Imitation with Transformer-Based Sensor Fusion for Autonomous Driving

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Team

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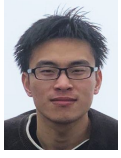


Zehao Yu

Katrin Renz

Andreas Geiger

Covered Papers

- **Multi-Modal Fusion Transformer for End-to-End Autonomous Driving**
  A. Prakash*, K. Chitta* and A. Geiger. CVPR, 2021.

- **TransFuser: Imitation with Transformer-Based Sensor Fusion**
  K. Chitta, A. Prakash, B. Jaeger, Z. Yu, K. Renz and A. Geiger. In Review.

Evaluating Self-Driving

Common Task Framework

Computer Vision

Semantic Segmentation

130 benchmarks

2537 papers with code

Image Classification

311 benchmarks

2189 papers with code

Object Detection

216 benchmarks

1910 papers with code

Image Generation

176 benchmarks

839 papers with code

Denoising

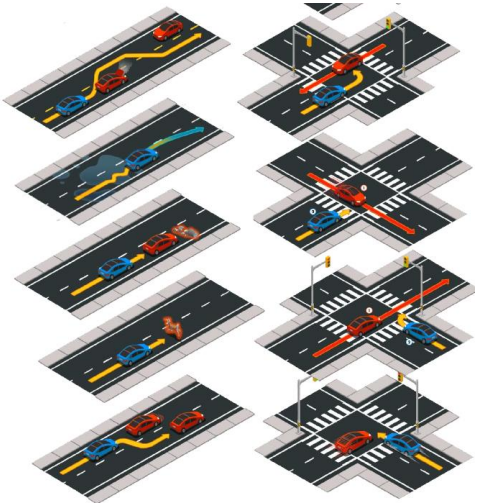
103 benchmarks

802 papers with code

See all 1235 tasks

- A **common task framework** accelerates research progress
- Computer vision: **static benchmarks**
- How can the community compare **dynamic self-driving** agents?

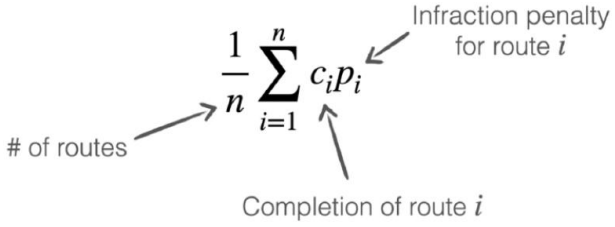
CARLA Leaderboard

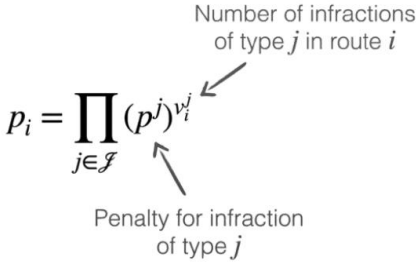


- 10 routes x 2 weathers x 5 repetitions
- 173 Km of driving experiences

Slide Credit: German Ros https://carla.org/ https://leaderboard.carla.org/

CARLA Leaderboard Evaluation





Imitation Learning for CARLA

Imitation Learning

Motivation: Hand-designing a sensor-based driving policy is difficult

Imitation Learning

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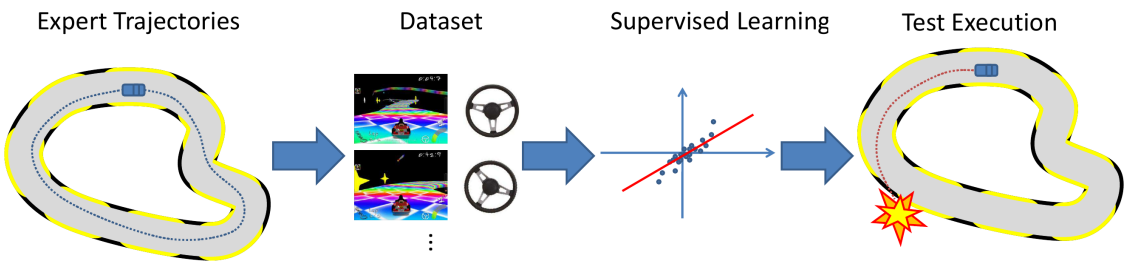
- **Step 1:** Hand-design expert which uses privileged information

