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Deep Variational Data Synthesis for AI Validation

Workshop **"Visuell-explorative Bewertung neuronaler Netze"**

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Outline

- Introduction
  - Problem, application space, What makes synthetic images ‘**realistic**’ ?
- Deep Variational Data Synthesis Approach
  - Realistic data synthesis
- Analysis and Comparison of Synthetic & Real Data Sets
  - Performance limiting factors to characterize objects
  - Visual analysis
- Summary

Application Space

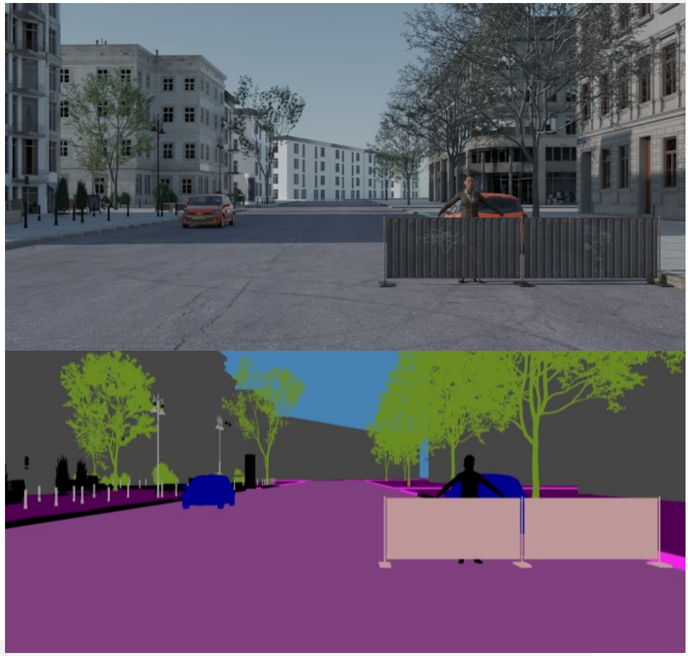

urtesy: www.carmagazine.co.uk

- Automated Driving, Robots in industrial environments
- In areas that involve presence of humans <u>**safety**</u> is paramount
- A major bottleneck in these cases is <u>**perception**</u>
  - → usually provided by AI/ML perception modules
- Operation requires validation and verification of functionality


Courtesy: https://www.wsj.com/

Data for AI/ML

- State-of-the-art AI training by means of machine learning (ML) requires rich annotated sensor data
  - Real data requires a lot manual annotations
  - Automation & rare cases: synthetic data
- Validation requires even more annotations, specifically to be able to:
  - find & explain failure of perception



What makes synthetic images '**realistic**' ?

- Easy to answer: Which one is real?
- Harder: What is missing?

