



# End to End Multimodal Imitation Learning

Group 3 | APP-RAS | Milestone 3 | WS 22/23

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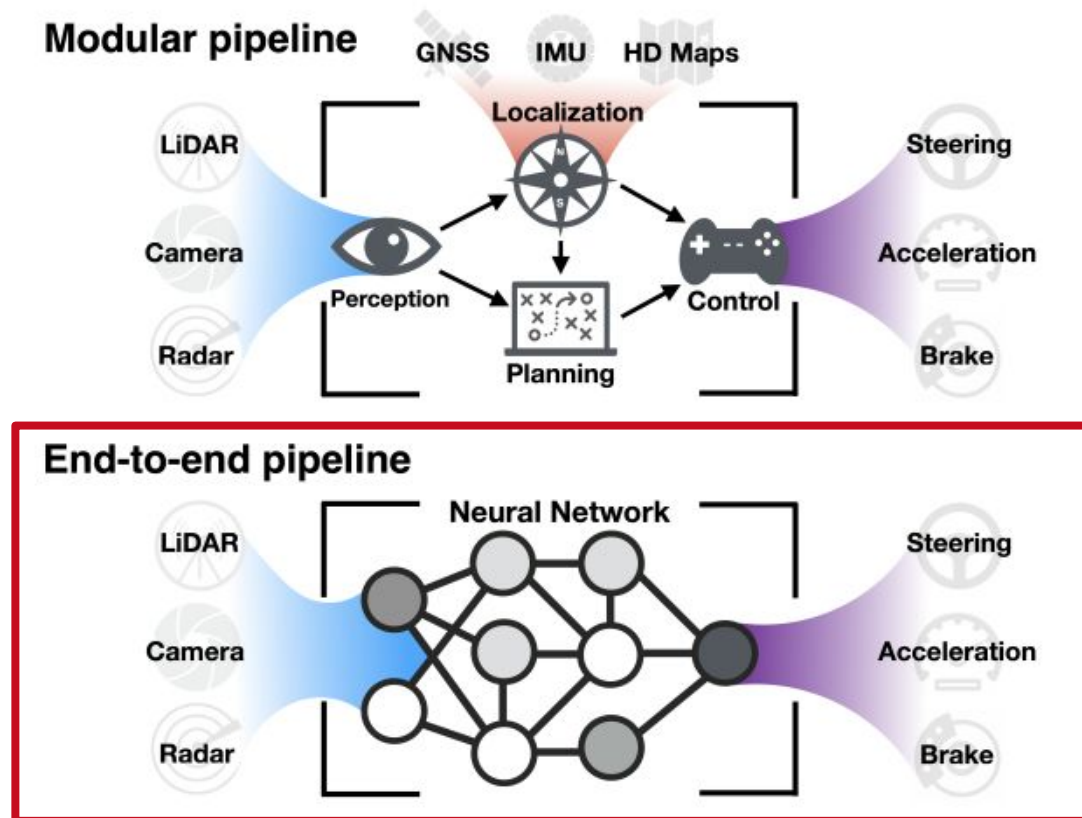


# Agenda

1. **End-to-End Imitation Learning in Autonomous Driving**
2. **Goal & Steps Overview**
3. **Dataset**
4. **Model Architectures**
5. **Model Training**
6. **Model Evaluation**