Imitation Learning

Motivation: Hand-designing a sensor-based driving policy is difficult

- **Step 1:** Hand-design expert which uses privileged information
- **Step 2:** Train sensor-based policy to mimic demonstrator



Sensor Fusion

Sensors

RGB Camera

- \+ Dense RGB input
- − Lacks reliable 3D information
- − Variation in weather

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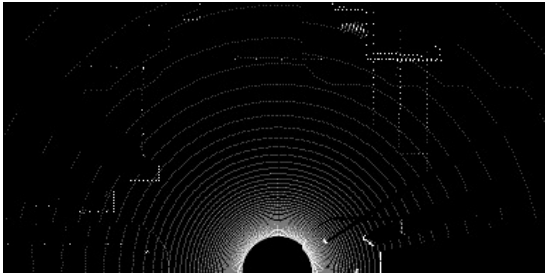
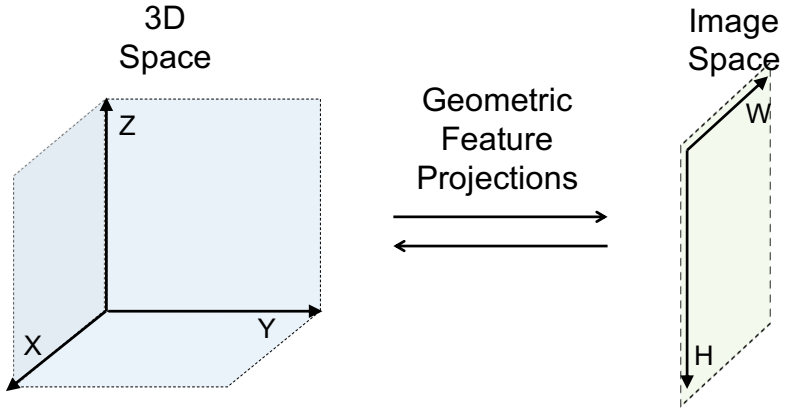
LiDAR Point Cloud



- \+ 3D information
- − Sparse input
- − No traffic light state

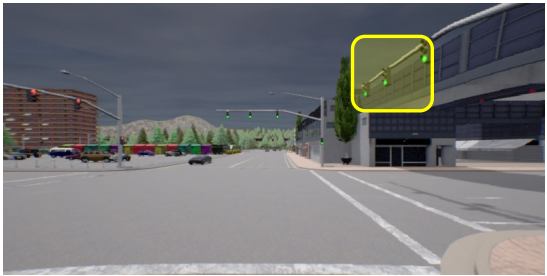
A. Prakash, K. Chitta and A. Geiger: Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. CVPR, 2021.

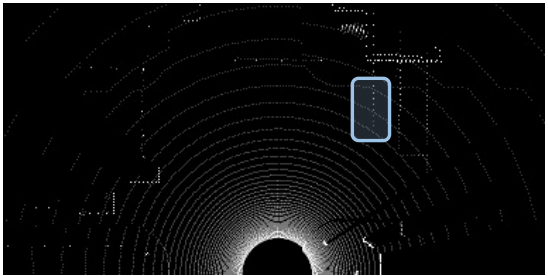
Geometric Fusion



A. Prakash, K. Chitta and A. Geiger: Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. CVPR, 2021.

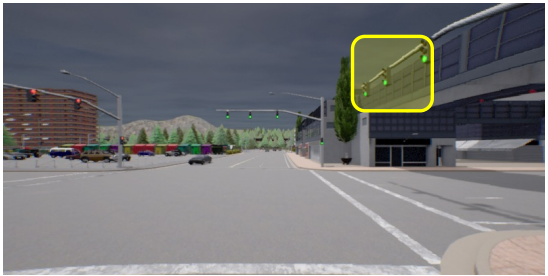
Geometric Fusion Lacks Global Context

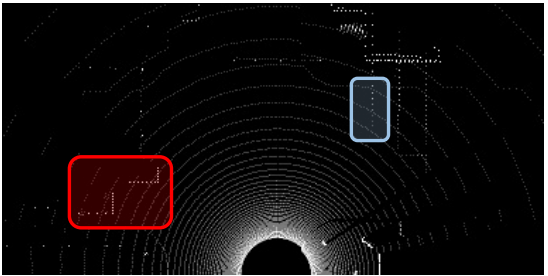




- From the yellow region, geometric fusion aggregates features to the blue region

