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Institute of
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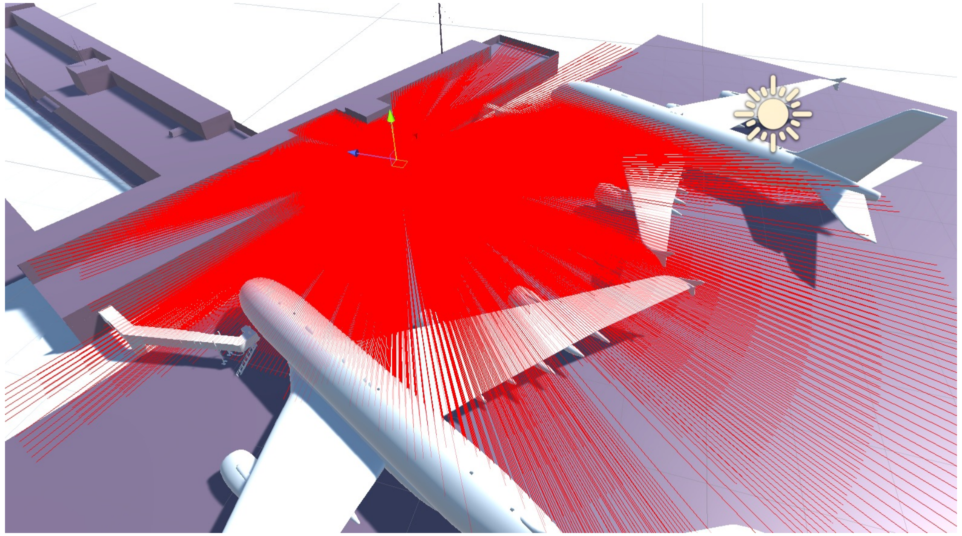

Department of Aerospace Engineering
Chair of Air Traffic Concepts

Winter Simulation Conference, 13. December 2022

Towards Automated Apron Operations - Training of Neural Networks for Semantic Segmentation using Synthetic LiDAR Sensors

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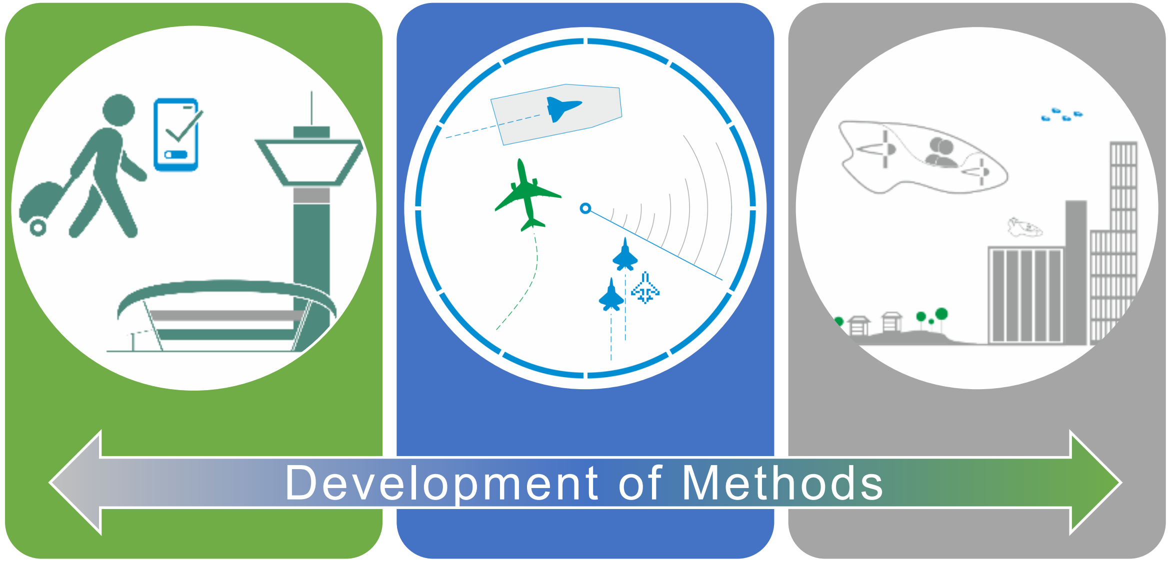
Since 2022
- Director Institute of Flight Systems
- Chair of Air Traffic Concepts

Since 2019
- Visiting Researcher at ATMRI NTU

2014 – 2019
- Head of Air Transportation Dpt. at German Aerospace Center (DLR)

Research areas and current topics



- Automated airport operations
- Flow-centered traffic management
- Smart passenger and transport

- Depth sensors, e.g. Light detection and ranging (LiDAR) have become ubiquitous in many application areas, also in air traffic management and airport operations
- Evaluation of point clouds: **deep learning adds significant value** identifying elements
- 3D point clouds obtained from LiDAR mapping need to get
  - semantically segmented: creation of **coherent regions** combining neighboring elements
  - classified: the assignment of elements to pre-established classes (labels)
- Challenges:
  - lack of data (unlabeled data or no data at all)
  - manual classification of objects by geometric shape or location of occurrence
- Synthetic data generator using **Singapore Changi Airport** environment as a reference

- **Part A: Synthetic training data**
  - LiDAR simulation considering different sensor specifications
- **Part B: Virtual environments**
  - Creating virtual 3D worlds and objects as reference
- **Part C: AI application**
  - Training of AI classifiers in the virtual environment
- **Part D: Transfer**
  - Export and transfer to simulation or reality

Part A.

