



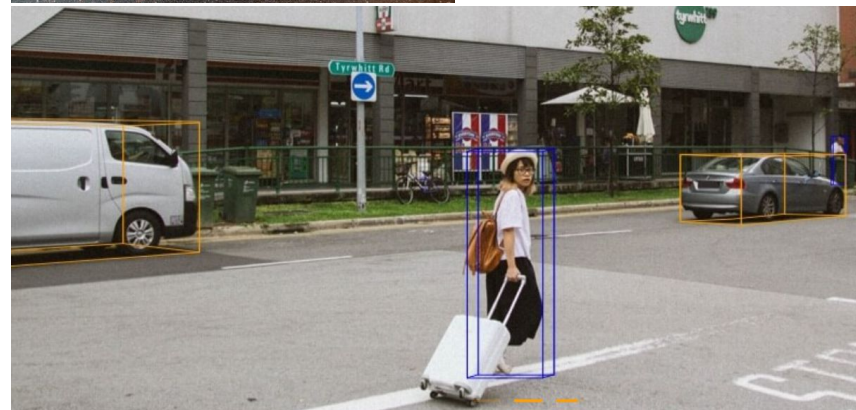
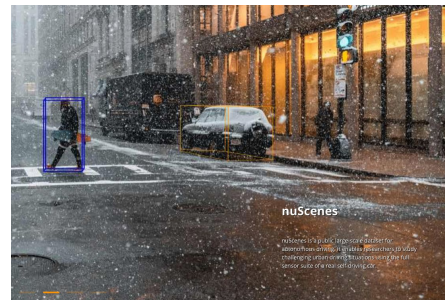
# Challenges in Assured Autonomy for Self-driving Cars

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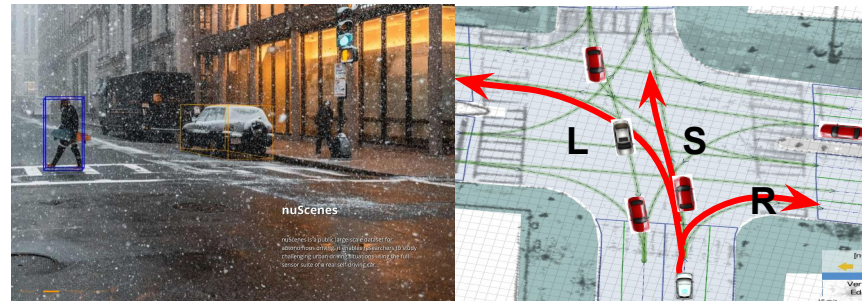
# Why is programming a self-driving car hard?

- Sense
  - “See” with cameras, lidar, and radar
  - High-dimensional input (pixels + pointclouds), occlusions, so many types of objects
- Plan
- Act



# Why is programming a self-driving car hard?

- Sense
  - “See” with cameras, lidar, and radar
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- Plan
  - Behavior depends on the scene context
    - Other cars, pedestrians, bicyclists, etc
    - Road geometry and markings (e.g., bus stops, stop signs)
  - Need to anticipate what others will do
  - Rules-of-the-road are not complete or followed
- Act
  - Need to drive smoothly and comfortably

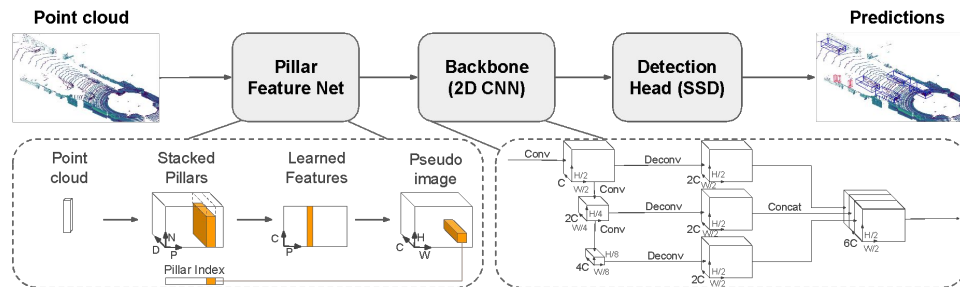


# Machine Learning is a key component of self-driving cars

- When to use ML?
  - Lots of data
  - Stable data distribution
  - No good analytical model

