and accuracy of an ML model for a given application [28]. While there have been efforts to both define evaluation metrics that integrate latency and accuracy of the perception module in the context of AVs [23], [25], and develop flexible backbones for object detection models that enable developers to choose an optimum point in the latency-accuracy curve [3], [29], they fail to account for the effect of the runtime on the end-to-end driving behavior. Moreover, to the best of our knowledge, such metrics do not exist for other modules in the AV pipeline.

On the other hand, open-source implementations of AV pipelines lack significantly in their ability to allow developers to explore the accuracy of individual components in the context of an end-to-end pipeline. For example, both AutoWare [20] and Baidu’s Apollo [21] provide limited interfaces to freely-available simulation platforms. Specifically, neither of these AV pipelines allow photo-realistic simulation of cameras, thus failing to account for the accuracy and runtime of the perception module. Moreover, they omit pre-trained models for other components specific to any simulation platform which raises the bar for testing a component. Finally, the debugging ability of these platforms is also limited by their choice of the underlying publisher-subscriber communication paradigm which complicates the deterministic replay of driving scenarios [30].

## III. PYLOT’S DESIGN GOALS

The central design goal of Pylot is to support the study of the tradeoff between the runtime of components and their accuracy in the context of the end-to-end driving behavior. To achieve this goal, Pylot must fulfill three key requirements: **Modularity**. To enable rich evaluation of new models and algorithms, Pylot must provide modular components that can be swapped out for alternate implementations. This allows developers to compare their components with state-of-the-art implementations on similar driving scenarios in addition to evaluating their components using standard metrics on offline datasets. Moreover, a “plug-and-play” architecture supports the future introduction of new modules and components without requiring a tedious overhaul of the entire pipeline. **Portability**. Developers must be able to transition between different simulators and real-world vehicles in order to evaluate their components across various driving environments. For example, a developer should be able to ensure that their

planning algorithm provides similar behavior on a traffic simulator such as SUMO [31], a dynamic world simulator such as CARLA [32] or AirSim [33], and real-world vehicles. A key stipulation of portability is that Pylot must be highly performant. This allows components developed in Pylot to be tested in simulation, and effortlessly deployed to a real vehicle without any additional changes that might affect the tradeoff between latency and accuracy. On the other hand, the runtimes of components observed in a real vehicle can be faithfully reproduced in order to ensure that the latency-accuracy tradeoff can be correctly explored in simulation.

**Debuggability**. Ensuring the safety of models and algorithms requires extensive testing across various scenarios. Thus, Pylot must provide developers with tools that allow them to understand and easily debug their components when they exhibit abnormal or unsafe behavior. In order to reproduce unsafe behaviors, the software system must be output deterministic (i.e. produce the same output given the same inputs) [34], and the pipeline must enable seamless logging of the data necessary to reconstruct the behavior of the AV pipeline.

## IV. ACHIEVING DESIGN GOALS

We realize the design requirements outlined in §III in our implementation of Pylot, which consists of approximately 28,000 lines of Python code. While Pylot executes atop our low-overhead open-source streaming dataflow system implemented in Rust [26], we chose to implement Pylot itself in Python in order to enable faster prototyping and easier interfacing to both simulators such as CARLA [32] and deep learning frameworks such as PyTorch [35] and Tensorflow [36]. The remainder of this section discusses the design of Pylot by focusing on how it achieves *modularity* (§IV-A), *portability* (§IV-B) and *debuggability* (§IV-C).

### A. Modularity

Pylot’s modular structure is achieved through a dataflow programming model, where the AV pipeline is structured as a directed graph in which vertices, also known as *operators*, perform computation (e.g. running object detection) and edges, also known as *streams*, enable communication through timestamped messages (e.g. transmitting bounding boxes of detected objects). This inter-component communication style is reminiscent of the familiar “publisher-subscriber” model with the operators akin to ROS nodes, and streams akin to the ROS publishers and subscribers. Similar to the publisher-subscriber model, the dataflow programming model limits interactions between operators to streams thus allowing them to be swapped as long as they conform to the same interface (e.g. an object detection component based on FasterRCNN [1] can be swapped for one based on EfficientDet [3]).