LiDAR simulation considering different sensor specifications

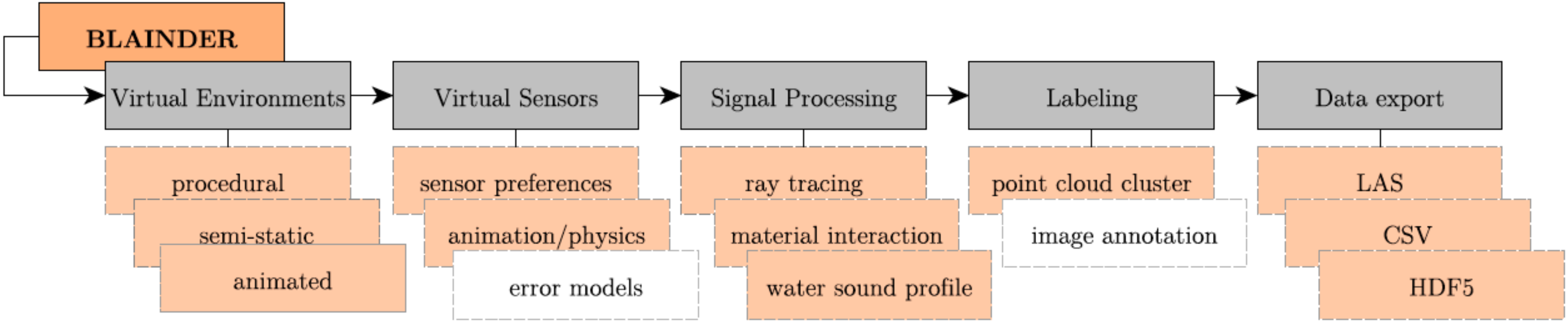
- BlAInder = addon for Blender Open Source 3D software [1, 2]
- avoid the time-consuming manual labeling process of 3D point clouds
- rapid generation of ML training data across many domains
- additional: image annotations

[1] *S. Reitmann, L. Neumann, B. Jung. BLAINDER — A Blender AI Add-On for Generation of Semantically Labeled Depth-Sensing Data. Sensors 2021, 21, 2144.*

[2] *https://github.com/ln-12/blainder-range-scanner*

- BLAINDER add-on contains of a modularized structure

- Allows complete adaptability of the add-on to other specific problems

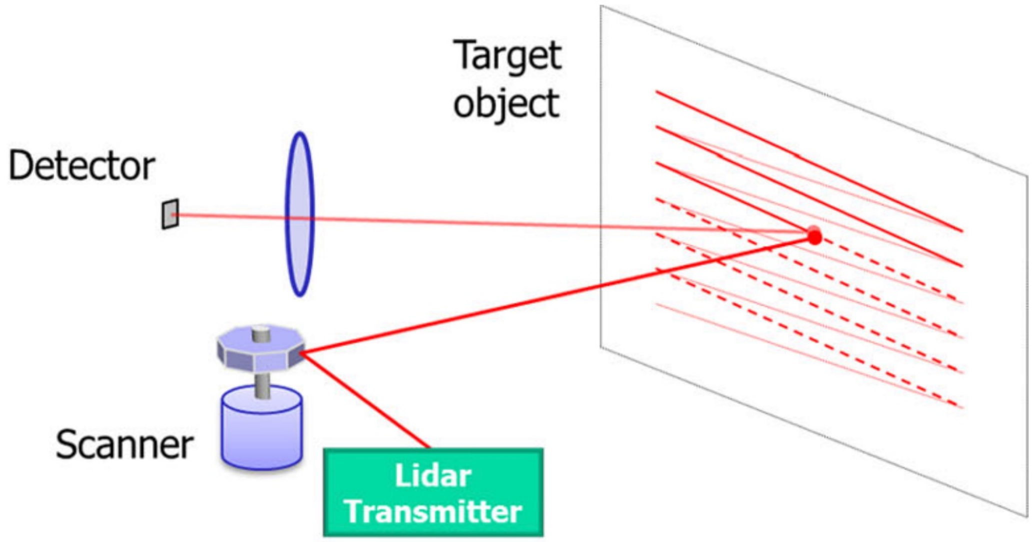


- common method for optical distance measurement
- focus on active distance measurement: radiation is introduced into the environment by the measuring device

$$P_r(R) = E_p \frac{c\eta A}{2R^2} \cdot \beta \cdot T(R)$$

$$T(R) = \exp\left(-2 \int_0^R \alpha(r) dr\right)$$

$P_r(R)$	..	power measured by the sensor at distance R
E_p	..	energy emitted by the transmitter
c	..	speed of light
η	..	efficiency of the system
A	..	size of the aperture
β	..	backscatter coefficient of the target object
T(R)	..	signal reduction
α (r)	..	extinction coefficient



- Optical environmental conditions like rain, dust, snow, and fog must be considered

- Approach
  - potential relation between the extinction coefficient α and rainfall rate R_f