Deep Variational Data Synthesis Approach

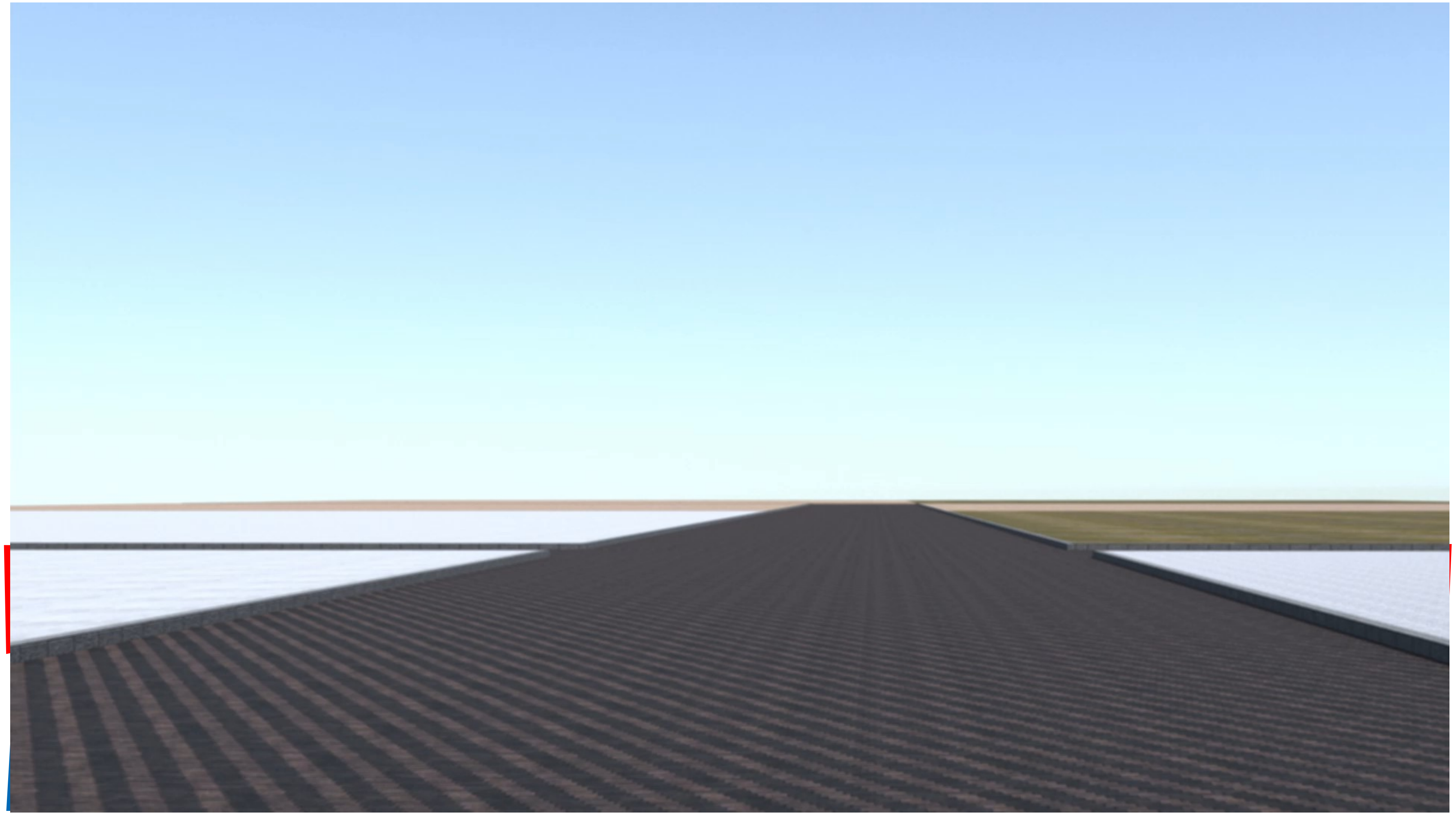
1. Parameterized Scene Complexity, many different objects