However, unlike the publisher-subscriber model, the dataflow programming model allows swapping of components that differ in their runtimes and resource requirements without requiring cascading changes throughout the entire pipeline. Specifically, while a ROS node synchronizes incoming data from multiple sources by fetching data from the required publishers at a fixed frequency, a dataflow system allows

developers to register callbacks that get invoked upon the arrival of synchronized data across the requested streams. The dataflow system underneath Pylot seamlessly synchronizes data across multiple streams by requiring the operators that publish on those streams to send a special *watermark* message upon completion of the outgoing data for a specific timestamp [37]–[40]. Hence, while swapping a component with a different runtime in the publisher-subscriber model requires fine-tuning the frequency at which the downstream operators invoke their computation, a dataflow system is robust to such runtime variabilities and enables highly modular applications.

### B. Portability

In order to allow pipelines developed in simulation to be ported to real-world vehicles, Pylot must support high-throughput processing of the data generated by a vehicle’s sensors [17], [30], [41]. This is enabled through our custom high-throughput and low-latency dataflow system that outperforms ROS, a commonly used robotics middleware, by 30% in terms of communication latency [26] while providing a shim layer that allows *operators* to interface with legacy ROS code. The underlying system *transparently* schedules the parallel execution of these operators across machines according to their resource requirements, and provides collocated modules with zero-copy communication via shared memory queues. Moreover, this transparent scheduling and communication does not require any code changes, and coupled with the shim layer for legacy ROS code allows seamless and piecemeal porting of Pylot to different hardware platforms.

Conversely, Pylot also enables the transition from real-world vehicles to simulation by enabling the precise replication of the runtimes of components in a simulator. We achieve this through Pylot’s integration with the CARLA simulator. CARLA provides two modes of execution: (i) *synchronous*, where the simulator allows the instantaneous application of control commands by pausing the simulator after sending sensor inputs to the client, and (ii) *asynchronous*, where the simulator moves forward and applies the control command when Pylot finishes execution. While CARLA’s asynchronous mode should allow control commands to be precisely applied when the computational pipeline finishes executing, it lags behind due to the high rendering cost of the underlying graphics engine. This results in the imprecise application of control commands from the pipeline to the simulated vehicle.

To enable a timely application of the control commands, we developed a *pseudo-asynchronous* execution mode that allows Pylot to maintain tight control over the simulation loop. In this mode, we run CARLA *synchronously* with a high frequency (over 200Hz), and attach a synchronizer between the control module and the simulator. This synchronizer tracks the runtime of the pipeline for each sensor input, and buffers the control command until the simulation time is at least the sum of the sensor input time and the runtime of the pipeline.

Both the synchronizer and Pylot can be ported to other simulators [33], [42] with minimal effort. Developers are only required to implement drivers to extract sensor data from the

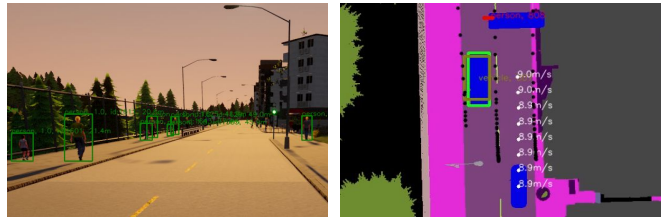


Fig. 2. Pylot’s visualizations for critical components. The object tracker view (left) shows the bounding boxes and the identifiers of detected agents in the camera frame. A bird’s eye view of the planning module (right) includes lanes, predictions for agents, and waypoints computed by the planner.

simulator (e.g., camera frames, LiDAR point clouds), and an operator to send control commands to the simulator.

### C. Debuggability

Pylot integrates with CARLA’s ScenarioRunner [43], and provides a suite of test scenarios based on the National Highway Traffic Safety Administration’s pre-crash scenarios [44]. In contrast to other AV pipelines implemented atop a publisher-subscriber model [20], [21], [30], Pylot’s underlying dataflow programming model enables deterministic replay of such scenarios, thus allowing easier debugging of components. This deterministic execution is achieved by performing computation on the receipt of *watermark* messages [38], [39], [45]. This reduces the execution of the entire AV pipeline to a Kahn Process Network [46], which guarantees determinism.

To aid in debugging the latency and accuracy of components, Pylot provides extensive logging of both output data and the runtime of each component. Specifically, Pylot can be configured to log sensor data, and outputs of internal modules such that scenarios can be reproduced and debugged offline. Moreover, Pylot provides fine-grained logs for the execution time of each component that can be visualized using trace profiling tools [47] and replayed in order to study the latency-accuracy tradeoffs in deterministic scenarios.