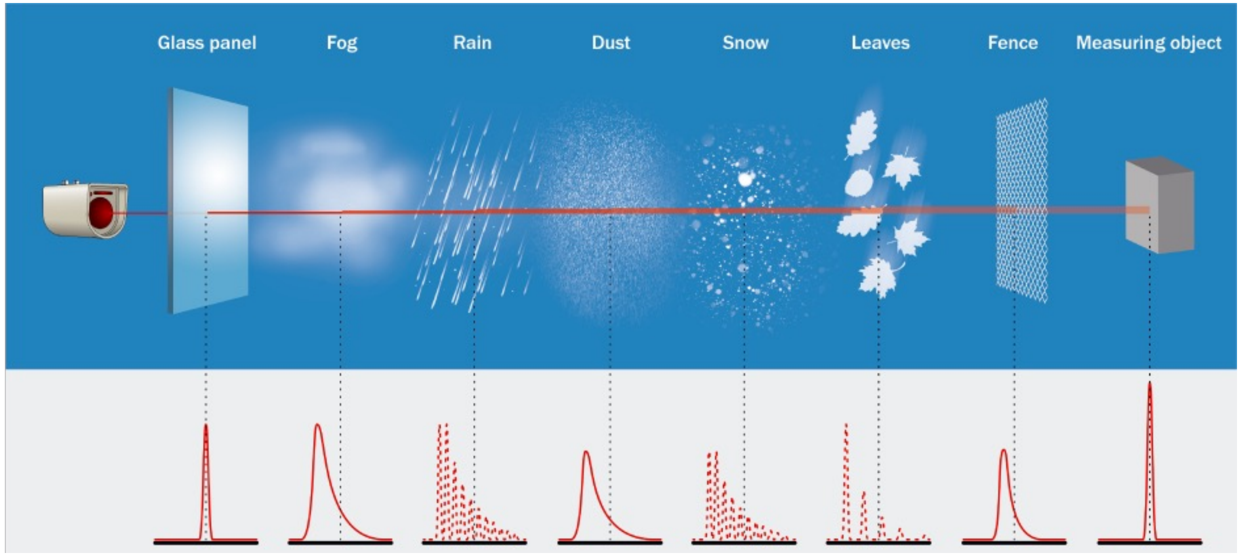
$$\alpha = a(R_f)^b$$

  - also affects the measured distance R:

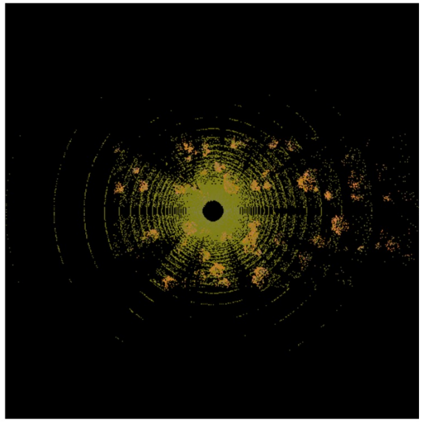
$$R' = R + \mathcal{N}(0, 0.02R(1 - e^{-R_f})^2)$$

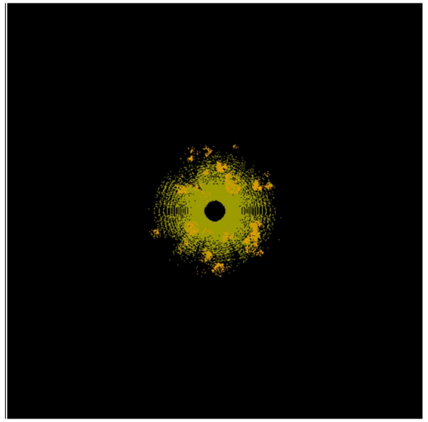
- Random measurement error

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$



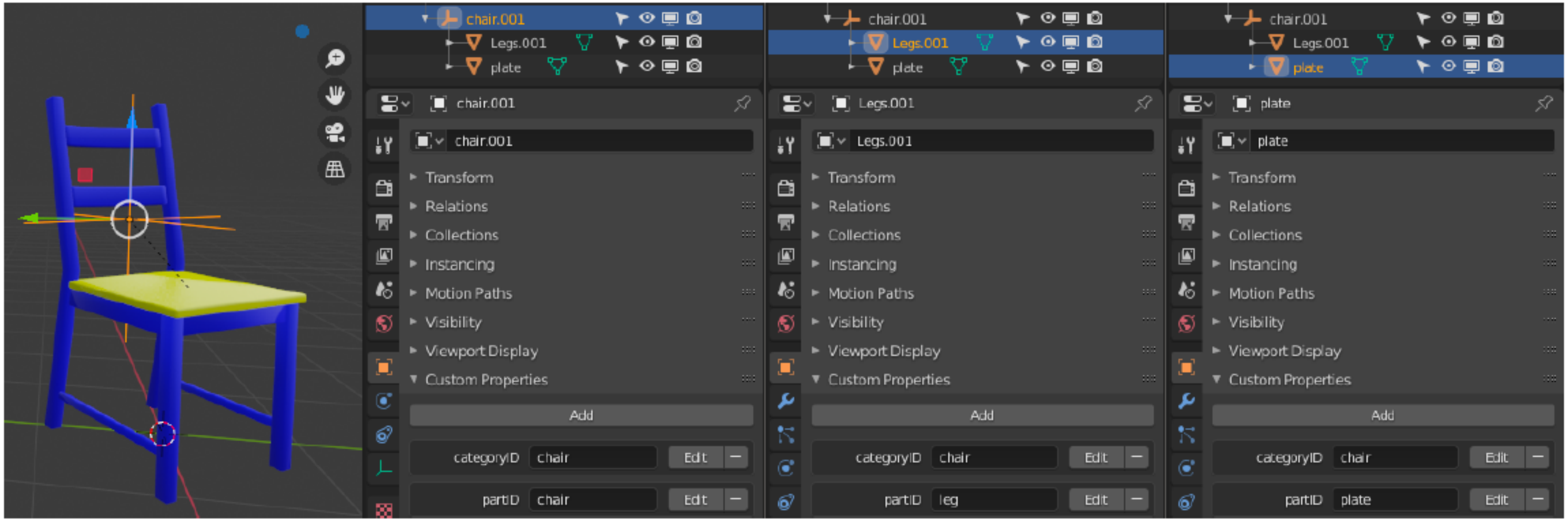
https://www.sick.com/de/de/glossar/multi-echo-technologie/g/p555059



