End-to-End Learning for Autonomous Vehicles using SVL

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Agenda

1. Background
2. Re-Implementation
3. Model Exploration
4. Demonstration
5. Conclusion & Future work

NVIDIA’s Attempt

Our Attempt

1. Background

1. Real World vs. Simulation

1. Advantages:

   Low-cost and flexible platform

   Realistic testing environment

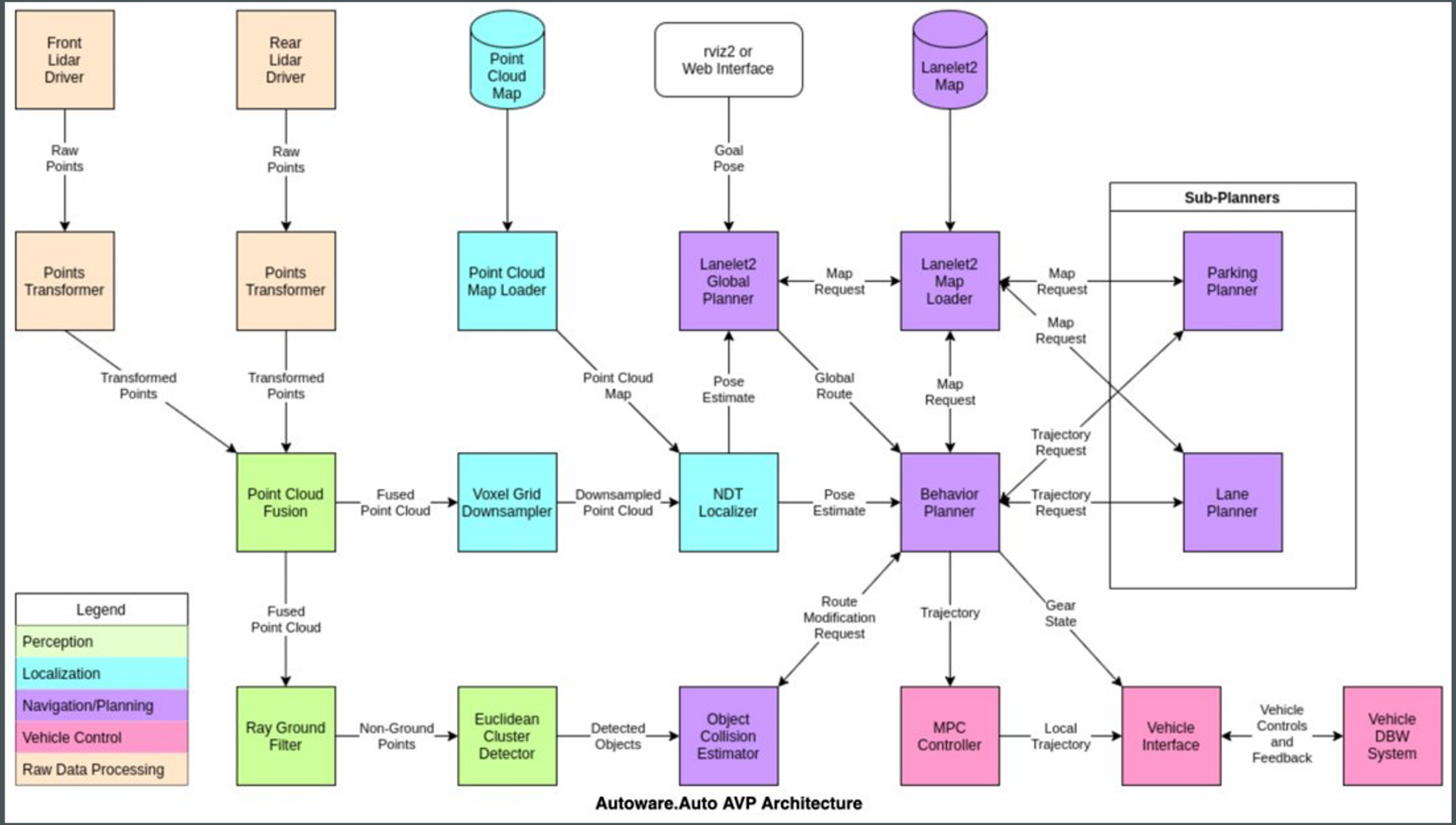
1. Constraints leading to unexpected driving behavior:

   Different weather conditions

   Road damage

   Low-visibility

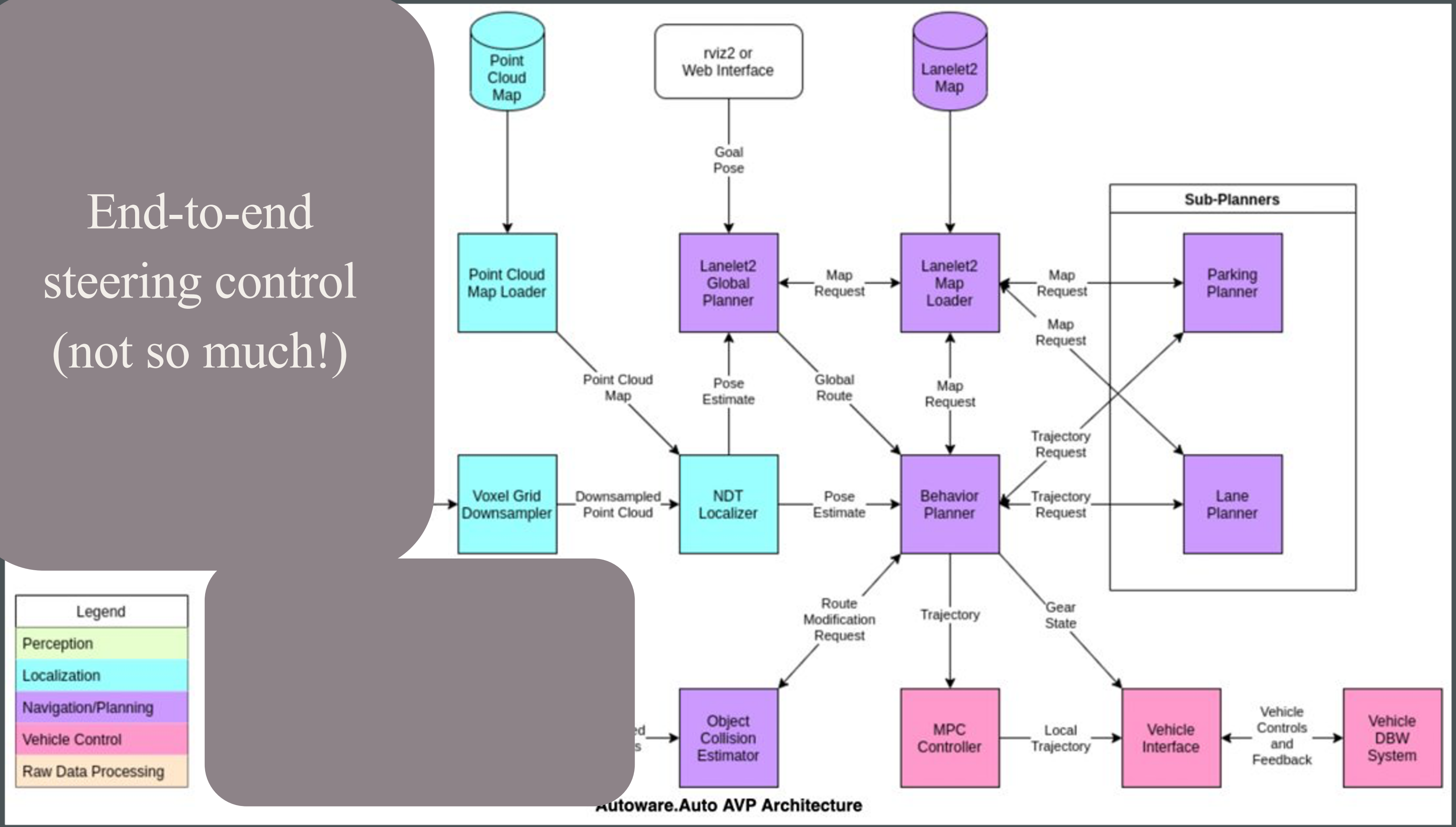
Standard Robotics Approach



Source: https://autowarefoundation.gitlab.io/autoware.auto/AutowareAuto/avpdemo.html