Geometric Fusion Lacks Global Context





- From the yellow region, geometric fusion aggregates features to the blue region
- However, for safe navigation, it is useful to aggregate features for the red region since it contains vehicles which are affected by the traffic light

A. Prakash, K. Chitta and A. Geiger: Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. CVPR, 2021.

TransFuser

Key Idea

Use **attention-based** feature fusion to capture the **global context** of the scene **across modalities.**

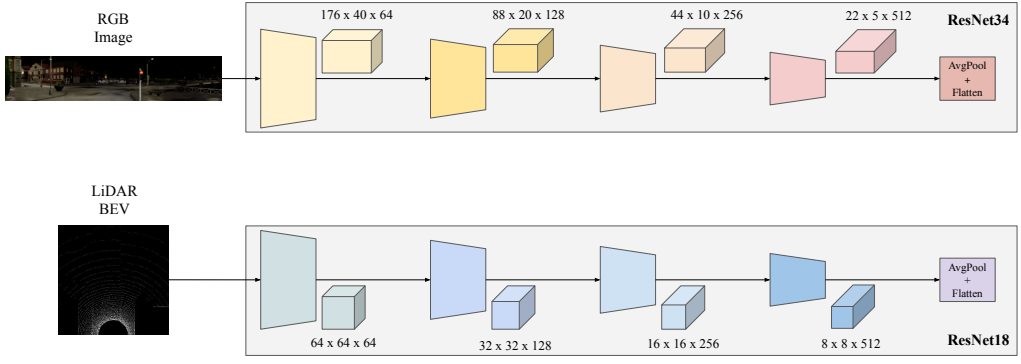
TransFuser

RGB
Image

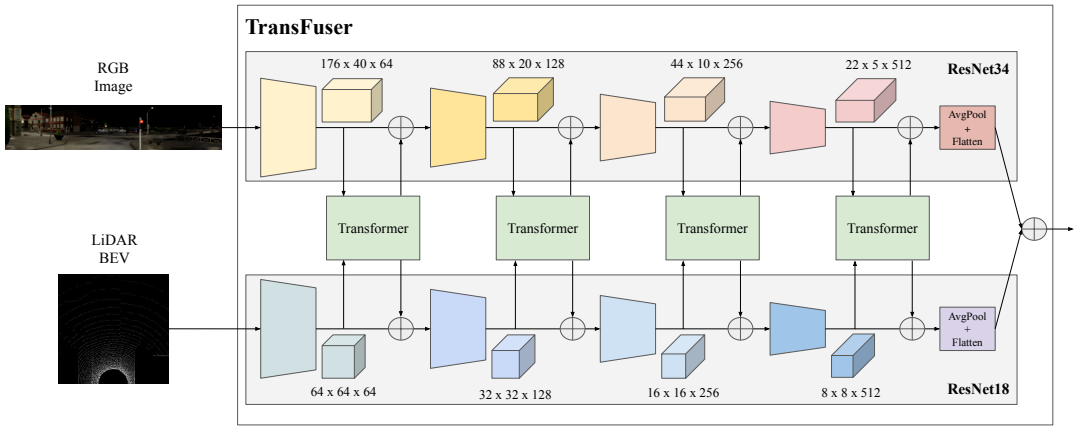
LiDAR
BEV

A. Prakash, K. Chitta and A. Geiger: Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. CVPR, 2021.

TransFuser


RGB
Image
176 x 40 x 64
88 x 20 x 128
44 x 10 x 256
22 x 5 x 512
ResNet34
AvgPool
+
Flatten
LiDAR
BEV
64 x 64 x 64
32 x 32 x 128
16 x 16 x 256
8 x 8 x 512
AvgPool
+
Flatten
ResNet18