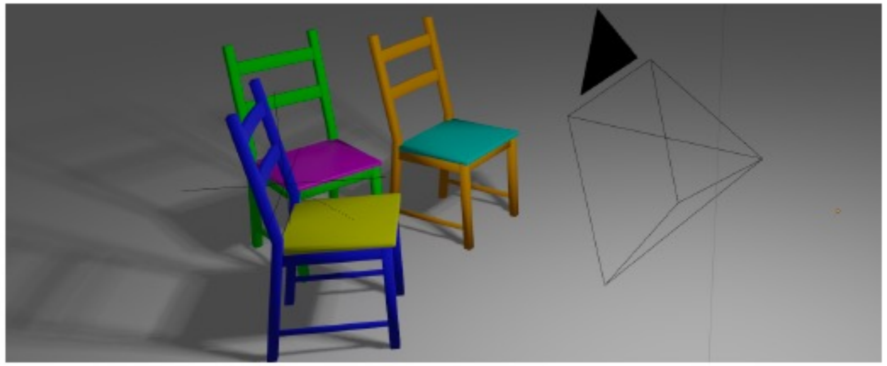


Electronics **2019**, *8*(1), 89; https://doi.org/10.3390/electronics8010089

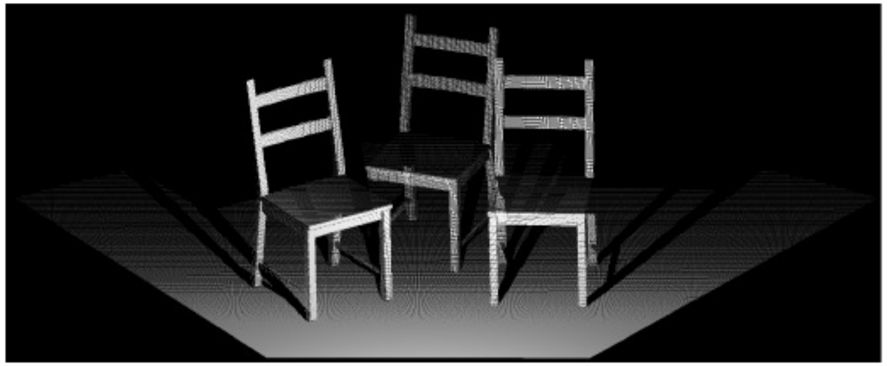
- All parts of the same object (here: chair) get the same categoryID
- To distinguish the parts, the attribute partID is used



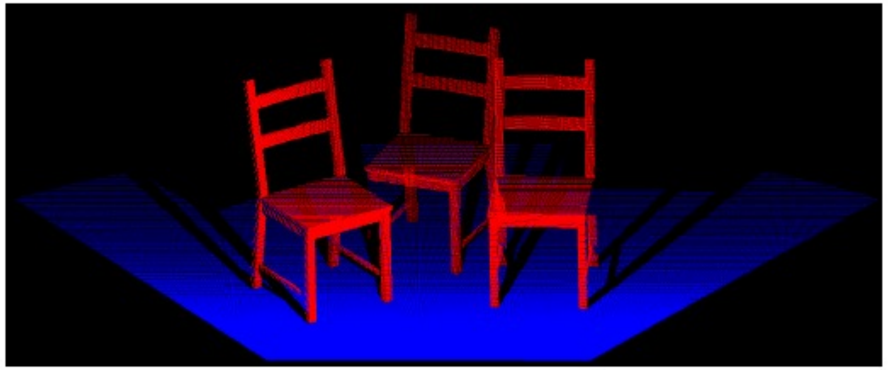
BLAINDER add-on: mark different objects and their components for classification



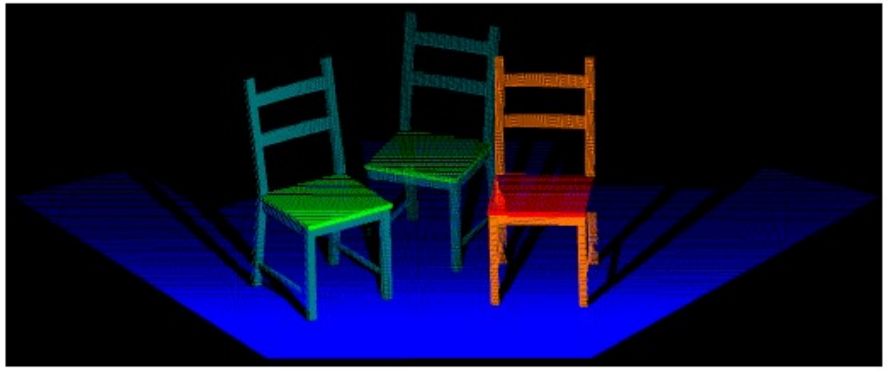
(a) Blender scene with 3 chairs; placement and field-of-view of a virtual Kinect v2.