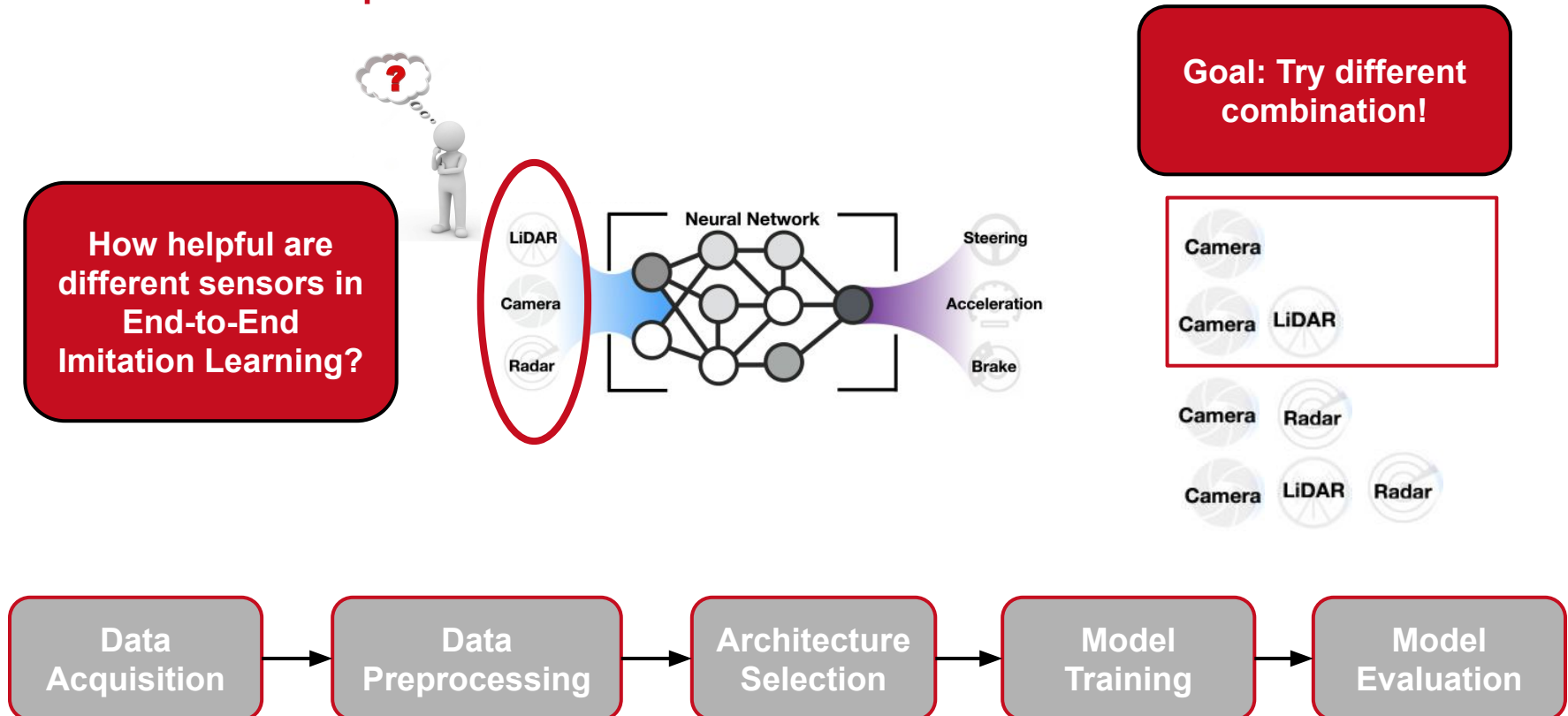


# 1. End-to-End Multimodal Imitation Learning in AD





## 2. Goal & Steps Overview

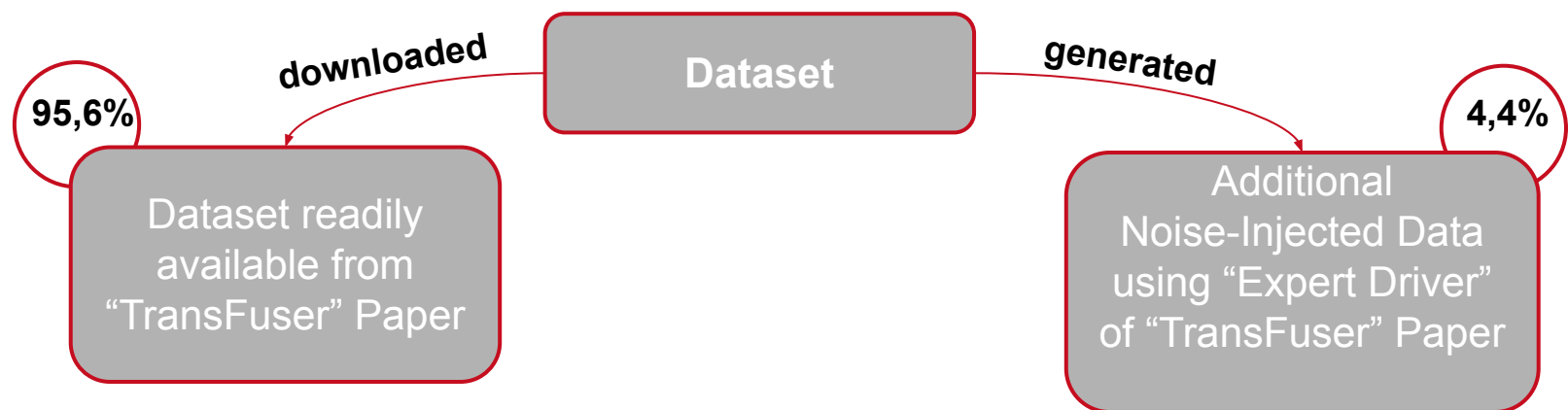




### 3. Dataset - Acquisition



Using CARLA  
Simulator for  
Data Acquisition

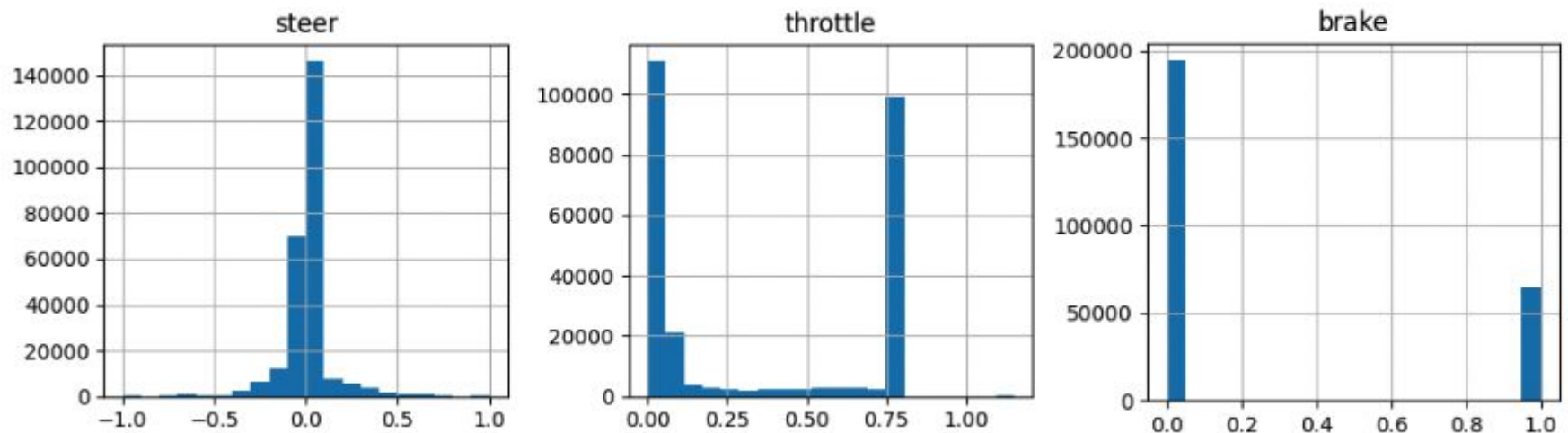






## 3. Dataset - Characteristics

- Driving Length: 1 day 14h
- Raw size: 61 GB
- Number Towns: 9
- Sensors: 3 RGB (160 x 960), LiDAR, Speedometer, ...
- Target values: Steer, Throttle, Brake (Control Commands)
- Additional: Navigational Command (turn left, turn right, go straight, ...)