2. Variation of scene parameters

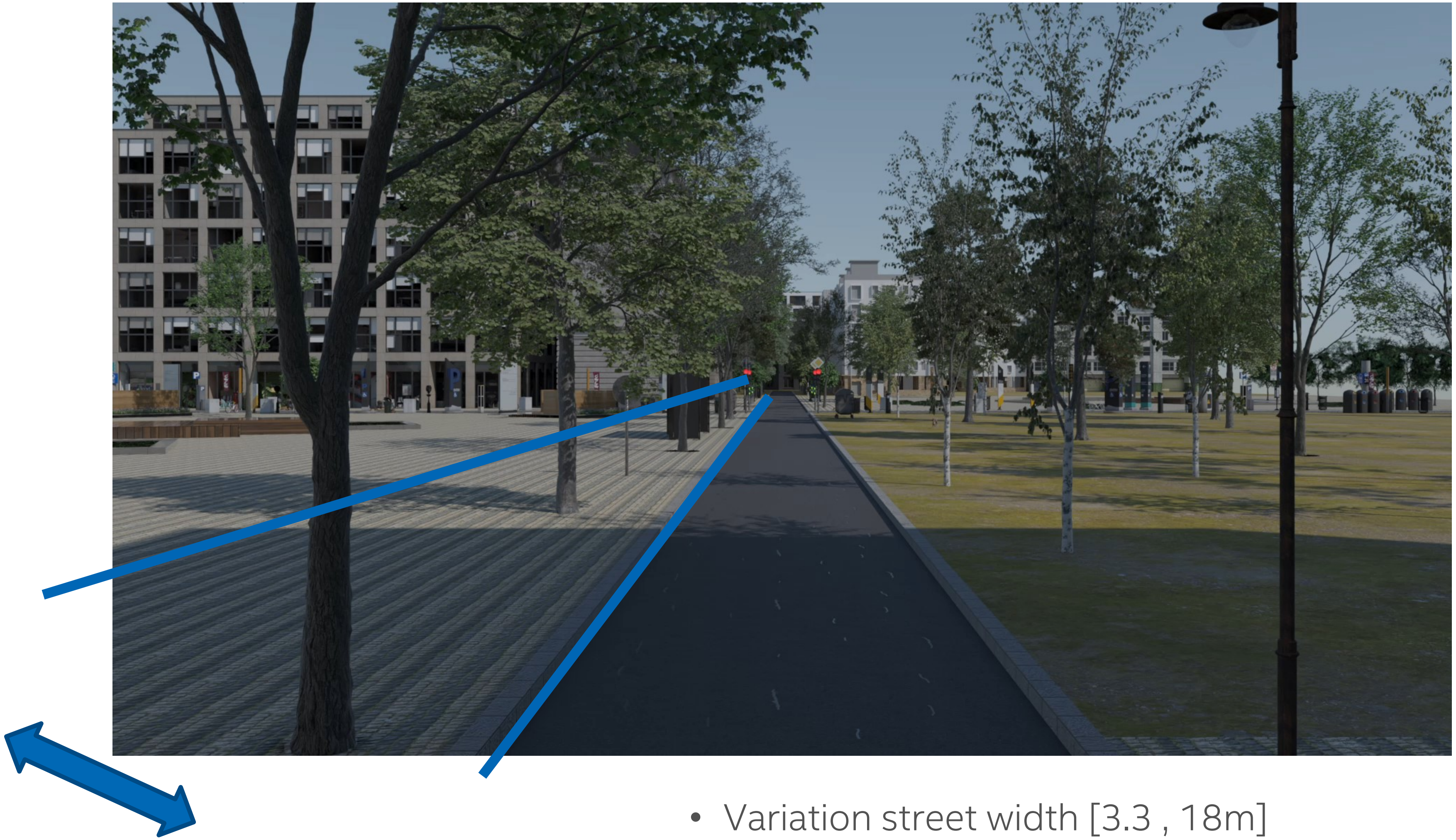
3. Realistic sensor simulation

Scene generation steps

1. Ground definition
2. Definition of placement areas
3. Placement of buildings
4. Random object placement



Parametric scene modelling



- Variation street width [3.3 , 18m]
- ‘Auto-lane’ enabled, generates lanes

Parametric scene modelling

- Variation sidewalk width
- 2m → 12m

Person Population density

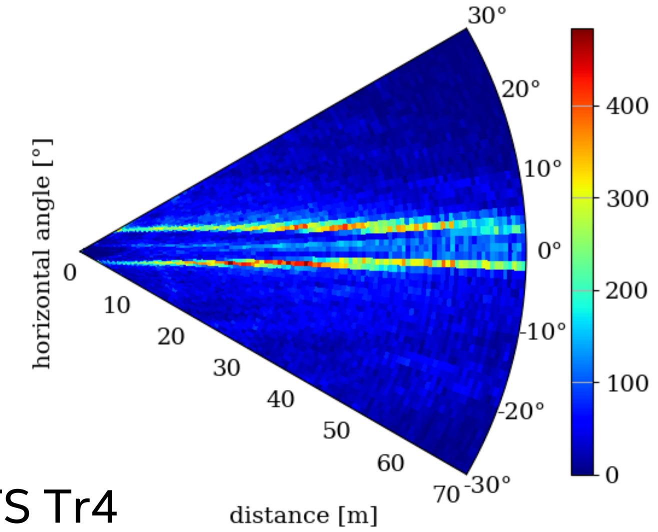
low

"density_road_persons": 0.001,
"density_side_persons": 0.02,

