Generation of training datasets for ML methods for autonomous vehicles from simulations

Dr. Bill Roungas, ICCS

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EVENTS

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- Augmenting an Existing Image Dataset
- Image Generation Issues
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  - Data Utilization
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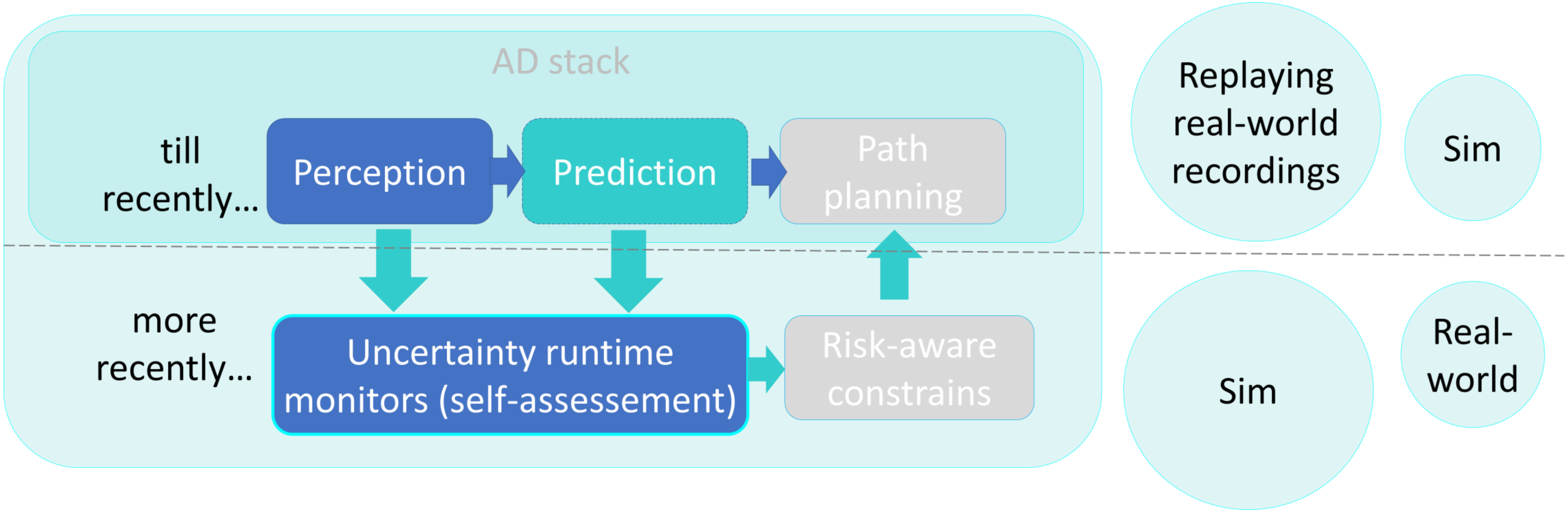
Intro: Training the AD stack layers



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Synthetic data generation: Theory- vs Data- Driven

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- Theory-driven approaches
  - ✓ Utilize existing theory on the subject of interest (image mathematical transformations/filters).
    - ➢ Very often theory is inadequate or completely lacking.
  - ✓ Strive to develop theory, if it doesn't exist.
    - ➢ Developing problem-solving theory takes time.

- Data-driven approaches
  - ✓ Minimizes the reliance on existing theory
  - ✓ Focus on building solutions directly from available data.
    - ➢ Large amounts of data can be compiled relatively easy by suitable sensor setups.
- However:
  - ➢ State-of-the art data-driven methods (i.e. Machine Learning) are data hungry.
  - ➢ More often than not, there is a large variety of corner cases which require special care during data collection.
  - ➢ Despite indicating a faster path towards a solution than developing theory, (annotated) data collection remains an intensely time-consuming and tedious process.