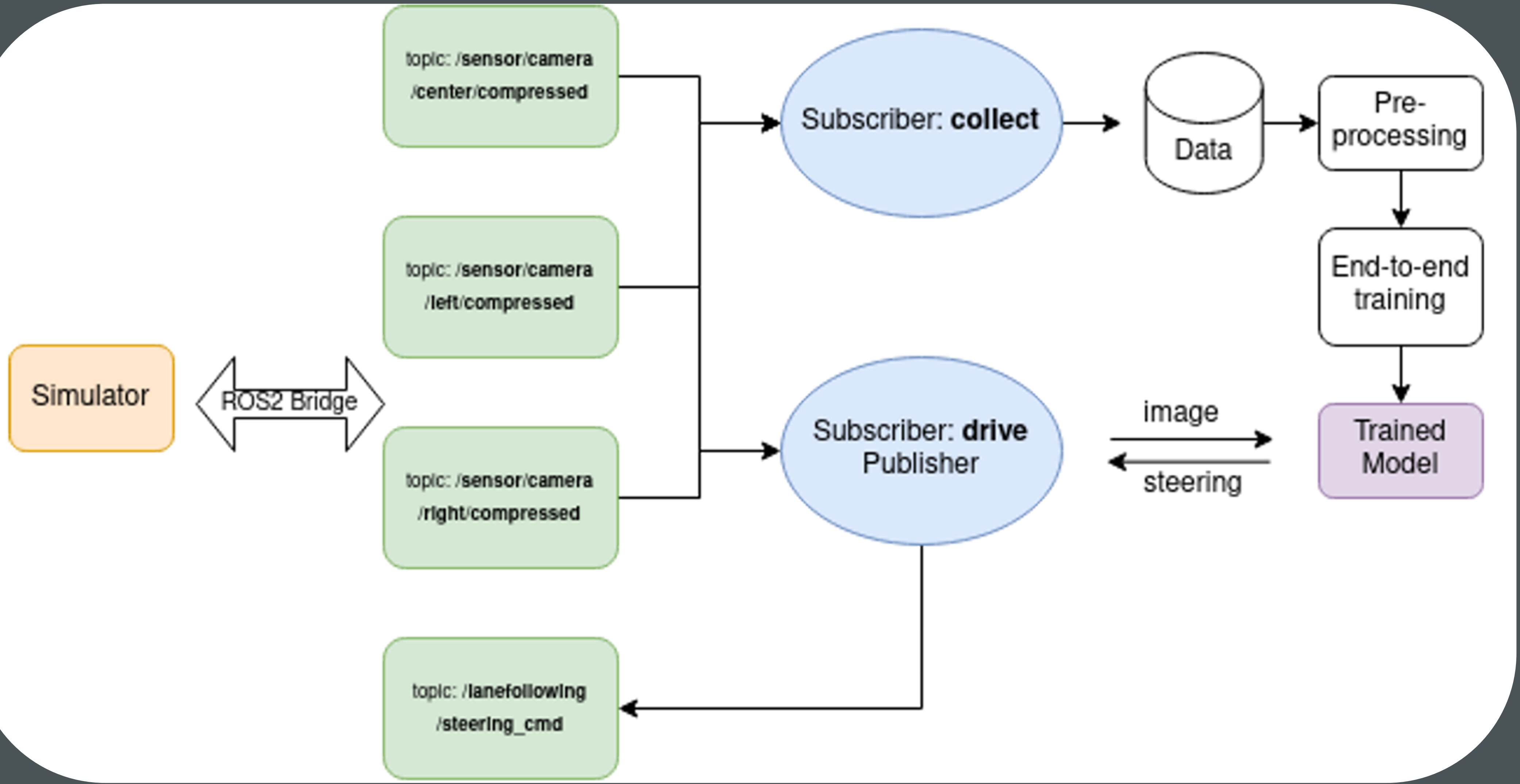
E2E Approach

End-to-end steering control (not so much!)



Source: https://autowarefoundation.gitlab.io/autoware.auto/AutowareAuto/avpdemo.html

2. E2E Architecture



Data Acquisition

1) Map:

   4 different maps (San Francisco, BorgesAve, CircularPath, Lane-less road)

2) Data:

   a. Camera feeds: left, right, center

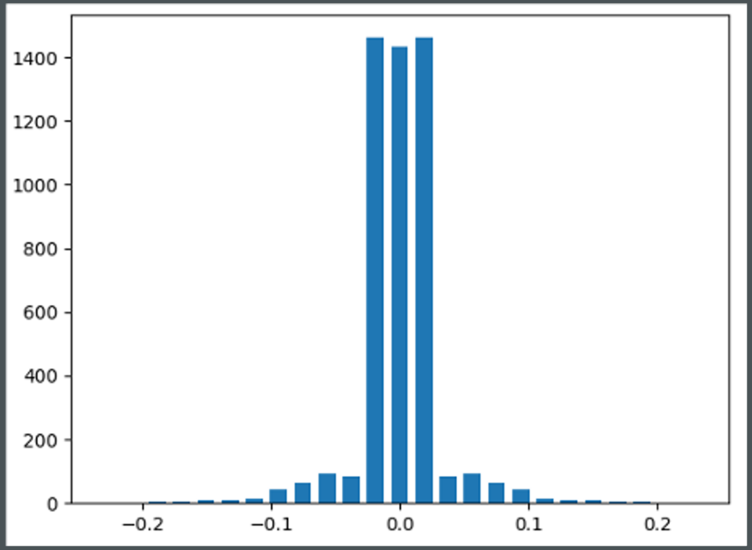
   b. Corresponding steering angle values