TransFuser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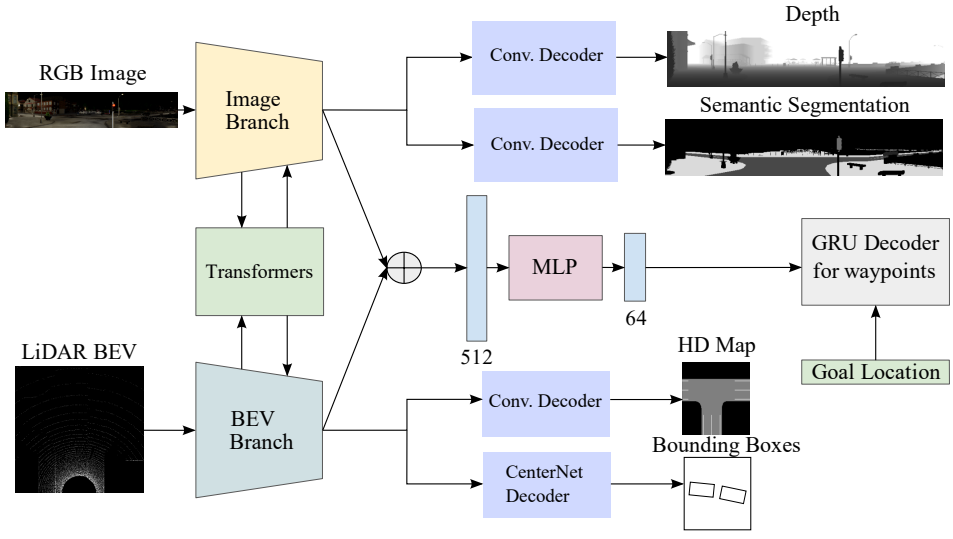
Full Architecture



Loss Functions

- L_1 loss on waypoints: $\mathcal{L} = \sum_{t=1}^{4} ||\mathbf{w}_t - \mathbf{w}_t^{gt}||_1$
- Cross-entropy loss on semantics
- L_1 loss on depth
- Cross-entropy loss on HD map
- Focal loss on CenterNet heatmaps
- L_1 loss on CenterNet offsets

Experiments

Dataset

- 8 Towns and randomized weather conditions in CARLA
- Expert policy based on MPC
- ∼3.5k short routes with hand-crafted scenarios

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Sensors

- RGB cameras: 704$\times$160 resolution, 132° FOV
- LiDAR: 32m range, 64 channels, 10 Hz rotation frequency

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Evaluation

- Long routes ($\sim$2km) with dense traffic
- Ensemble of 3 training runs to reduce variance

Results: Internal Benchmark

Method	Driving Score ↑	Route Completion ↑	Infraction Score ↑
Late Fusion	22 ± 4	83 ± 3	0.27 ± 0.03
Geometric Fusion	27 ± 1	91 ± 1	0.30 ± 0.02
TransFuser (Ours)	$\mathbf{47 \pm 6}$	$\mathbf{93 \pm 1}$	$\mathbf{0.50 \pm 0.00}$
Privileged Expert	*77 ± 2*	*89 ± 1*	*0.86 ± 0.03*

- Geometric Fusion, TransFuser and Expert have similar route completion
- Clear trend in infraction score (Expert $>$ TransFuser $>$ Baselines)

CARLA Leaderboard

Method	Driving Score ↑	Route Completion ↑	Infraction Score ↑
LAV	61.85	94.46	0.64
TransFuser (Ours)	61.18	**86.69**	**0.71**
GRIAD	36.79	61.85	0.60
WOR	31.37	57.65	0.56

- Simple end-to-end IL (competitors have complex multi-stage training pipelines)
- Rank 2 at submission (April), with **best infraction score** among top methods
- Still **gets blocked** more often than LAV
- DS > 60, rapid overall progress on leaderboard since 2020 (DS < 20)

Summary

Conclusions

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- Attention is effective in aggregating information from multiple modalities
- Driving Score of simple Imitation Learning baseline is competitive (rank 2)

Code

- www.github.com/autonomousvision/transfuser

Other Work

- Ohn-Bar et al.: Learning Situational Driving. CVPR, 2020.
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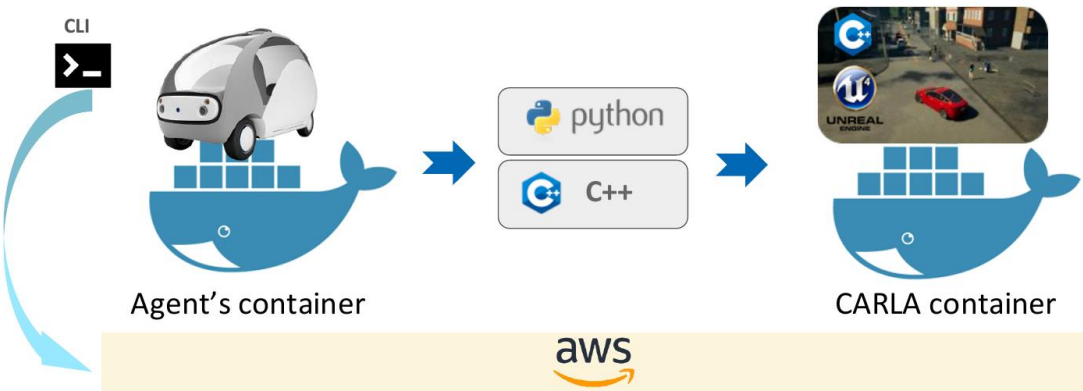
  “Visual abstractions help, but annotating less can be more.”
- Chitta et al.: NEAT: Neural Attention Fields. ICCV, 2021.
  “BEV predictions from 2D images via neural fields can improve safety.”