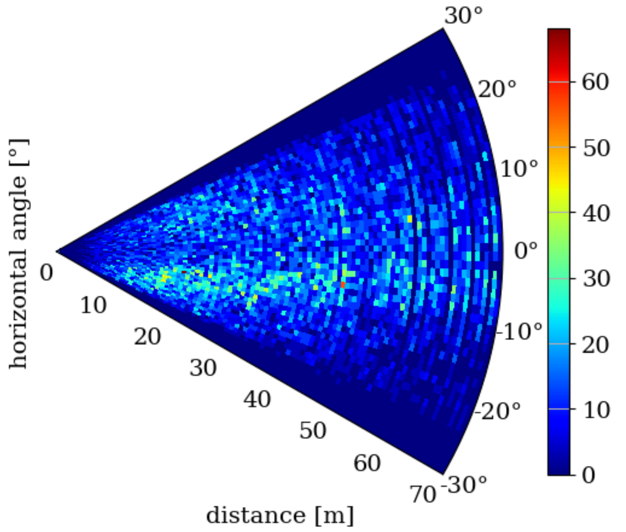
mid

high

Pedestrian Distribution Synthetic (KI-A) vs. Real

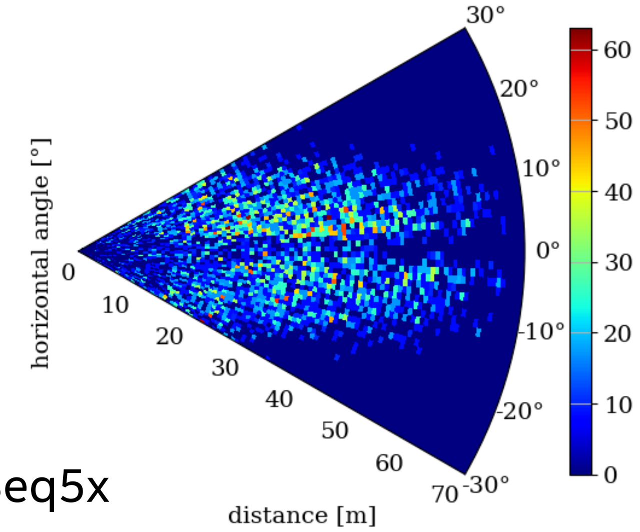


BIT-TS Tr4



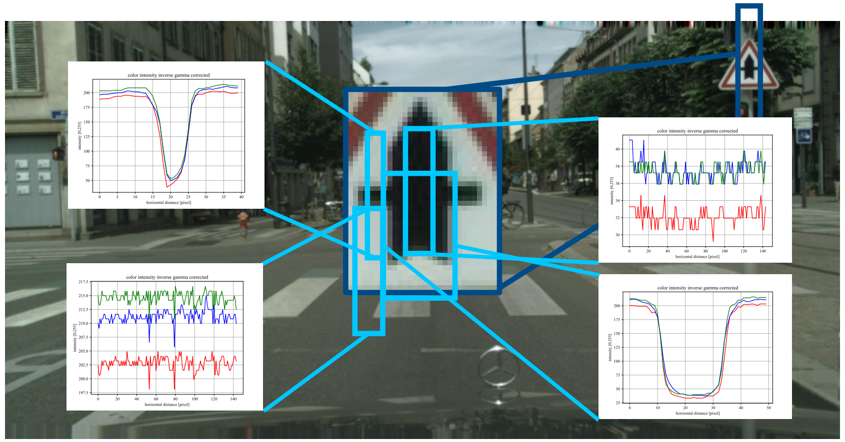
Cityscapes

- Specifically, the first project data sets had quite un-natural spatial distribution of pedestrians (and other objects)
- Low number of different objects from one class -> low variety and complexity
- We build a probabilistic scene generator, leading to more homogeneous and better approximation of natural distribution