(b) Point cloud acquired, gray scale color according to intensity of reflected light.



(c) Point cloud colored according to semantic segmentation at object level.



(d) Point cloud with seat plates classified separately.

Part B.

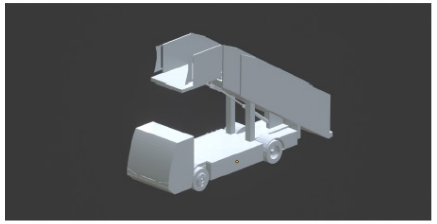
Virtual environment

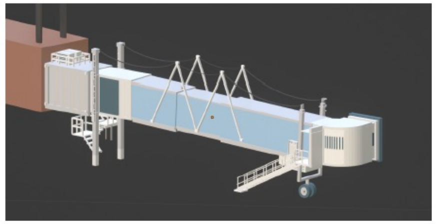
Virtual environment

- worlds generated completely or mostly procedurally, simple way to provide a variation of a specific scene
  - particularly useful for scene containing a lot of nature like landscapes or vegetation
  - various sources of open geo data

```
// fetch area \airport" to search in
area[icao~"WSSS"]->.searchArea;
// gather results
(
  nwr(area.searchArea)
  ["aeroway"~"parking_position|taxiway|runway"];
);
out body;
>;
out skel qt;
```

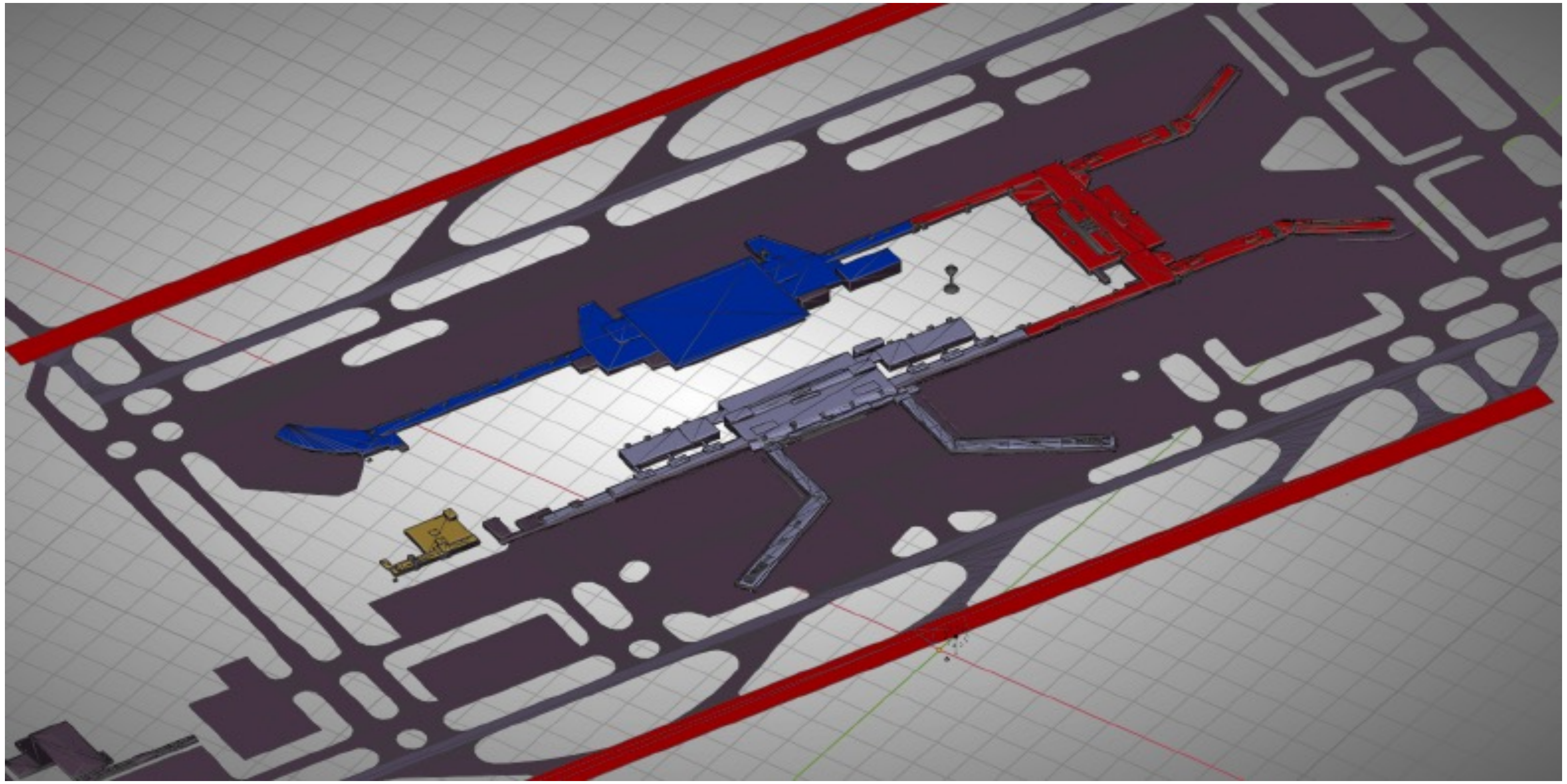
- Operational airport environments are **semi-static**
  - essential part is static even with advancing time (e.g., airport terminal buildings)
  - smaller parts of the scene vary (e.g., specific aircraft models)