To aid in development, Pylot provides “perfect” modules that obtain ground-truth data from CARLA, which can be used to test other modules in isolation (e.g., planning using perfect perception), and to generate new training data sets. Moreover, Pylot can be deployed with different sensor setups (e.g., cameras only, cameras and LiDARs), and can be used to study the end-to-end performance of each setup, and as well the robustness of solutions when only partial or noisy sensor data is available [48].

In addition, Pylot provides visualizations for important information, such as detected objects, lanes, and traffic lights; sensors including cameras, LiDARs, and inertial measurement units; and algorithmic outputs for depth perception, pose estimation, behavior prediction, semantic segmentation, and planning. Fig. 2 exemplifies two such visualizations: (i) the output of one of Pylot’s reference object trackers, and (ii) a bird’s eye view of the information used by Pylot’s planners to compute trajectories (detected obstacles, lanes, traffic signs, predicted trajectories, and proposed waypoints).

## V. PYLOT: AN AV DEVELOPMENT PLATFORM

The goal of Pylot is to accelerate research into new algorithms and models for autonomous driving as well as the



design of the underlying software systems. To support this goal, Pylot provides: (i) state-of-the-art algorithms, pre-trained models, and evaluation metrics, (ii) the ability to selectively replace components and modules with ground-truth data from simulators, (iii) an easily extensible deterministic runtime environment, and (iv) a range of challenging driving scenarios. In the rest of this section, we describe the key components and modules in Pylot (c.f. Fig. 1), and our experience of porting Pylot from a simulator to a Lincoln MKZ test vehicle <sup>2</sup>.

### A. Object Detection

The object detection component comprises of operators that process camera and LiDAR data to detect, and localize objects, lanes, and traffic lights. These operators communicate their results via an `ObstacleMessage` that contains the bounding box of the detected object along with the confidence score returned by the ML model. Users may run multiple versions of these models in parallel in order to benchmark against each other and against perfect detection by using the standard accuracy metrics (e.g. mAP) provided by Pylot.

Pylot allows drop-in replacements of models conforming to the Tensorflow Object Detection API [28], and provides several configurations of Faster-RCNN [1] and SSD [2] models trained on data collected from the CARLA simulator using Pylot. In addition, we also utilize the EfficientDet [3] family of models which are built atop of a variable-sized network backbone. This property of EfficientDet along with the different configurations of Faster-RCNN and SSD allow the exploration of the runtime-accuracy tradeoff space.

### B. Object Tracking

The tracking component estimates the bounding boxes of objects over time, and maintains consistent identifiers for the objects across detections. Pylot provides three object trackers that cover the two main tracking approaches: (i) *tracking-by-detection* continuously updates tracker state with bounding boxes received from object detection, and (ii) *detection-free tracking* follows a fixed number of objects over time. These trackers utilize the bounding boxes from the `ObstacleMessage` and communicate their results via an `ObstacleTrajectoryMessage` that contains the bounding box along with the identifier for each obstacle.

We find that each tracker has context dependent performance and accuracy tradeoffs. For example, the SORT [49] tracker is a lightweight multiple object tracker of the tracking-by-detection variant that uses Kalman filters to estimate object positions between frames assuming a constant linear velocity model, and the Hungarian algorithm to match bounding boxes upon detection updates. While SORT is fast, it offers low accuracy in the presence of object occlusions or camera motion. However, DeepSORT [50] improves on these limitations by incorporating appearance information for each tracked object, at the cost of an increased runtime from executing a convolutional feature extraction model.

On the other hand, DaSiamRPN [51] is a detection-free single object tracker that leverages a siamese feature extraction network to learn distractor-aware features. The tracker relies on neural network inference to track an object thus providing more accurate estimations between detections at the cost of increased runtime. However, the “best” choice of tracker depends on the situation. For example, SORT performs best in emergency scenarios when low runtime is critical and DeepSORT is best in regular driving situations, while DaSiamRPN excels in scenarios that demand high accuracy for a small number of objects (e.g. urban driving).

### C. Prediction

The prediction module uses the tracked history of nearby agents (vehicles, pedestrians, etc.), along with scene context from LIDAR, to predict future agent behavior. Specifically, it receives the bounding box and the identifier of each obstacle at every time instant through the `ObstacleTrajectoryMessage`, and generates an `ObstaclePredictionMessage` containing the past and the predicted trajectory for each obstacle.