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Two examples of data-driven dataset generation

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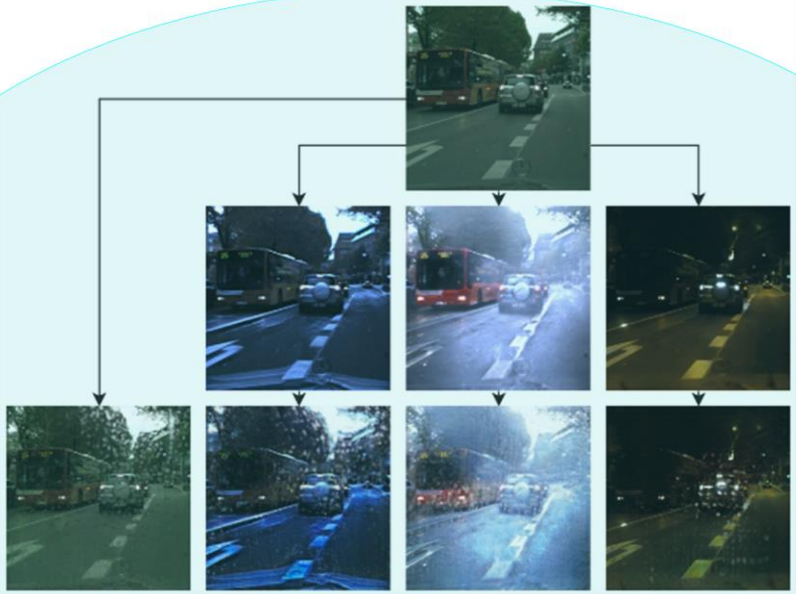
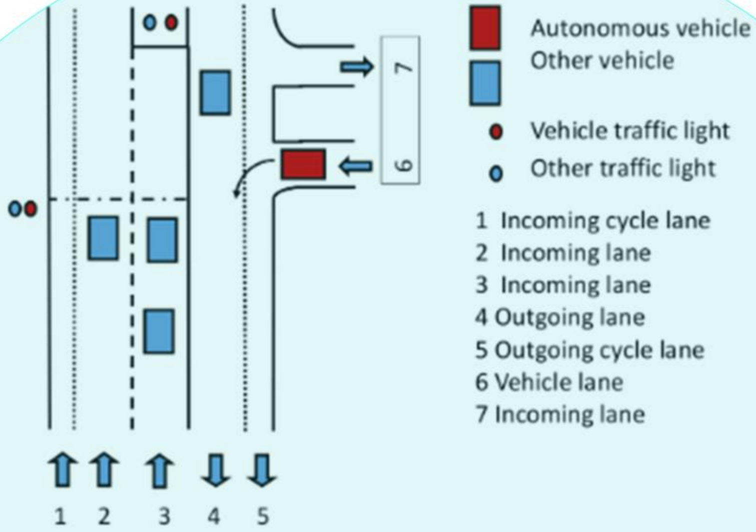
Creating artificial bad weather images from original images using ML



*Source: Multi-weather city: Adverse weather stacking for autonomous driving, ICCV, Oxf Brookes Uni

Annotating events in videos using ML



*Source: ROAD: The ROad event Awareness Dataset forAutonomous Driving, PAMI, 2022

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ML for AVs – What kind of data?

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Current research on AVs develops perception and decision mechanisms on a variety of sensor suites. → Different datasets required for each layer of the AD stack!

- Most commonly included sensors for perception:
  - Lidar.
  - Set of radar sensor(s).
  - Set of RGB, stereo and/or RGB-D (depth) camera sensors.
- Most commonly included data for path planning:
  - Set of trajectory points
  - Topology/Map data
  - Traffic rules contextual data

→ Cross-annotating AV perception/motion data even for a simple scenario can be extremely time consuming!