### 3. Dataset - Preprocessing

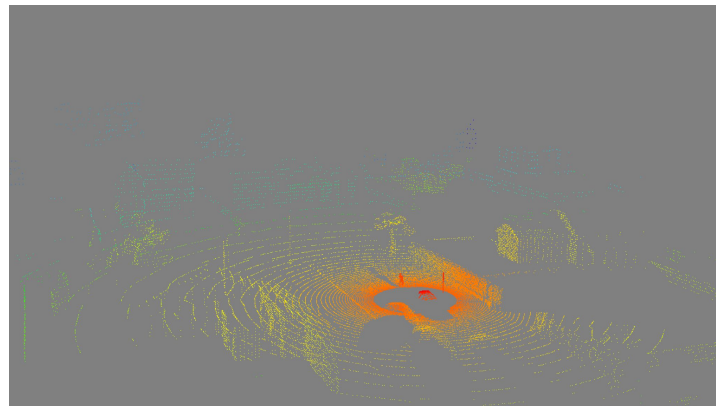
RGB

Resize to  
88 x 224 x 3

Scale to [0, 1]

Z - Normalization

LiDAR

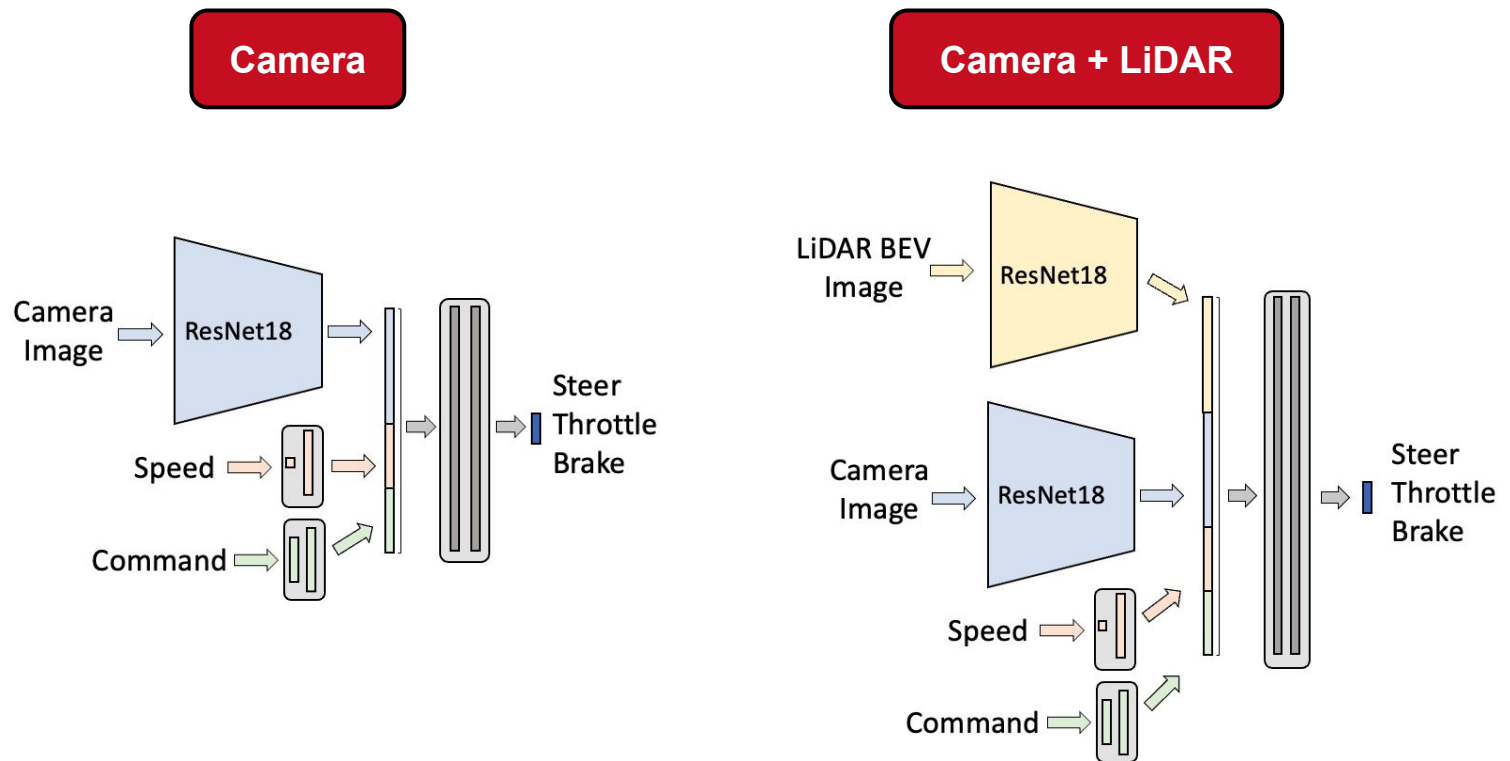


Scale to [0, 1]