Extra Slides

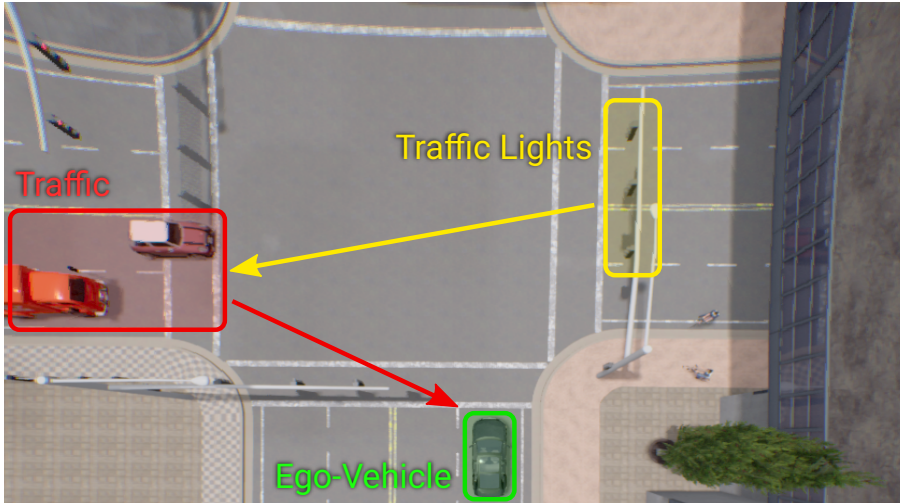
CARLA Leaderboard

- Open **test bed** to evaluate AD agents for the driving task
- Common maps, situations, and metrics
- Built upon the CARLA simulator
- Aim to **accelerate progress** in the research community

CARLA Leaderboard Submission



Motivation



A. Prakash, K. Chitta and A. Geiger: Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. CVPR, 2021.

Research Questions

- How to integrate representations from multiple modalities?

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- To what extent should the different modalities be processed independently?

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- To what extent should the different modalities be processed independently?
- What kind of fusion mechanism to use for maximum performance?

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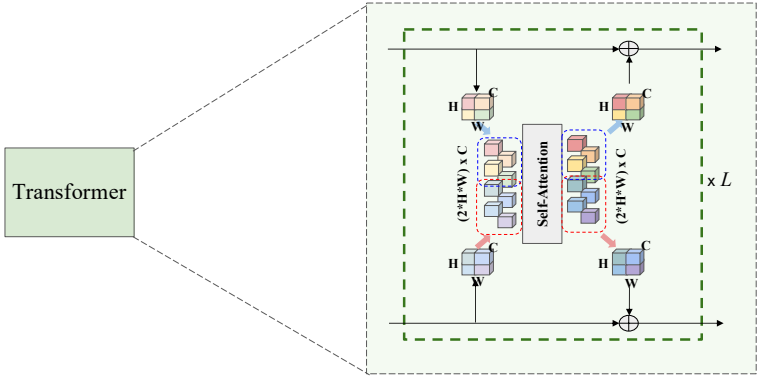
Attention-based Feature Fusion



- Consider feature maps as **sets of tokens** (cells of grid = tokens)
- Pass all tokens to **self-attention** module and reshape back into grid form

A. Prakash, K. Chitta and A. Geiger: Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. CVPR, 2021.

Overall Pipeline

- **Step 1 - Privileged Agent (Data Collection)**
  - Demonstrator
  - Routes
  - Sensors