Pylot contains multiple implementations of the prediction module trained on CARLA data that represent the major classes of ML based approaches for trajectory prediction. As a baseline, Pylot also provides a linear predictor that utilizes a linear regression model that assumes that each agent will travel at a constant velocity and predicts their forward position based on their past trajectory. While this predictor is fast and hence ideal for emergency collision-avoidance scenarios, it does not account for the behavior of multiple agents.

Additionally, Pylot provides R2P2 [10], a state-of-the-art single-agent trajectory forecasting model which learns a distribution over potential future trajectories that is parameterized by a one-step policy using a gated recurrent unit, and attempts to optimize for both quality and diversity of samples. To extend R2P2 to the multi-agent setting, Pylot runs R2P2 on every agent by rotating the scene context and past trajectories of other agents to the ego vehicle coordinate frame.

Finally, Multipath [52] uses a lightweight neural network to obtain a useful representation of the scene and then applies a smaller network features for each agent to output predictions. Because the per-agent computation can be batched, Multipath is fast but less accurate owing to its inability to explicitly consider agent interactions. In contrast, Multiple Futures Prediction (MFP) [53] jointly models agent behavior, leading to increased runtime but more accurate predictions.

### D. Planning

The goal of the planning module is to produce a safe, comfortable, and feasible trajectory that accounts for the present and future possible states of the environment. To achieve this, the planning module in Pylot synchronizes the output from all the other modules to construct a `World` representation that contains the past and future trajectories of all agents in the scene, along with the location and state of static objects such as traffic lights, traffic signs etc. Crucially, this allows Pylot to selectively utilize ground truth information

<sup>2</sup>A demo video of Pylot running on the MKZ is available at <https://tinyurl.com/y5vsly3f>.

for any of the previous components or modules and ascertain the effects of the accuracy and runtime of a selected set of components on the end-to-end driving behavior of the AV.

The planning module is comprised of three components: route, behavioral, and motion planners, with the latter having the greatest effect on the comfort and the end-to-end runtime of the AV. Hence, Pylot provides implementations for each of the three main classes of motion planners: graph search, incremental search, and trajectory generation [54]–[56].

*Graph-based search planners* (e.g. Hybrid A\* [5]) discretize the configuration space as a graph and provide fast results at lower discretizations. However, a poor choice of the discretization value may produce infeasible paths. On the other hand, *incremental search planners* (e.g. RRT\* [4]) gradually build a path by sampling the configuration space instead of precomputing a fixed set of configuration nodes. They are not limited by the initial graph construction, and thus provide the ability to fine-tune the accuracy of the result for any given computation time. Finally, *trajectory generation planners* (e.g. Frenet Optimal Trajectory [6], [57]) construct a set of candidate paths, which they validate for collisions and physical constraints. While the resulting paths are usually smoother than their counterparts, trajectory generation may omit feasible paths if the discretization is too coarse.

#### E. Control

The control module receives waypoints and target speeds from the planning module. It aims to closely follow the provided waypoints while maintaining its target speed. Pylot offers two control options: a Proportional-Integral-Derivative (PID) controller, and a Model Predictive Control (MPC) controller. Both options compute commands that adjust brakes, steering, throttle, and send these to the simulator or a real-world vehicle’s drive-by-wire kit.

While Pylot currently comprises of the modules described above, developers can integrate multi-functionality modules (e.g. MPC for both motion planning and control [58], [59]) or replace entire subgraphs of the pipeline with end-to-end learning-based solutions [60]–[62].

#### F. Deploying Pylot on an Autonomous Vehicle

In order to port Pylot from the CARLA simulator to a Lincoln MKZ AV, we made the following minimal changes:

- 1) **Sensors:** we utilized the shim layer that injects data from ROS topics exposed by the drivers of the AV’s sensors.
- 2) **Control:** we modified Pylot to send control commands to the ROS node exposed by a drive-by-wire kit [63].
- 3) **Localization:** we used the Normal Distributions Transform (NDT) algorithm [64] implemented in Autoware [20].
- 4) **Model replacement:** we replaced our CARLA-trained detection and tracking models with off-the-shelf models trained on real-world datasets.

As mentioned previously, porting from simulation to a real vehicle required only 434 lines of Python code. This efficiency demonstrates the flexibility of our interfaces.

## VI. EVALUATION

We now show how Pylot enables researchers to study: (i) the trade-off between accuracy and runtime for different components (§VI-A), (ii) the effects that changes in a single component have on an end-to-end driving metric (§VI-B).