Z - Normalization



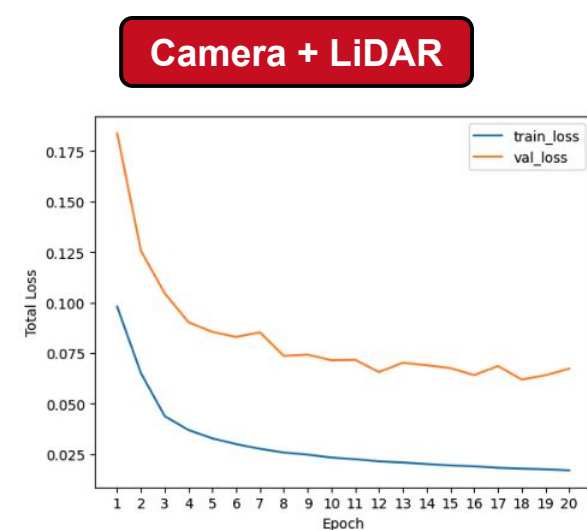
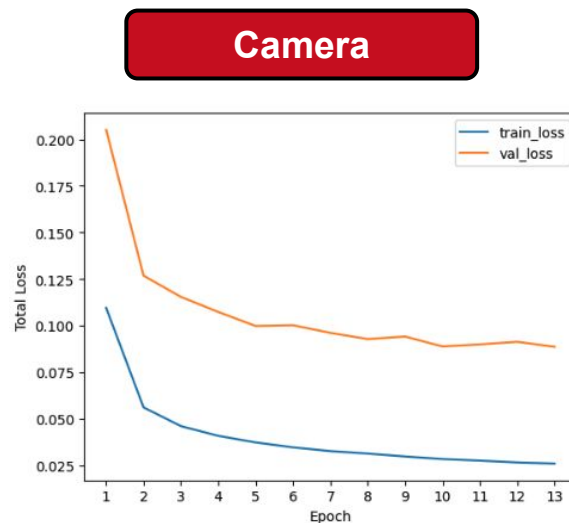
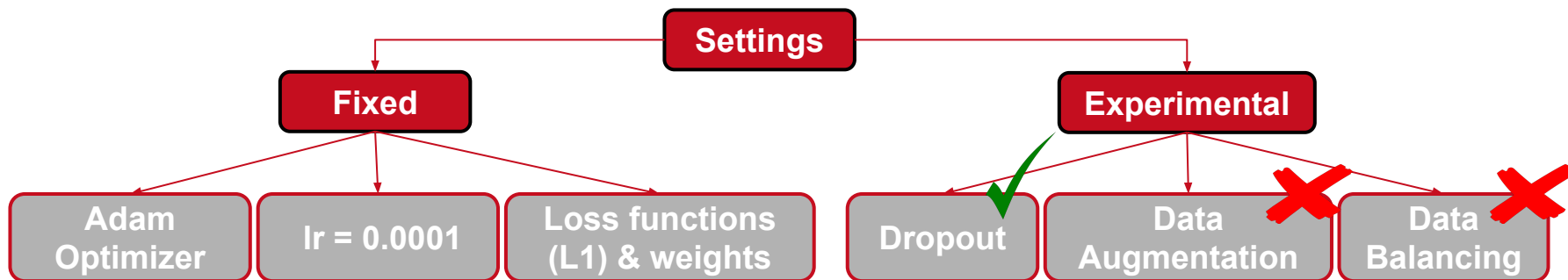
## 4. Model Architectures