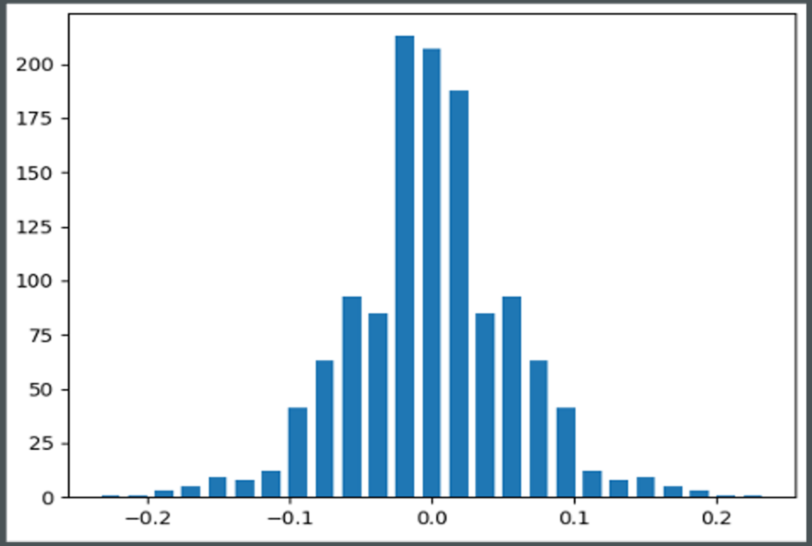
3) Drive speed: constant speed

4) Time: 10+ hours of driving

Preprocessing 1: Data Augmentation

- Data addition:
  - Flipping images
  - Negating corresponding steering angles
- Histogram balancing
  - Randomly resampling to the mean to remove bias