**Experimental Setup.** The experiments were performed atop CARLA on a machine having 2×Xeon Gold 6226 CPUs, 128GB of DDR4 RAM and 2×Titan-RTX 2080 GPUs.

#### A. Accuracy vs. Runtime

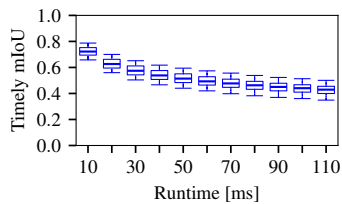
We introduce a new family of metrics, **timely accuracies**, in order to capture the impact of runtime on accuracy of modules. The timely accuracy is a metric of how accurate a module’s results are with respect to the present world, and not the past world captured by the input on which the result was based. The key idea is to evaluate a module’s output performed on inputs at time  $t_1$  with the ground truth labels at  $t_2 = t_1 + l_t$ , where  $l_t$  is the module’s runtime. Thus, timely accuracy captures how accuracy degrades as a function of runtime in dynamic worlds.

In the experiment, we attached a camera to a simulated AV, and set up a scenario in which the AV drove in a city at 20 m/s. For each frame we collected the ground-truth semantic segmentation and computed the *timely* (i.e. time-delayed) mean Intersection over Union (mIoU) by emulating different prediction runtimes. Fig. 3a shows that a runtime of 10ms is sufficient to reduce mean *timely* mIoU of a perfect semantic segmentation component to approximately 0.75, which is less than the mIoUs of the top three Cityscapes submissions [14]. Similarly, we measured the tradeoff between accuracy and runtime for pedestrian detectors by computing *timely* Average Precision at IoU 50% ( $AP^{50}$ ) for a perfect detection component (i.e. with 1.0  $AP^{50}$ ). Fig. 3b shows that mean *timely*  $AP^{50}$  halves with a runtime of 35ms. Thus, an object detector with long runtimes must be accompanied by a tracker or a prediction component that can predict accurate trajectories for longer than the detector’s runtime.

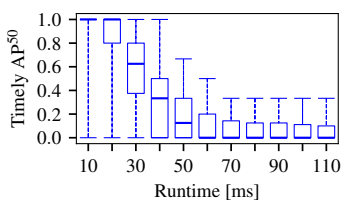
The timely accuracy does not only depend on runtime, but also on the AV’s driving speed. The faster an AV drives, the quicker the world changes. To show the effect of an AV’s speed on timely accuracy, we emulated a 20ms runtime for the perfect semantic segmentation and detection components, and varied the driving speed. In Fig. 3d, we illustrate that the *timely* mIoU for semantic segmentation decays as speed increases: median *timely* mIoU is 28% smaller at 40m/s than at 10m/s. In the case of object detection, speed has a bigger effect on *timely*  $AP^{50}$ : median *timely*  $AP^{50}$  is 1.0 when driving at 10m/s, but it decreases to 0 at 40m/s (Fig. 3e). In Fig. 3f we illustrate the trade-off between model accuracy and runtime using models from the KITTI pedestrian detection challenge [65]. We observe that fast, low-accuracy detectors obtain higher timely accuracy than slow, high-accuracy detectors when driving at high speeds.

#### B. Effects of Component Changes on End-to-end Driving

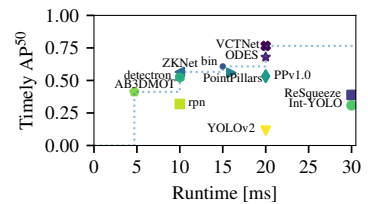
We now leverage Pylot’s *pseudo-asynchronous* execution mode to study both the effect of component changes and



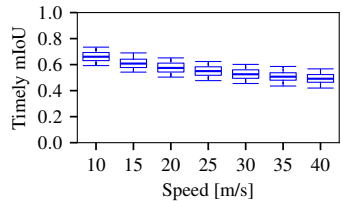
(a) Semantic segmentation timely mIoU.



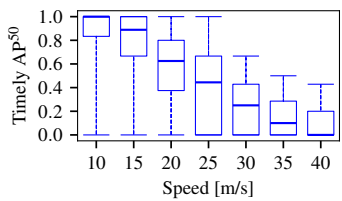
(b) Pedestrian detection timely AP<sup>50</sup>.