- animations results in variations within a topologically constant scene by translation of the sensor, movement of figures, or physical simulation

- Blender for creating and modeling a custom scene of triangular meshes representing Singapore Changi Airport (WSSS) infrastructure



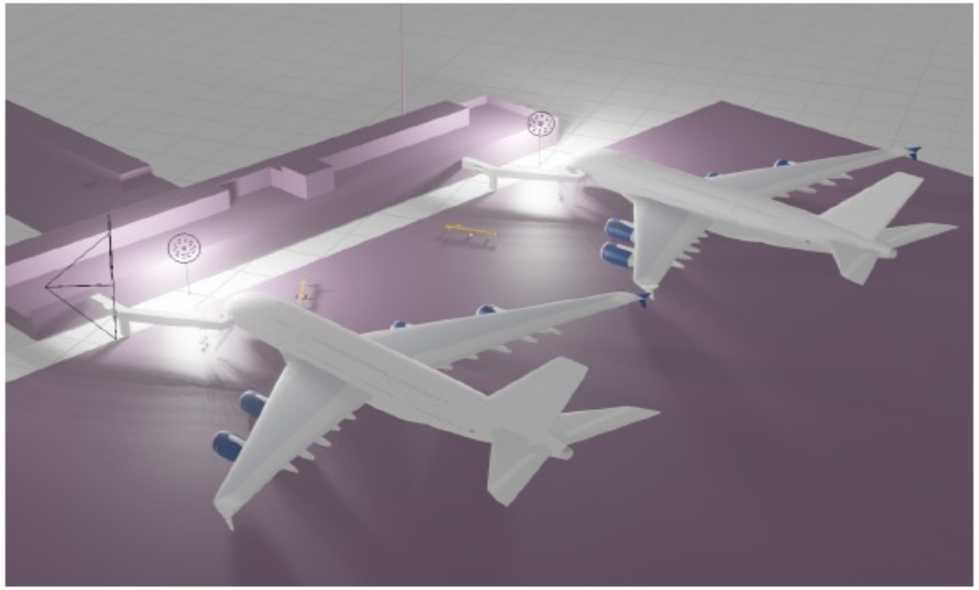
Singapore Changi Airport - 3D Model with a polygon count of 29.412

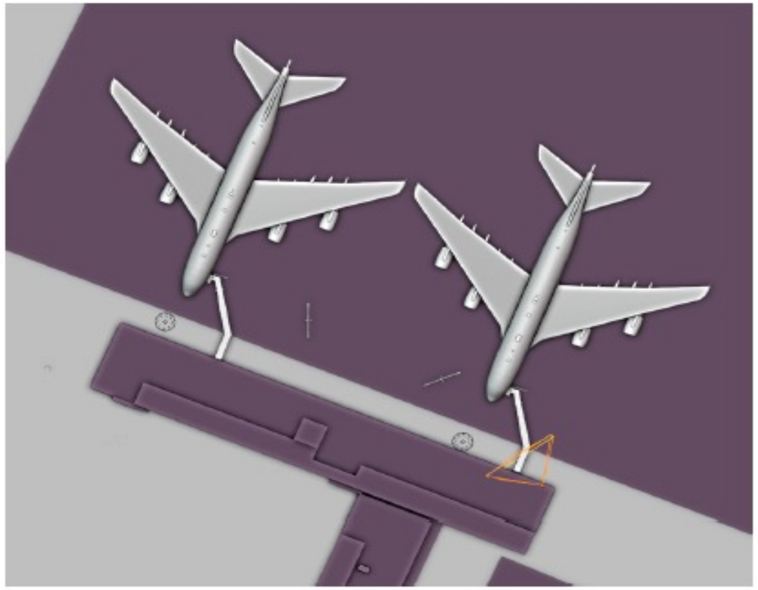
Virtual environment
aircraft models

- Challenge: variety of aircraft types in many different poses
- `ShapeNetCore.v2` with categories `aircraft`, `aeroplane`, `plane/transport airplane`
- 338 models for separate scenes, following defined patterns implemented Blender

3D model of Airbus A380 from `ShapeNetCore.v2`

- completely static objects (buildings)
- objects static in its format but pose-dynamic (ground vehicles, fingers)
- variable objects (different aircraft types, but constant class/label)





virtual airport environment including a synthetic LiDAR sensor

Part C.