## 5. Model Training





## 6. Model Evaluation - “Longest6” Benchmark Statistics

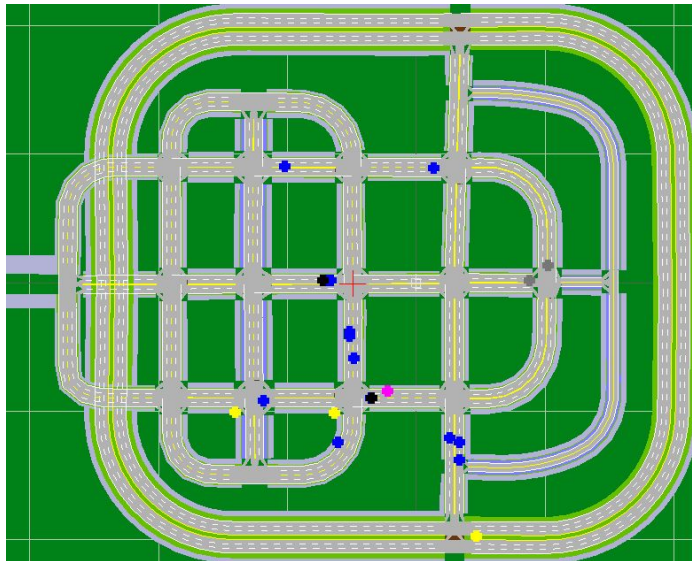
	Camera	Camera + LiDAR
<b>Avg. driving score ↑</b>	9.601	<b>13.365</b>
<b>Avg. route completion ↑</b>	<b>39.452</b>	33.597
<b>Avg. infraction penalty ↑</b>	0.358	<b>0.464</b>
Collisions with pedestrians ↓	0.000	0.000
Collisions with vehicles ↓	3.031	<b>1.601</b>
Collisions with layout ↓	0.421	<b>0.378</b>
Red lights infractions ↓	<b>0.512</b>	0.608
Stop sign infractions ↓	0.162	<b>0.123</b>
Off-road infractions ↓	0.855	<b>0.273</b>
Route deviations ↓	<b>0.389</b>	0.828
Route timeouts ↓	0.097	<b>0.032</b>
Agent blocked ↓	<b>0.943</b>	0.956

→ **Camera + LiDAR**  
outperforms Camera in the  
“Average driving Score”

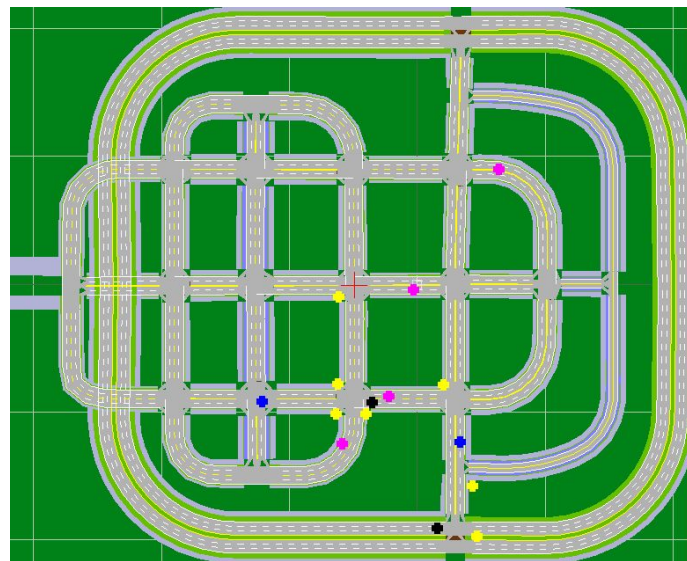


## 6. Model Evaluation - Visual Inspection

Camera



Camera + LiDAR



- collisions\_layout
- collisions\_pedestrian
- collisions\_vehicle
- outside\_route\_lanes
- red\_light
- route\_dev
- route\_timeout
- stop\_infraction
- vehicle\_blocked