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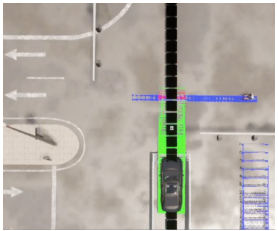
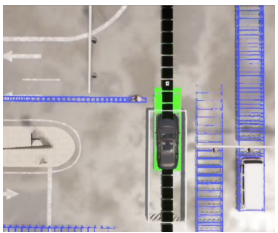
- **Step 1 - Privileged Agent (Data Collection)**
  - Demonstrator
  - Routes
  - Sensors
- **Step 2 - Sensorimotor Agent (Training)**
  - Architecture
  - Loss function
  - Controller

Demonstrator: Components

Lateral Control

- Input: HD Map
- A* Planner
- PID controller

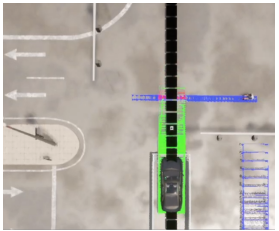


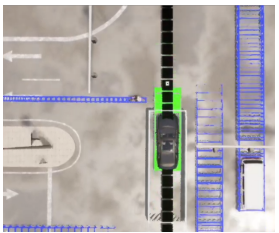


Demonstrator: Components

Longitudinal Control

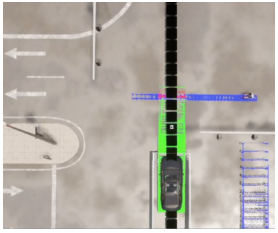
- Input: traffic light states
- Input: nearby actor states
  - Position
  - Orientation
  - Velocity
- Kinematic bicycle model
- PID controller

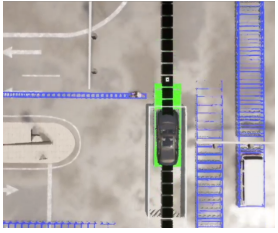




Demonstrator

- Simplified version of Model Predictive Control (MPC)
- 2 candidate trajectories using HD map + PID controllers
  - Greedy: target speed = 4 m/s
  - Conservative: target speed = 0 m/s
- Roll out greedy trajectory with bicycle model
- Choose conservative trajectory if infraction is detected





Routes

- $\sim$ 3000 Junctions ($\sim$100m long)
- $\sim$ 500 Curves ($\sim$400m long)
- 8 CARLA towns (1, 2, 3, 4, 5, 6, 7, 10)
- 7 CARLA scenarios (1, 3, 4, 7, 8, 9, 10)

Routes

- $\sim$ 3000 Junctions ($\sim$100m long)
- $\sim$ 500 Curves ($\sim$400m long)
- 8 CARLA towns (1, 2, 3, 4, 5, 6, 7, 10)
- 7 CARLA scenarios (1, 3, 4, 7, 8, 9, 10)
- Time of day: custom distribution around 6 preset values
- Weathers: 7 CARLA presets
- Dataset size: 300k frames

Sensors

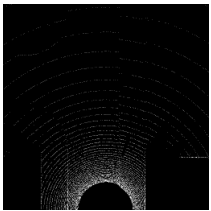
RGB cameras

- 3 cameras: front, 60° left, 60° right
- Field of view: 60° each
- Resolution: 320×160 pixels each
- Composited into 704×160 input

Sensors

64 beam LiDAR

- 10 Hz frequency: use alternate frames
- Field of view: 180°
- Rasterized into BEV (256×256, 32m range)
- 2 channels: ground plane, objects