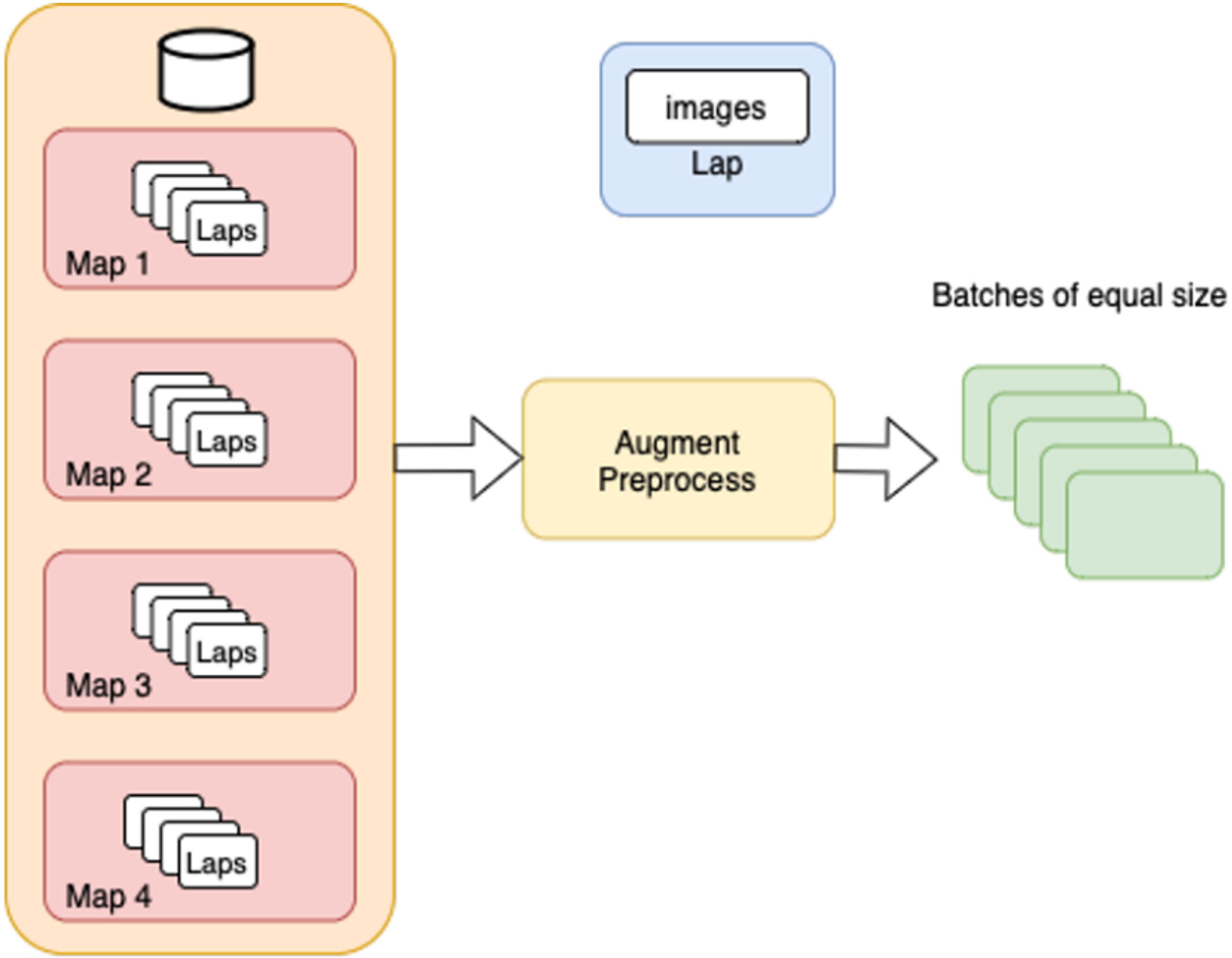
Preprocessing II: Crop and Scale

- Cropping
  - Removal of irrelevant information (sky, hood, etc.)
- Scaling
  - Reducing resolution
  - Less data-intensive

1920x1080x3

780x222x3

Preprocessing III : Batching



Training

Baseline: NVIDIA Model

- Covnet : 9 (5 conv+4 dense)
- # of Parameters : 250k
- Inference time : 10ms
- FPS : 100 FPS
- Successfully completed laps on all maps

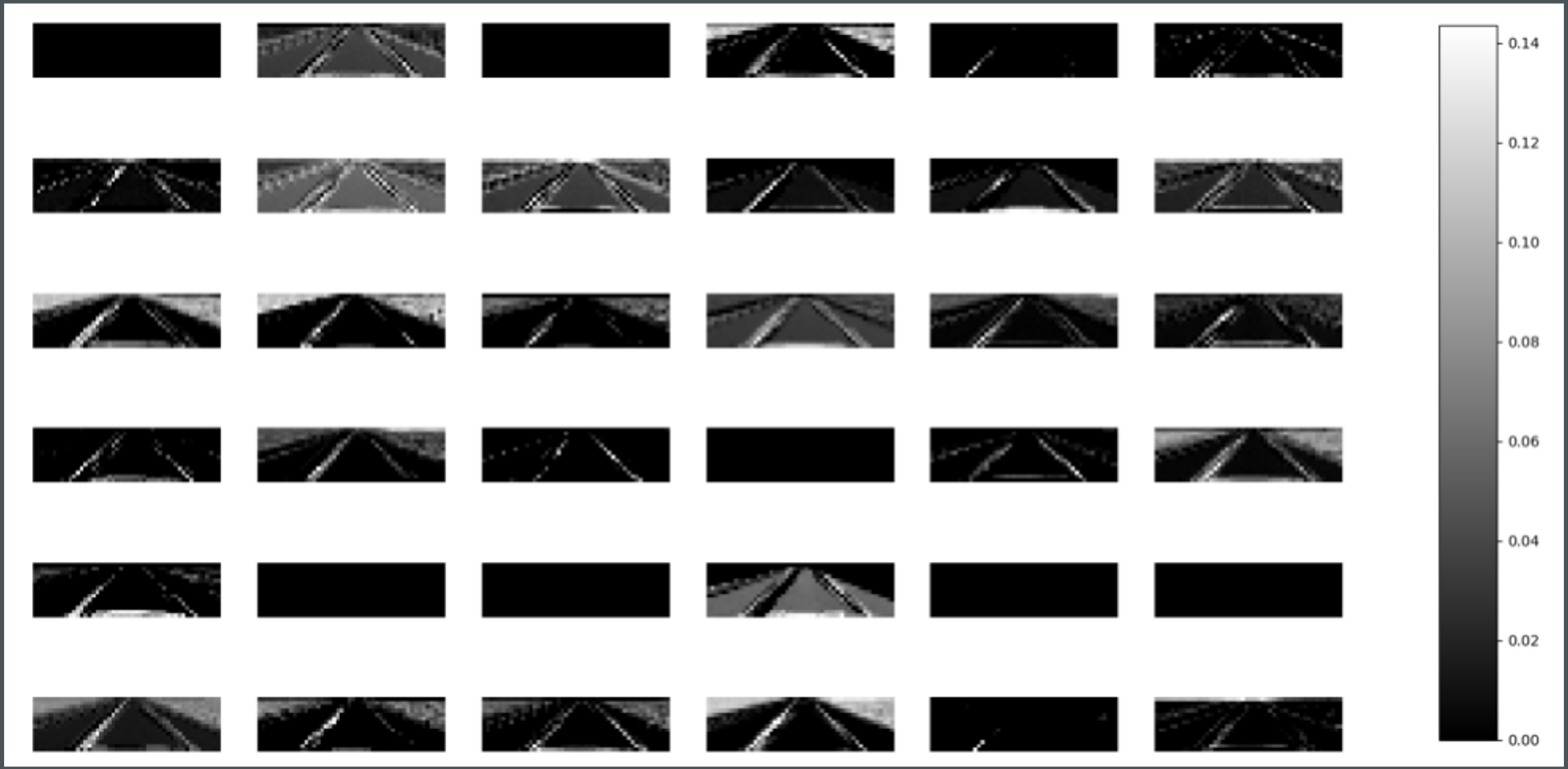
Convnet training details:

- Optimizer : Adam
- learning rate : 10-4
- Epochs : 10
- Batch size : 32 or 128
- Callbacks : Early stopping
- GPU : GTX 1080 8GB

What matters?

- Lower number of parameters leads to lower inference time
- Validation MSE < 0.002

Training: Feature Maps



4. Network Exploration

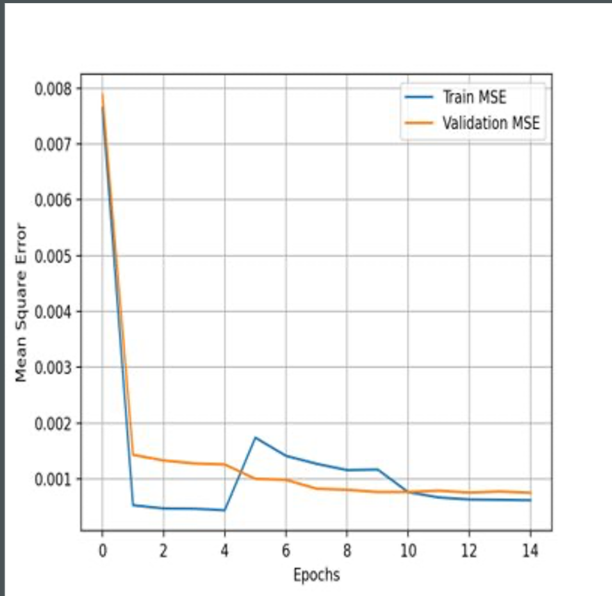
- Following the principles we obtained in simple Convnet models, e.g. # of params, we choose networks as below:

backbones	# of params	FPS	comment
Convnet v1 (NVIDIA)	0.25 m	100	🐝
Convnet v2	70 m	20	☠️
Simple Resnet	0.95 m	24	☠️
RNN	31 m	15	🐝
Shufflenet v1	3.8 m	-	☠️
Shufflenet v2	4.0 m	-	☠️
Resnet10	4.9 m	50	☠️
Resnet18	11.2 m	35	☠️