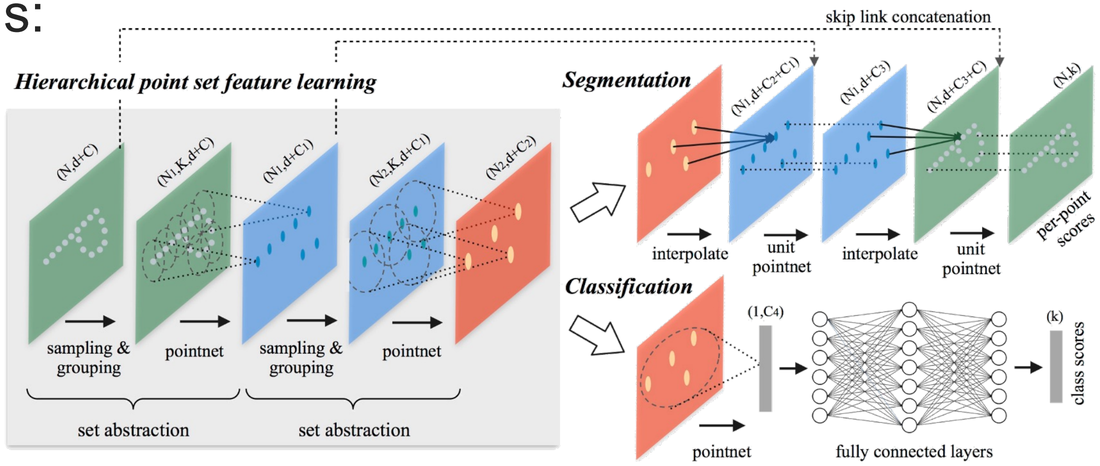
AI application

AI application
deep learning for point clouds

- Main properties point clouds
  - **Unordered**: points in a point cloud are typically not assumed to have any particular structure
  - **Density variability**: non-constant density within the point clouds due to perspective effects, movements or measurement errors
  - Invariance under transformation: as a set, such data must be invariant to mutations of its members

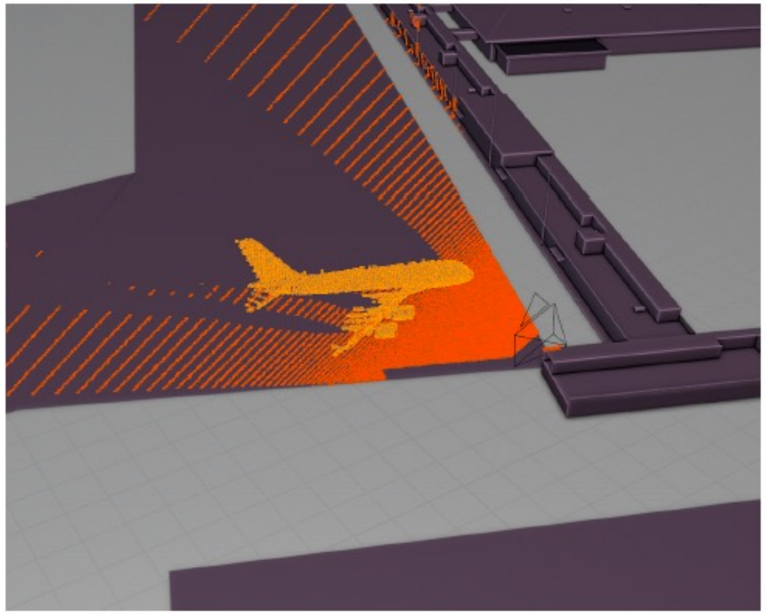
- several approaches for deep learning for point clouds:
  - PointNet, **PointNet++**, MVCNN, …
  - for time-delay signals: Spiking Neural Networks

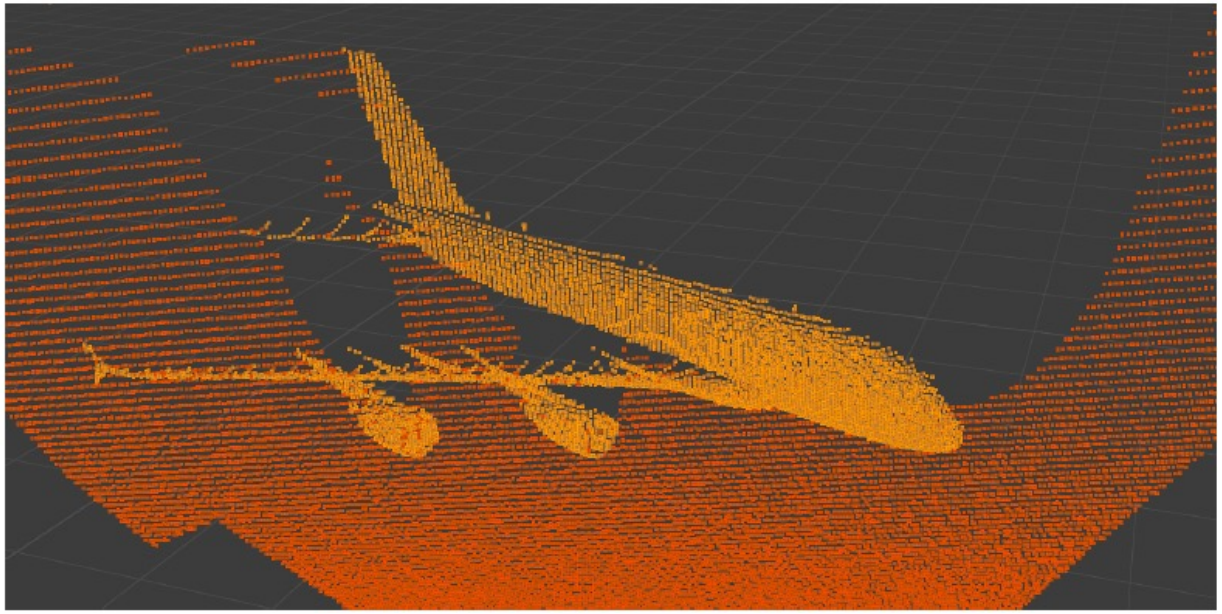
- **PointNet++:** Deep Hierarchical Feature Learning on Point Sets in a Metric Space



- 1,690 point clouds (exported as HDF5 file format) in total: 1,115 for learning, 575 for validation

- Training on GPU with CUDA on NVIDIA DGX-2 AI for 819.624 trainable parameters





Synthetic LiDAR sensor feedback at WSSS environment

- Scenario definition for clean and noisy point clouds created from synthetic LiDAR sensor feedback