## 6. Model Evaluation - Camera + Lidar during Night







## 6. Model Evaluation - Camera + Lidar - Right Turn







## 6. Model Evaluation - Camera - Alignment to the Lane





## 6. Model Evaluation - Camera - Crash during Right Turn





## 6. Model Evaluation - Camera - Crash in Straight Lane





# Conclusion

## Objectives

- **Sensor choices:** Decide on a set of sensors and different combinations (setups). ✓
- **Expert Driver:** Choose an expert driver for CARLA. ✓
- **Dataset:** Generate a Dataset with the expert driver. ✓
- **E2E Model:** Implement an E2E model capable of driving autonomously. ✓
- **Data Preprocessing** (for all sensor setups): Build a pipeline to generate compatible data for the chosen architecture. ✓
- **Training:** Train the different models with varying sensor setups and varying data sizes. ✓
- **Evaluation:** Conduct the experiments and compare the sensor setups. ✓

## Use Cases

We expect **route completions and low infractions** in:

- Easy environment: (short routes, less cars) empty roads, good weather (on training routes) ✓
- Hard environment: (long routes, max cars) “Longest6” ✗





## Future Work

- Room for improvement in terms of hyperparameters (functions architectures)
- Validation using CARLA after every epoch (Model Selection)
- Changing to Vision Transformer architectures
- More sensor configurations
- More in-depth comparative analysis and more context





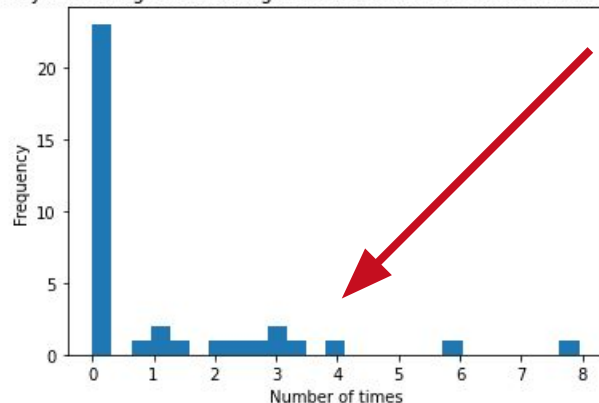
# Thank you for listening!

Any questions?

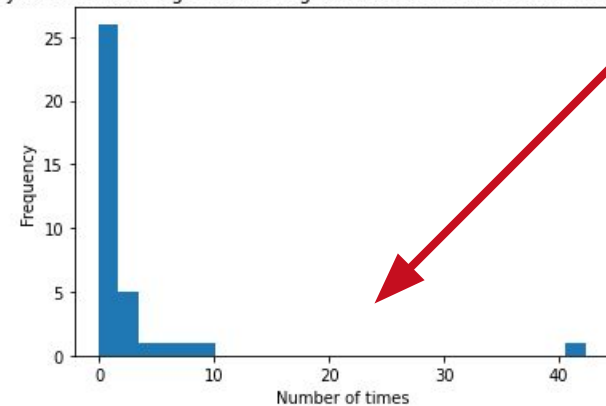


# Visualising Dev and Collision improvement

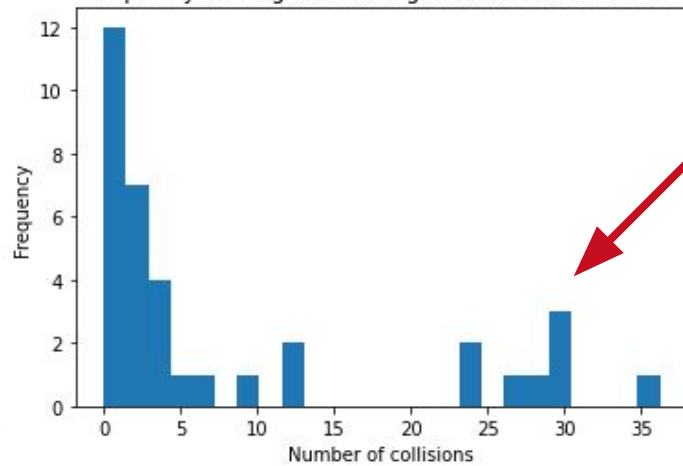
Frequency of RGB agent deviating more than 30 meters from the assigned route.