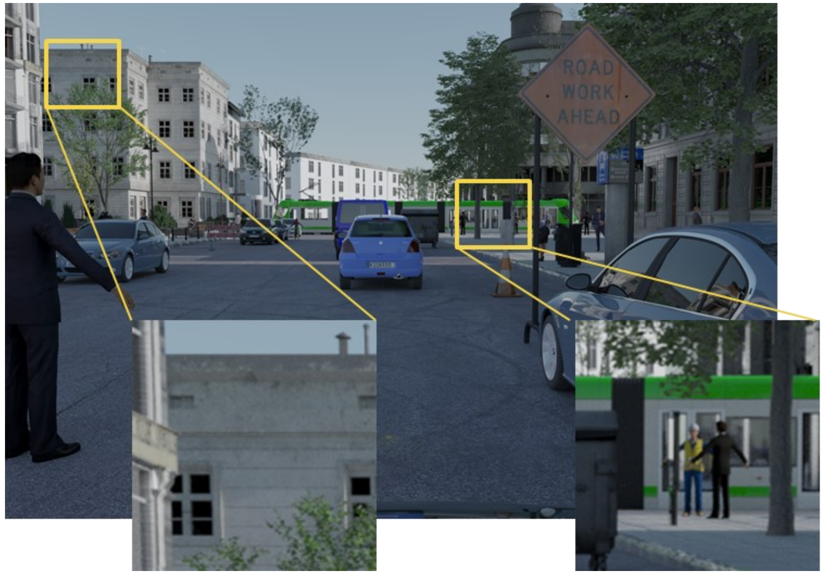
Intel Seq5x

Sensor simulation



Parameter estimation from real images

Rendering output



Output of our sensor simluation

More info, publication: K Hagn, O Grau, Improved Sensor Model for Realistic Synthetic Data Generation, Computer Science in Cars Symposium, 2021.

Example: Urban crossing

- Appr. 500 different assets (3D models)
- Street wid. 6m – 20m, auto layout
- Light variations day-night
- Each frame induvial 'scene'

Analysis and comparison of synthetic & real data sets

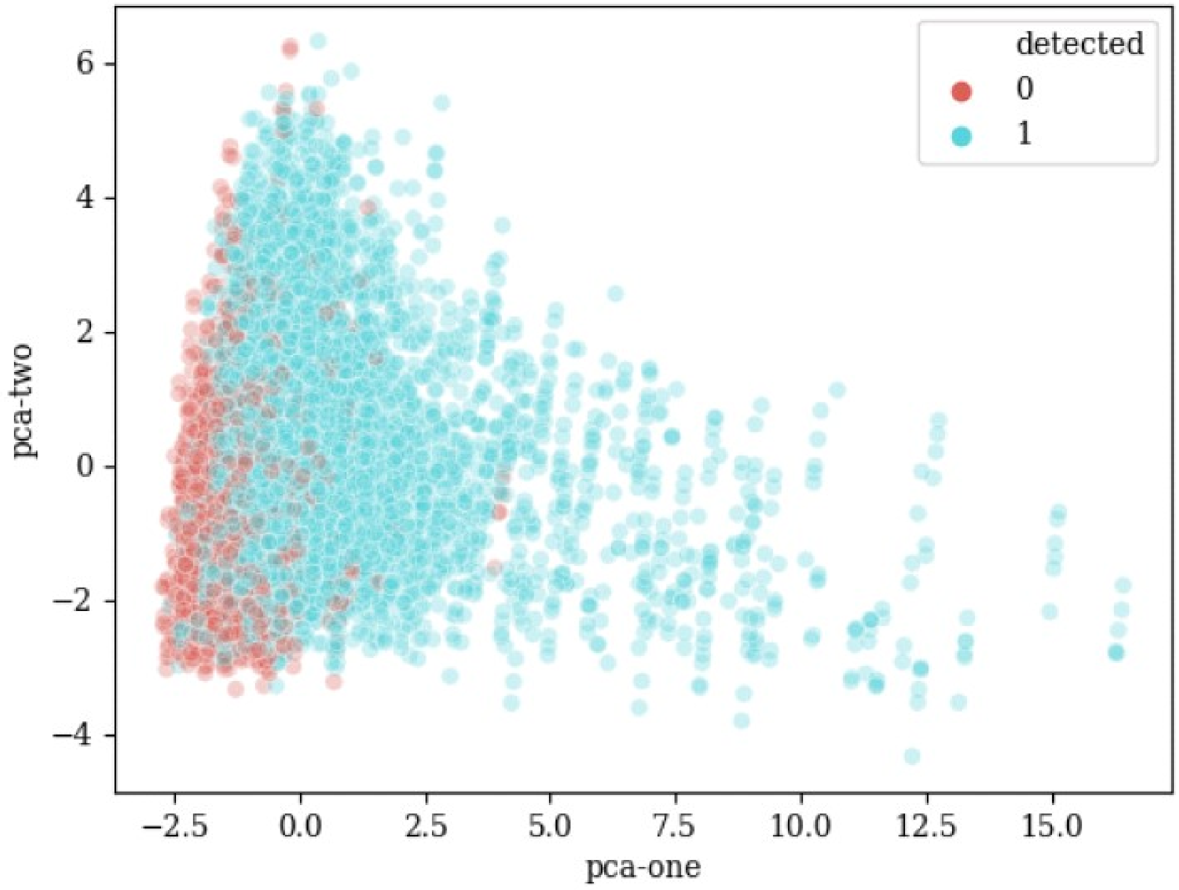
Definition of Performance Limiting Factors