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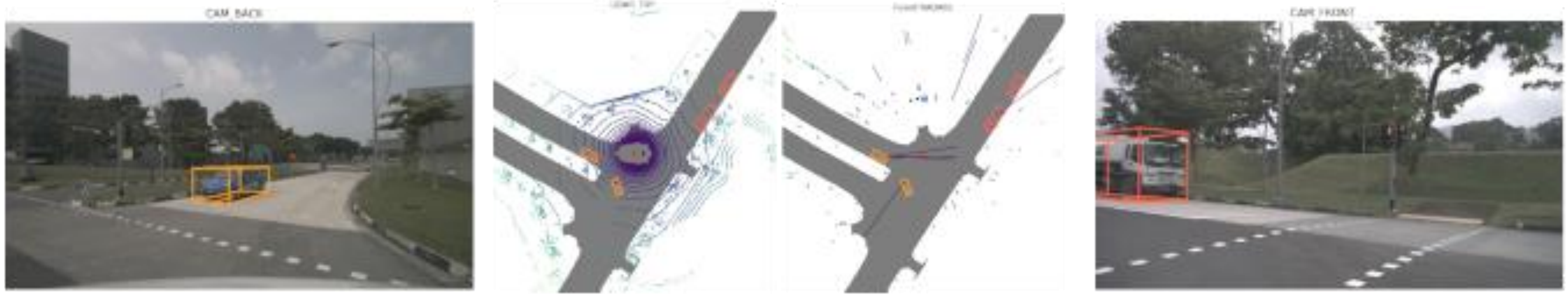
ML for AVs – Required data sample



Source: NuScenes Dataset

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Augmenting an existing image dataset

- Simply augmenting an existing dataset is quite standard and can be done via classic Computer Vision tools including
  - ✓ Geometric (perspective/affine/mirror/rotating) transformations.
  - ✓ Blurring plus combinations of morphological filters.
  - ✓ Color transfer between images via suitable of color spaces.
- The above have been shown to be effective in improving performance of object detection algorithms, <u>but only up to a point</u>.
- Questions like *how many data are required*, or *what are the limits of a resulting perception/decision algorithm trained on that data* <u>remain largely intractable.</u>

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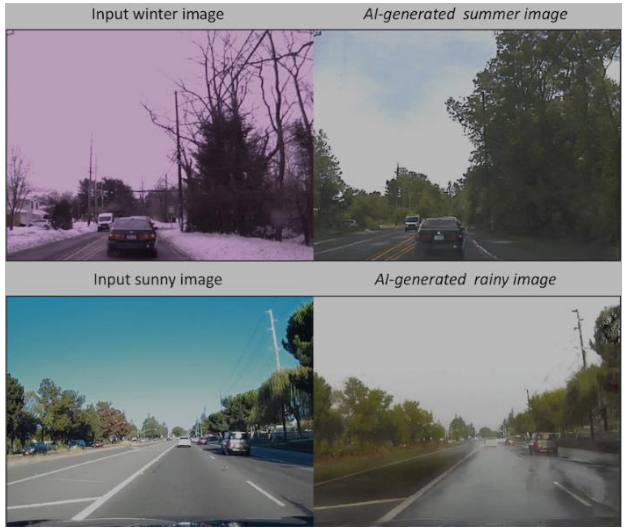
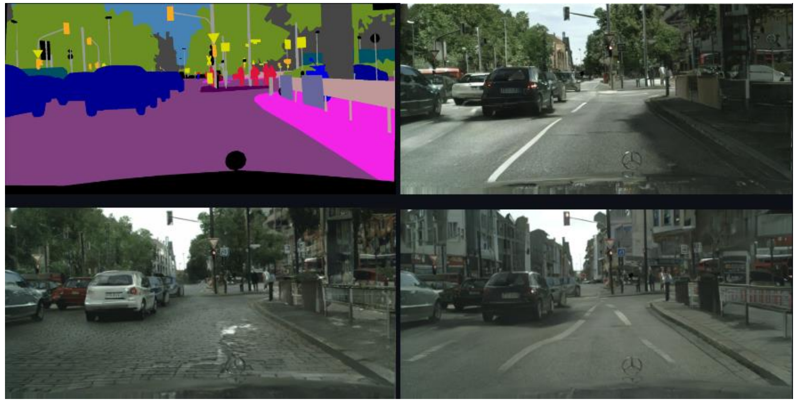
Augmenting an existing image dataset

- Currently under exploration:

- Image translation techniques, particularly for the adverse weather conditions case (e.g. via MUNIT-UNIT *).