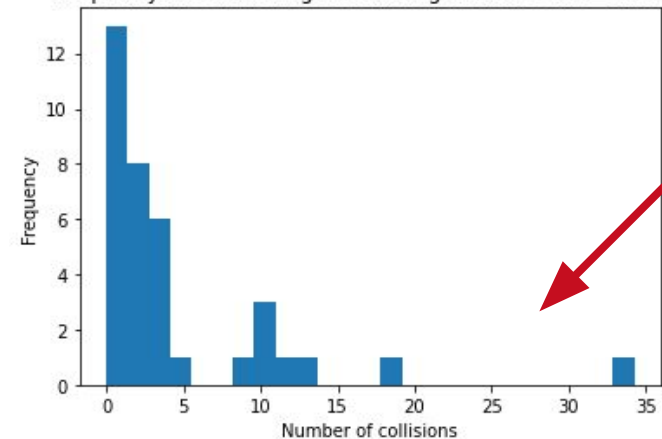
Frequency of RGB+Lidar agent deviating more than 30 meters from the assigned route.



Frequency RGB agent colliding with the other vehicles



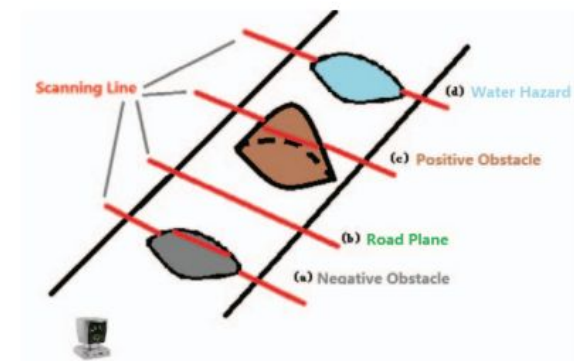
Frequency RGB+Lidar agent colliding with the other vehicles





## Lidar Preprocessing

- Transform  $[X, Y, Z, I]$  (coordinates, intensity loss during travel)
- To 2d Histogram representing a horizontal plane in front of the car
- Birds eye view, can process both other cars in traffic (positive obstacles), as well as holes in the ground or small objects below the eye level (negative obstacles)
- “Lidar-histogram for fast road and obstacle detection”





## Leaderboard

How do we measure performance, specifically?

We use the Longest6 benchmark!

- 36 routes
- Average route length 1.5 km (official leaderboard ~1.7km)
- High density of dynamic agents: vehicles spawned at all possible locations in CARLA
- Unique environmental conditions with combinations of:
  - Six weather conditions: Cloudy, Wet, MidRain, WetCloudy, HardRain, SoftRain
  - Six daylight conditions Night, Twilight, Dawn, Morning, Noon, Sunset.



## Measuring performance

The Longest6 benchmark uses three major factors to measure performance:

- **Driving score:**  $R_i P_i$ , — Main metric of the leaderboard, serving as the product between the route completion and the infractions penalty. Here  $R_i$  is the percentage of completion of the  $i$ -th route, and  $P_i$ , the infraction penalty of the  $i$ -th route.
- **Route completion:** Percentage of the route distance completed by an agent.
- **Infraction penalty:**  $\prod_j^{\text{ped.}, \dots, \text{stop}} (p_i^j)^{\# \text{infractions}}$ . The leaderboard tracks several types of infractions and this metric aggregates all of these infractions triggered by an agent as a geometric series. Agents start with an ideal **1.0** base score, which is reduced each type an infraction is committed.





## Breaking it down

### Infractions and shutdown events

The CARLA leaderboard offers individual metrics for a series of infractions. Each of these has a penalty coefficient that will be applied everytime it happens. Ordered by severity, the infractions are the following.

- **Collisions with pedestrians** — 0.50.
- **Collisions with other vehicles** — 0.60.
- **Collisions with static elements** — 0.65.
- **Running a red light** — 0.70.
- **Running a stop sign** — 0.80.