- Performance Limiting Factors (PLFs) are influential on the detection performance of a DNN on a pedestrian
  - ➢ These PLFs characterize an object of a dataset
- The following PLFs are considered:
  - The Bounding Box Location (c_x, c_y)
  - The Bounding Box (w, y)
  - Distance to the camera
  - Occlusion (visible pedestrian/ whole pedestrian)
  - Number of Visible Pixels
  - Contrast of object to background

PLF visualization by PCA

C_X	C_Y	W	H	Distance	Occlusion	Visible Pixels	Contrast	Detection

PCA transform to reduce dimensionality

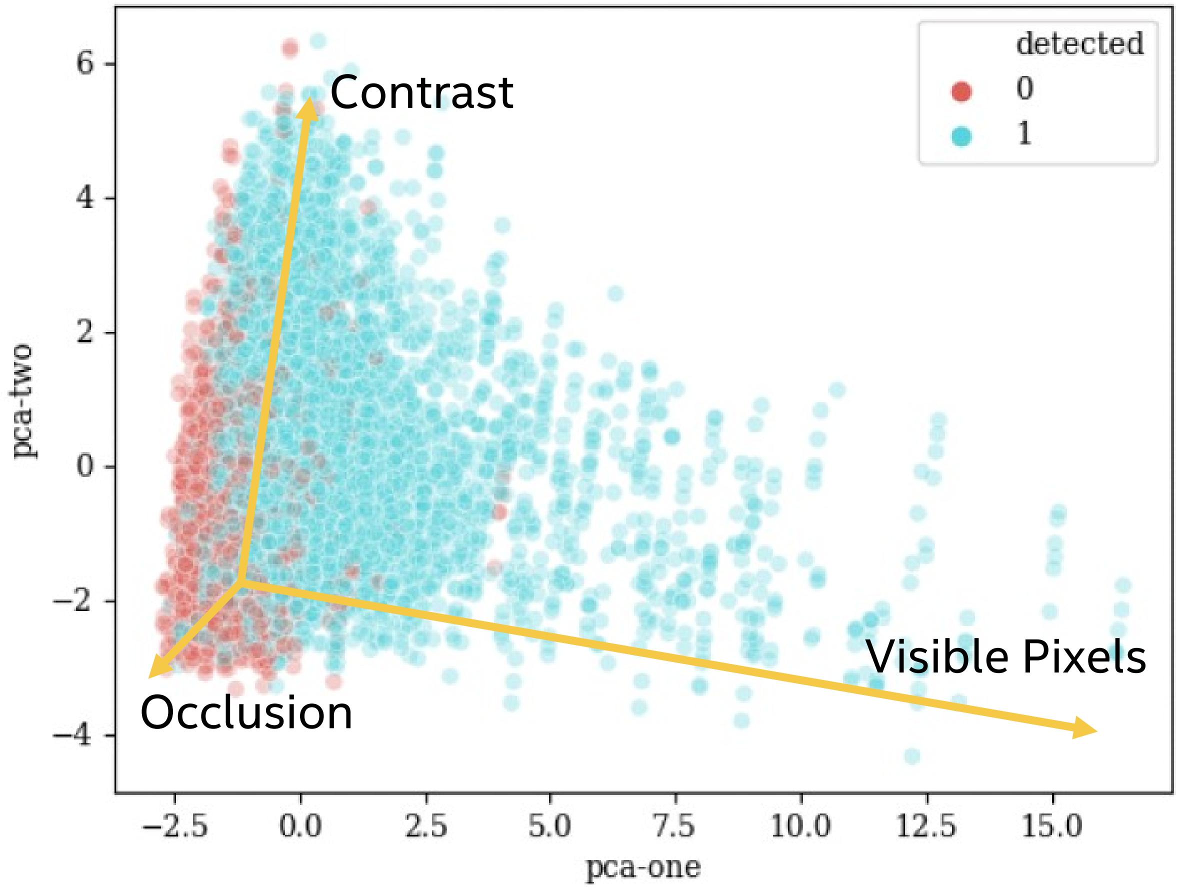


- Visualization of our (Intel) synthetic data by PCA transformation of per pedestrian PLFs
- The Hue indicates if the 2D Bounding-Box detector could detect the pedestrian instance