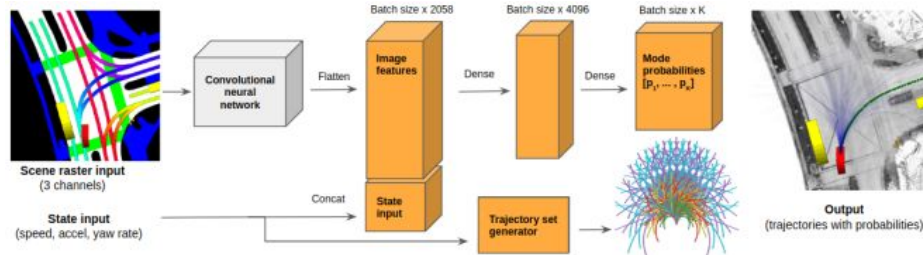
# Machine Learning is a key component of self-driving cars

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A. Lang et al. "PointPillars: Fast Encoders for Object Detection from Point Clouds." CVPR 2019 <https://arxiv.org/abs/1812.05784>

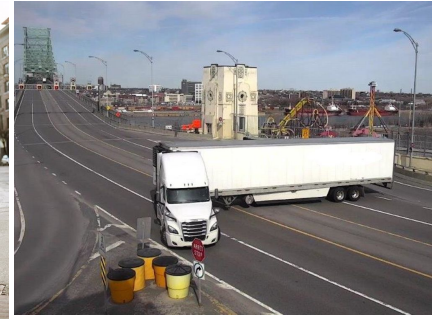
- Where is ML typically used in self-driving cars?
  - Perception (heavily)
  - Motion prediction (moderately)
  - Planning (partially)



T. Phan et al. "CoverNet: Multimodal Behavior Prediction using Trajectory Sets." CVPR 2019. <https://arxiv.org/abs/1911.10298>

# How to assure safety of ML systems?

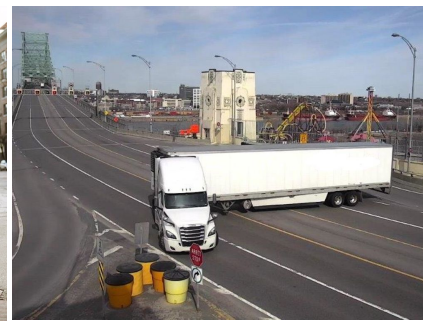
- There is no silver bullet
- A key challenge is rare events (the long tail)





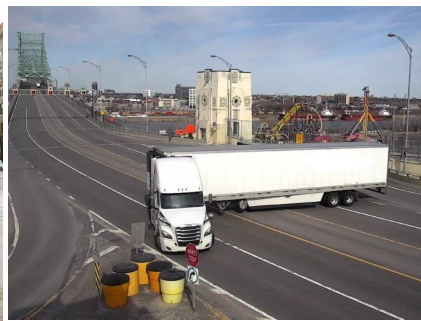
# How to assure safety of ML systems?

- There is no silver bullet
- A key challenge is rare events (the long tail)
- Safety certification of ML systems
  - Compute (easy)
  - Data pipeline (med)
  - Model (hard)
    - Meets performance targets across a comprehensive test set
    - Non-ML safety checks and limits
    - Within operating domain?
    - Uncertainty estimates



# How to assure safety of ML systems?

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    - Uncertainty estimates
- Shared data and evaluation across the industry?
  - Eval and metrics must be carefully determined
  - Research: [www.nuscenes.org](http://www.nuscenes.org), [www.argoverse.org](http://www.argoverse.org), [www.waymo.com/open](http://www.waymo.com/open)
  - Safety
    - [www.pegasusprojekt.de/en/](http://www.pegasusprojekt.de/en/)
    - [hwww.safetypool.ai/](http://hwww.safetypool.ai/)





# How to convince the public?

- Multiple stakeholders
  - Users
  - Other road users
  - Local, state, and federal government
- Safety is not apparent from a test drive
- Can we adapt current auto regulations? Or look to aerospace?



# Conclusions

- Machine Learning is a core part of self-driving cars
  - Perception
  - Prediction
  - Planning
- How to assure safety of an ML system?
  - A grand challenge
  - Compute, data pipeline, and model
  - Comprehensive evaluation and data sharing