- Utilization of segmented images for relevant image generation. Possible pipeline: Image -> Segmented Image -> Image synthesis via px2pixHD **





- * (Multimodal) UNsupervised Image-to-image Translation
- ** This could also exploit the segmentation camera provided in many simulation environments

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Image generation issues

- Based on Generative Adversarial Networks.
- Training process can be expected to be unstable, unpredictable and time consuming.
- Required computational resources are highly intensive in terms of time and hardware.
- Resulting images can be of questionable usability in terms of resolution and image quality, especially in VRUs.



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So, what about…

- Lidar data?
- Radar data?
- Is there a way to *rationally* augment – enrich respective datasets?
  1. Maintaining data realism
  2. Preserving the soundness of the annotations
- (Open) questions like:
  - ***Q1***: How much and what kind of data can be considered satisfactory to train an algorithm on a specific scenario or corner case?
  - ***Q2***: How much and what kinds of noise/uncertainty/variability can be filtered out and/or tolerated by an algorithm trained on a specific dataset before it fails?

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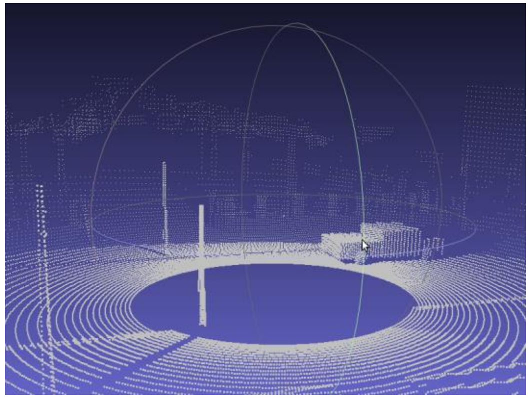
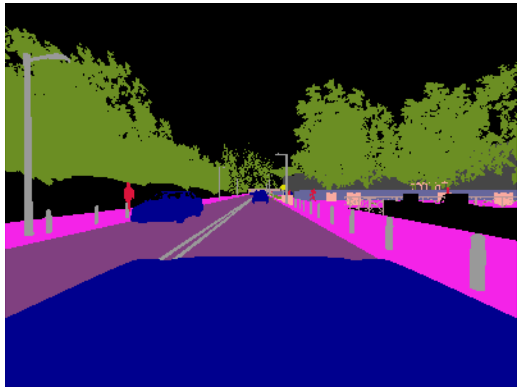
Simulated data – Generation

- Simulation software offers a fully controllable environment where a large variety of the parameters involved in an experiment can be pre-defined or arbitrarily tuned.
- Besides the ground truth, simulation software offers adjustable models for the entire sensor suite of AVs, including lidar, radar and cameras.



- Collected data are readily annotated by the simulation’s contextual ground truth and simulated scenario.
- Flexibility in scenario building and parameter tuning implies greater ease in considering data collection pertaining to corner cases.

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Simulation data – Utilization

- Simulations facilitate the benchmarking of designed algorithms solutions by:

1) Being able to exactly replicate the original experiment and/or scenario
2) Being able to include various sources and levels of uncertainty/variability to the original experiment and/or scenario, ranging from uncertainty in sensor measurements to large deviations from the original scenario.

- Recall (open) questions ***Q1*** and ***Q2.***

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Conclusion

- We cannot claim that, in absolute terms, data generated from simulations can replace real-world data

BUT

- They can greatly enhance incomplete real-world data
- Produce data for extreme, high-risk or rare events
- Provide 100% accurate goundtruth data (skipping the need for the cumbersome task of data semantic annotation)

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Thank you for your attention!

Dr. Bill Roungas, ICCS
vroungas@iccs.gr

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