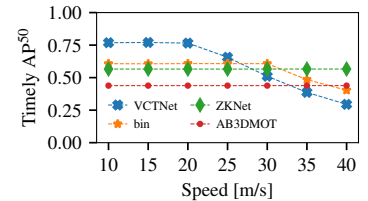
(c) Choice of best detector changes.



(d) Semantic segmentation timely mIoU degrades faster at high speeds.



(e) Pedestrian detection timely AP<sup>50</sup> degrades faster at high speeds.



(f) Different object detectors are best at different driving speeds.

Fig. 3. Timely mIoU and AP<sup>50</sup> degrade when runtime and driving speed increase. Thus, accuracy, runtime, and driving speed are all important when making model decisions (3c and 3f).

TABLE I

CONFIGURATIONS THAT AVOID A COLLISION ARE MARKED IN GREEN, WHILE FAILING CONFIGURATIONS ARE MARKED IN RED.

	Speed [m/s]	16	18	20	22
Planner [P <sub>99</sub> runtime]					
FOT [P <sub>99</sub> = 30 ms]		Green	Green	Red	Red
FOT [P <sub>99</sub> = 550 ms]		Red	Red	Red	Red
RRT* [P <sub>99</sub> = 15 ms]		Green	Green	Green	Red
RRT* [P <sub>99</sub> = 76 ms]		Red	Red	Red	Red
Hybrid A* [P <sub>99</sub> = 25 ms]		Green	Red	Red	Green
Hybrid A* [P <sub>99</sub> = 760 ms]		Red	Red	Red	Red

model hyperparameter tweaks on end-to-end driving. For this experiment, we developed a scenario which simulates the illegal crossing of the AV’s lane by a person, as shown in Fig. 2. The scenario is further complicated by the presence of a truck on the opposite lane, which occludes the person until it reaches the AV’s lane (20 meters away). This presents an imminent threat to the AV, and requires the AV to perform an emergency maneuver to avoid a collision.

In this experiment, we omit the perception models and use ground truth to compare each planner in isolation<sup>3</sup>. For the Frenet Optimal Trajectory (FOT) planner [6], [57] we executed a fast and a slow configuration with 0.3 seconds time discretization and 0.5 meters space discretization, respectively 0.1 space and time discretization. Similarly, for RRT\* [4] we experimented with 0.1 and 0.5 meters step sizes. Lastly, we explore Hybrid A\* [5] with step sizes of 3.0 and 6.0, and radian step discretizations of 0.25 and 0.75.

In Table I we show which configurations avoided a collision with the person and the truck for different *target speeds* the AV drove at before it detected the person. Since avoiding a collision requires a fast, *swerving* maneuver from the AV, the planner configurations that minimized runtime performed better. Furthermore, Fig. 4 compares the three configurations that succeed at 16m/s target speed by plotting the lateral jerk (i.e. ride comfort) while performing the *swerving* maneuver to

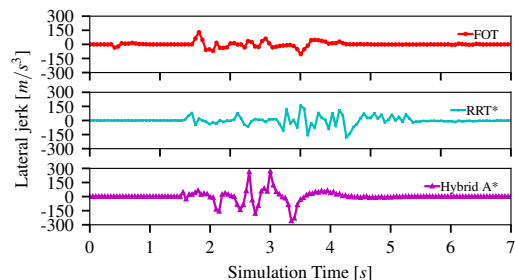


Fig. 4. Comparison of the ride comfort offered by the planners that avoid the collision when driving at 16 m/s target speed.

avoid a collision. We see that the three planners have markedly different jerk profiles. While FOT avoids a collision in fewer cases than RRT\*, it provides a more comfortable ride. This experiment illustrates the realistic end-to-end “A/B testing” of AV components enabled by Pylot.

## VII. CONCLUSION

We have presented an open-source platform for AV research. Pylot’s modular and portable structure enables iterative development and evaluation of components in the context of an entire AV pipeline. This approach to AV development supports the study of interactions between modules, resulting in a better understanding of the effects of runtime and accuracy on end-to-end driving behavior.

Pyilot provides reference and ground-truth implementations for several components of an AV pipeline. These state-of-the-art implementations have been used to both drive a real-vehicle and attain a high score on the CARLA Challenge.

In the future, we aim to enable a similar study of reinforcement learning based approaches to autonomous driving by providing an OpenAI Gym interface [66]. We hope that our work on Pyilot will help broader AV community conduct impactful research that will lead to a safer autonomous future.

<sup>3</sup>Visualizations are available at <https://tinyurl.com/y3coq57r>.



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