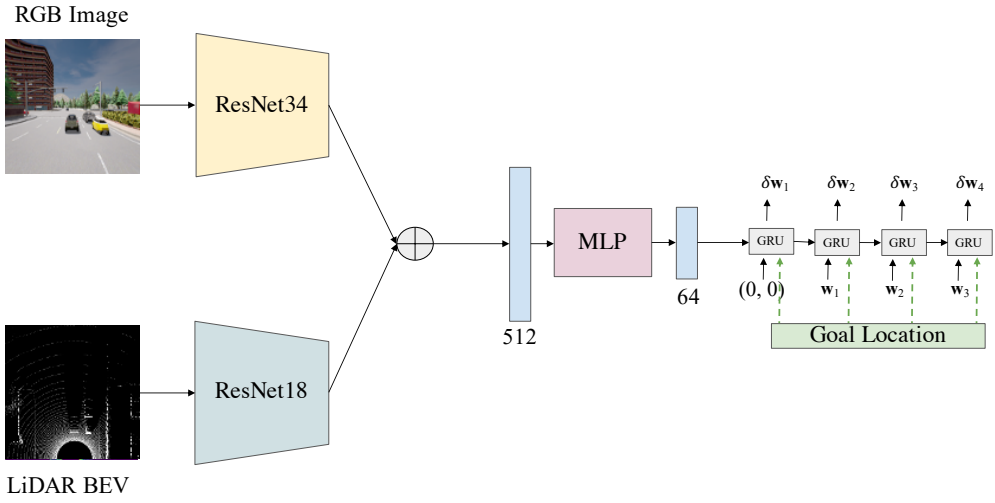


Sensors

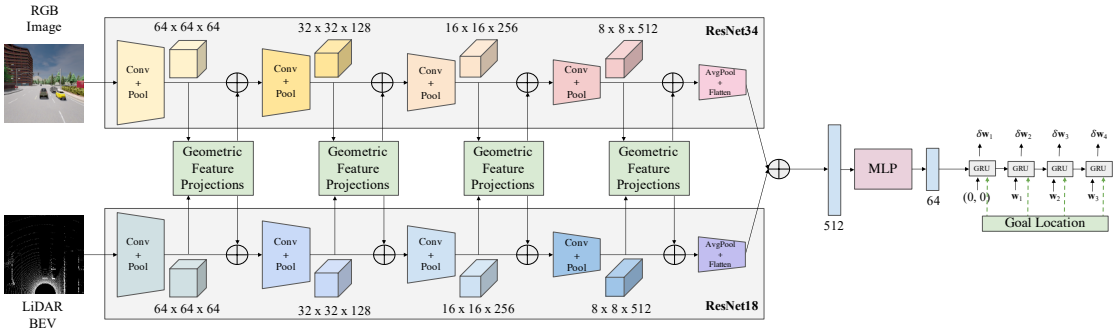
Additional sensors used for auxiliary supervision

- Semantic Segmentaion
- Depth
- HD Map: same coordinate frame as LiDAR

Baselines - Late Fusion



Baselines - Geometric Fusion



Controller

- Heading and target speed from waypoints
- PID controllers
- Inertia problem: creep forward if still for $\sim$1 minute
  - Safety check: no creeping when LiDAR indicates close proximity

Runtime

Method	Single Model	Ensemble (3)
Late Fusion (LF)	23.5	46.7
Geometric Fusion (GF)	43.5	69.1
TransFuser (Ours)	27.6	59.6

Table: We show the runtime per frame in ms for each method averaged over all timesteps in a single evaluation route. We measure runtimes for both a single model and an ensemble of three models. A single TransFuser model runs in real-time on an RTX 3090 GPU.

Auxiliary Tasks

Auxiliary Losses	**DS** ↑	**RC** ↑	**IS** ↑
None	44.29	78.17	0.58
No Depth	55.66	90.87	0.61
No Semantics	53.76	88.40	0.61
No HD Map	50.96	89.52	0.58
All Losses	**56.68**	**92.28**	**0.62**

Table: Results shown are the mean over 3 evaluations on the Longest6 benchmark. HD Map prediction is the most important among the auxiliary tasks.

Architecture

Parameter	Value	DS ↑	RC ↑	IS ↑
Fusion Scales	1	49.35	84.47	0.57
	2	53.52	91.78	0.59
	3	48.77	85.33	0.60
Attention layers	2	53.49	90.65	0.60
	6	56.24	**92.56**	0.61
	8	54.00	89.83	**0.62**
Default Config	-	**56.68**	92.28	**0.62**

Table: Results shown are the mean over 3 evaluations on the Longest6 benchmark. The default configuration with 4 fusion scales, and 4 attention layers obtains the best results.

Model Inputs

Parameter	Value	DS ↑	RC ↑	IS ↑
LiDAR Range	64m × 32m	49.08	91.10	0.54
	64m × 64m	47.55	90.72	0.52
Camera FOV	120°	49.90	90.05	0.56
	90°	42.18	88.49	0.51
No Rasterized Goal	-	54.80	91.63	0.60
No Rotation Aug	-	**56.85**	**92.73**	0.61
Default Config	-	56.68	92.28	**0.62**

Table: Results shown are the mean over 3 evaluations on the Longest6 benchmark. The default configuration with a 32m × 32m LiDAR range and 132° camera FOV obtains the best results.