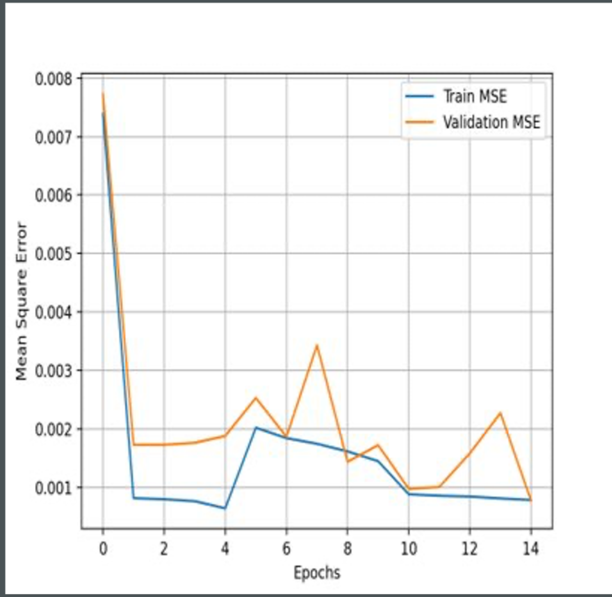
🐝 – completed Lap
☠️ – Accident

4. Network Exploration

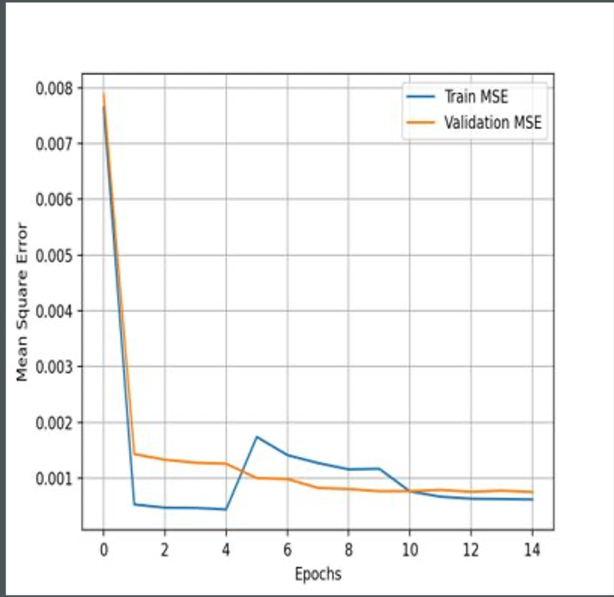
- Training details:



Convnet v1 (NVIDIA)