Scenario	State / noise	Description
A	clean	baseline LiDAR
B	Gaussian	severe weather
C	Gaussian and autoencoder	severe weather and reconstruct

- Mean accuracies of semantic segmentation of scene objects with autoencoder (AE) improvement

Scenario	A	B	C	AE
Accuracy (%)	75.4	66.7	68.9	+2.2 %
1 - aircraft	81.2	76.8	79.9	+3.1 %
2 - airport buildings	84.7	81.0	84.1	+3.1 %
3 - finger	73.3	62.1	65.1	+3.0 %
4 - ground vehicles	75.0	54.8	55.3	+0.5 %
5 - apron misc	63.0	58.6	60.1	+1.5 %

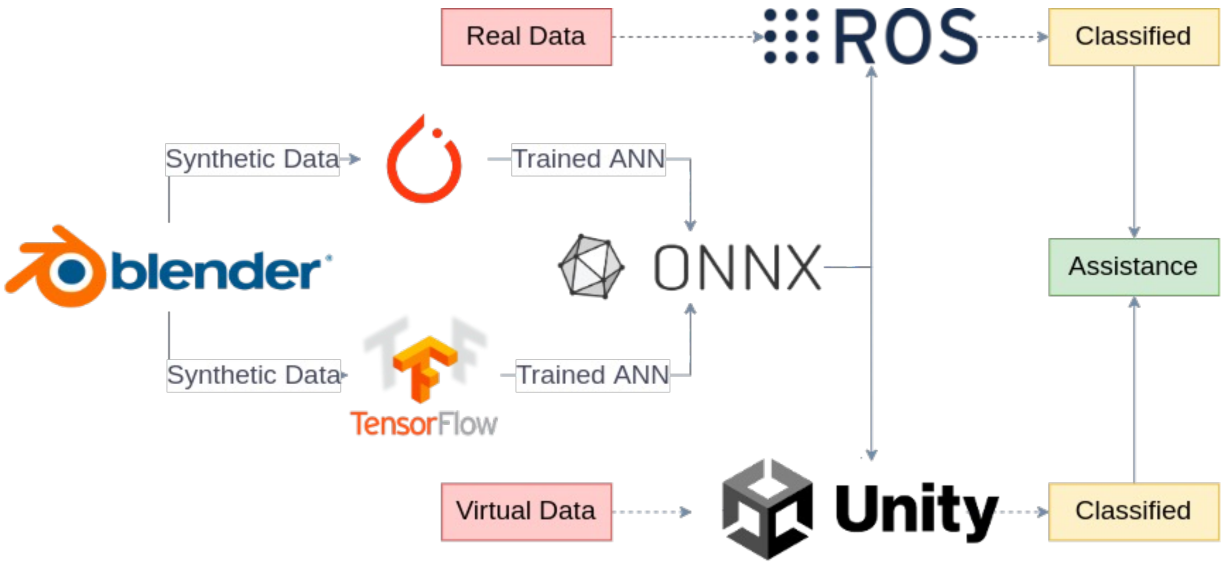
Part D.

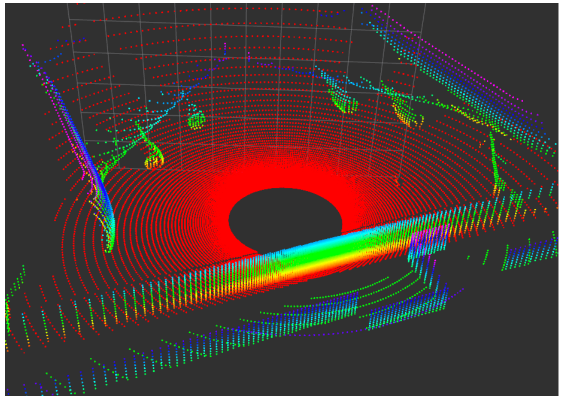
Transfer

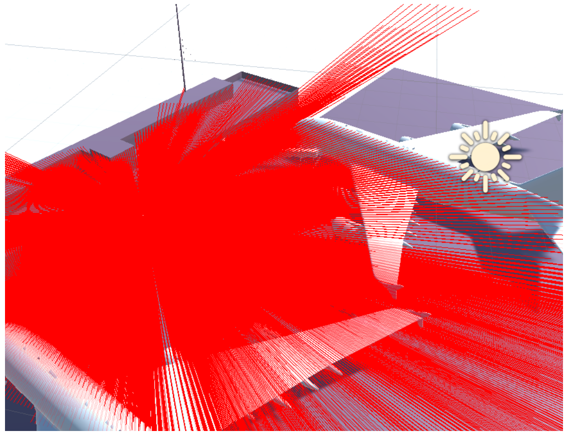
Transfer

- Integration of synthetically trained models for real sensors as well as for airport simulators

- Open Neural Network Exchange (ONNX) format is suitable for this export and independent of AI framework







Conclusion

- Achieved so far:
  - prototypical implementation of a synthetic LiDAR sensor in a virtual airport environment
  - exemplary operational and environmental conditions
  - creation of synthetic depth sensing data for AI training
  - training of common deep learning models with synthetic data

- Further research:
  - Combine all components
  - Transfer of trained deep learning models to simulation environments
  - Experiments with other deep learning models for temporal depth sensing data classification
  - transfer to and tests with more complex WSSS operational scenarios

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Thank you.

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