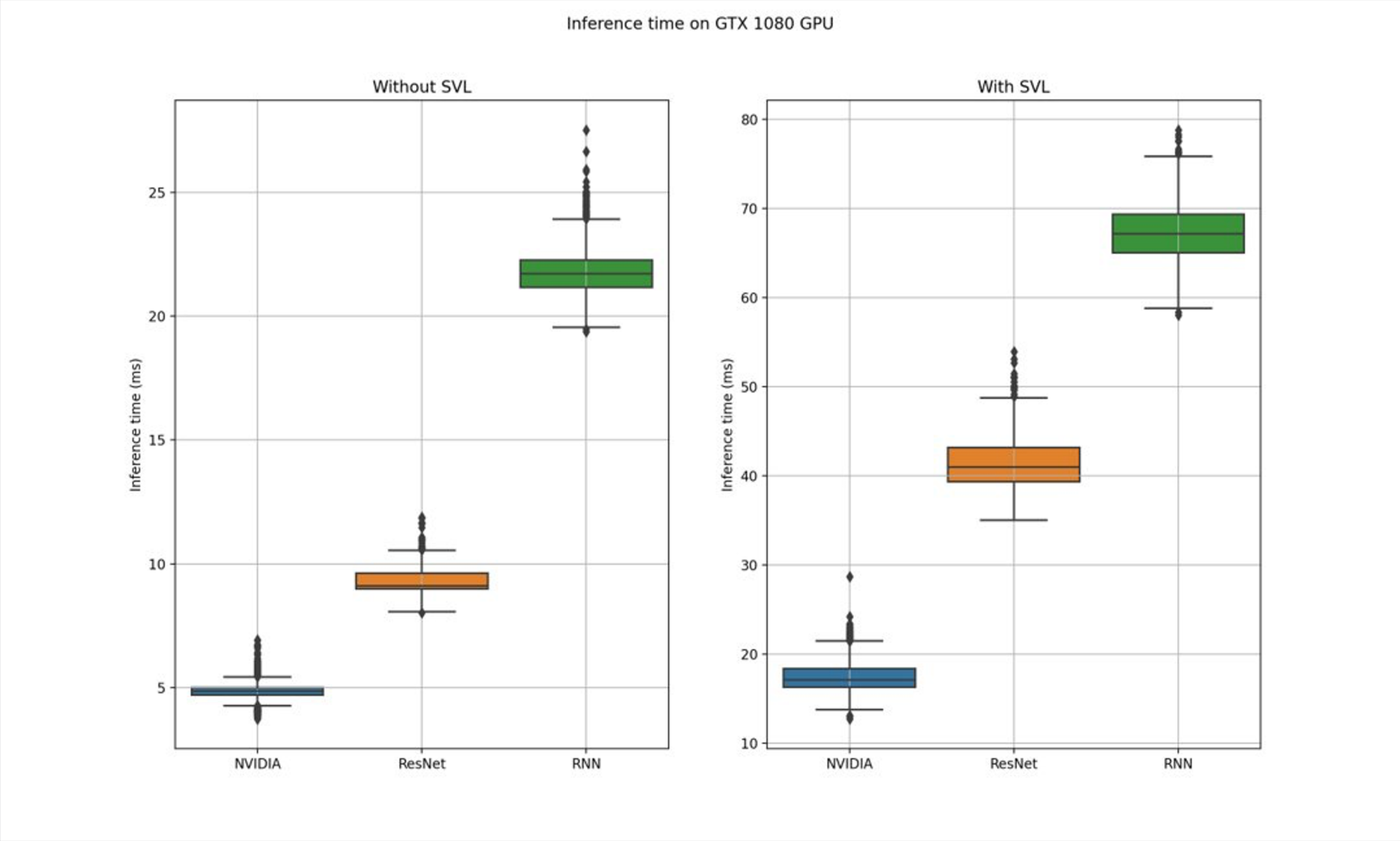
Simple Resnet



RNN

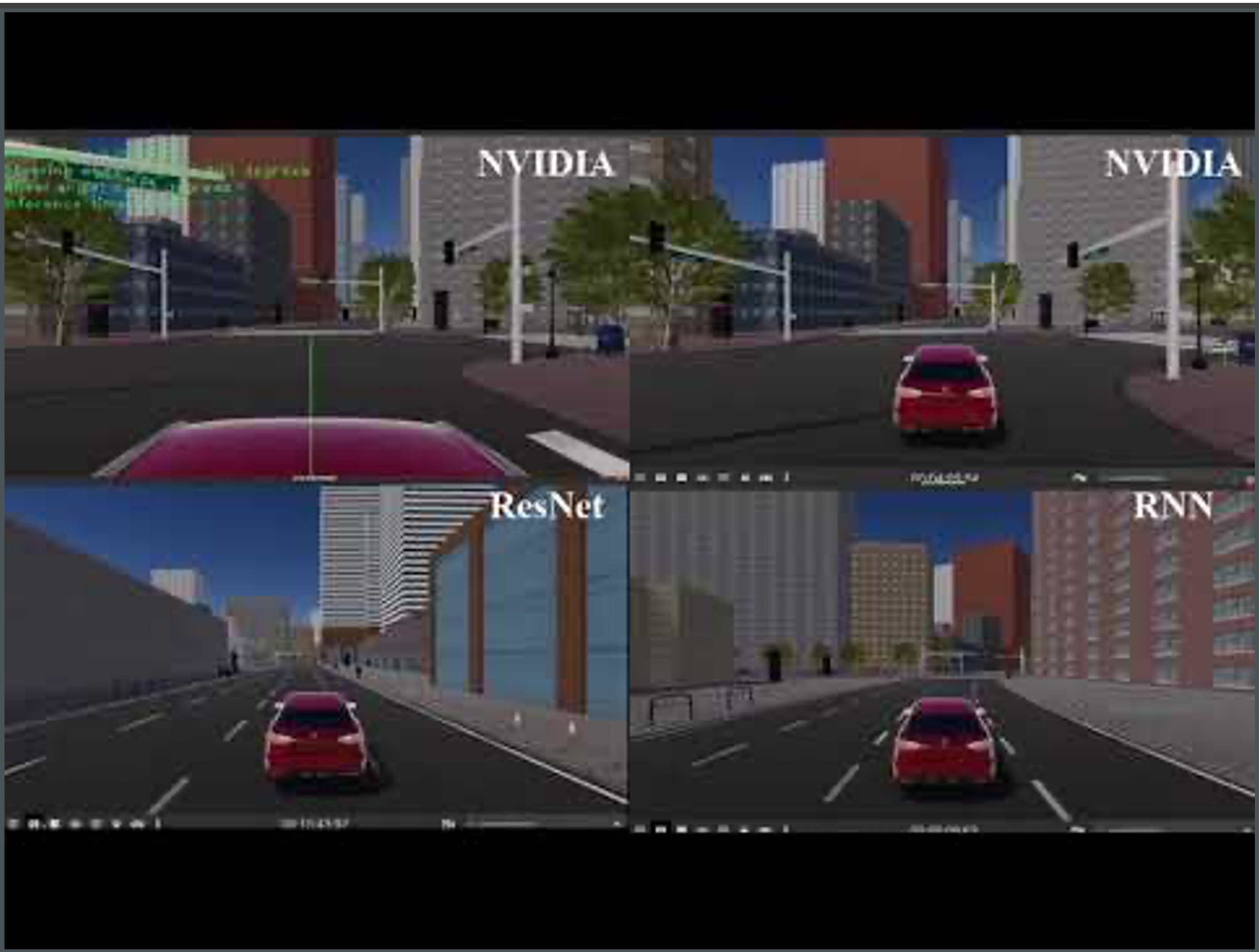
4. Network Exploration

- Inference time:



Demos

Demos



5. Conclusion & Future work

- Multiple maps – one model
- RNN sliding window
- Resnet50 with cluster
- Training with traffic
- Predicting throttle

REFERENCES

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THANK YOU