PLF visualization by PCA

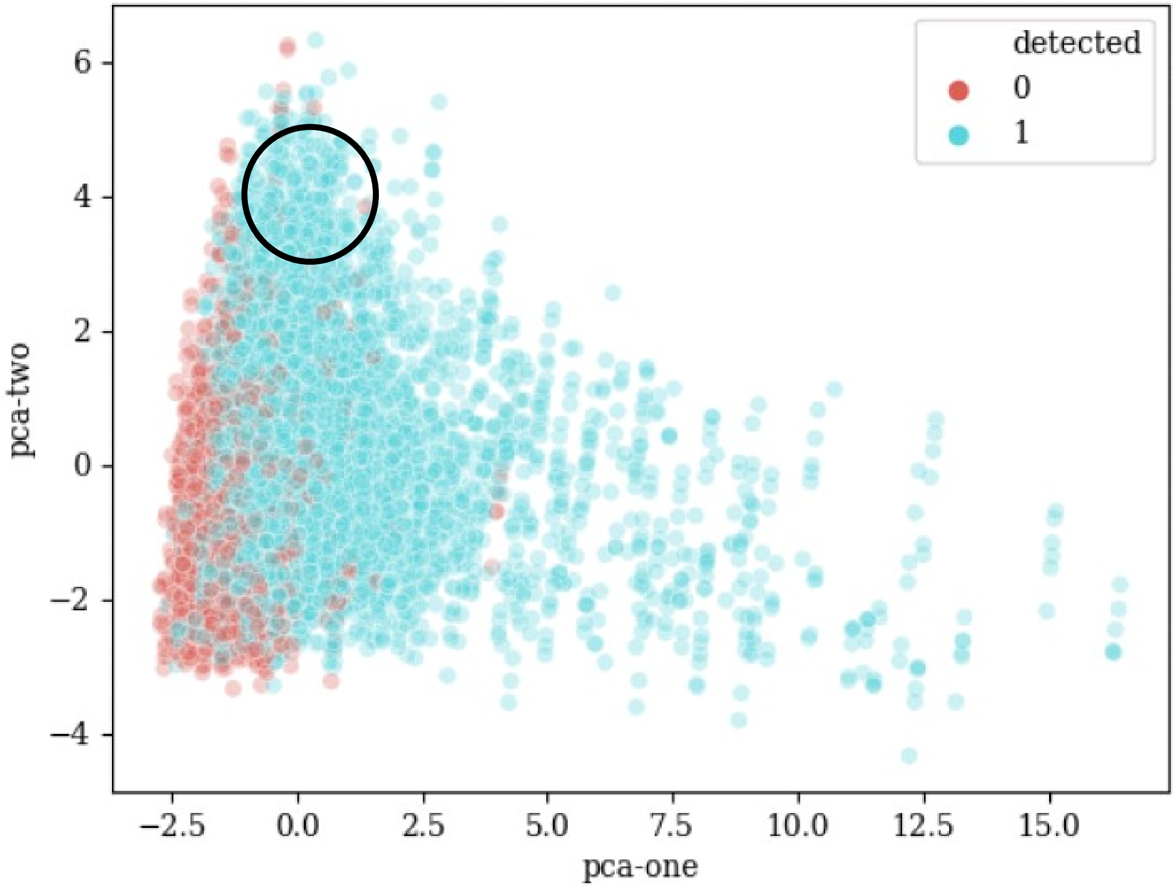
C_X	C_Y	W	H	Distance	Occlusion	Visible Pixels	Contrast	Detection

PCA transform to reduce dimensionality



- Showing the directions of three PLFs
  - Occlusion
  - Contrast
  - Visible Pixels
- The arrow direction indicates increasing in value for this PLF

Investigate Outliers in PCA

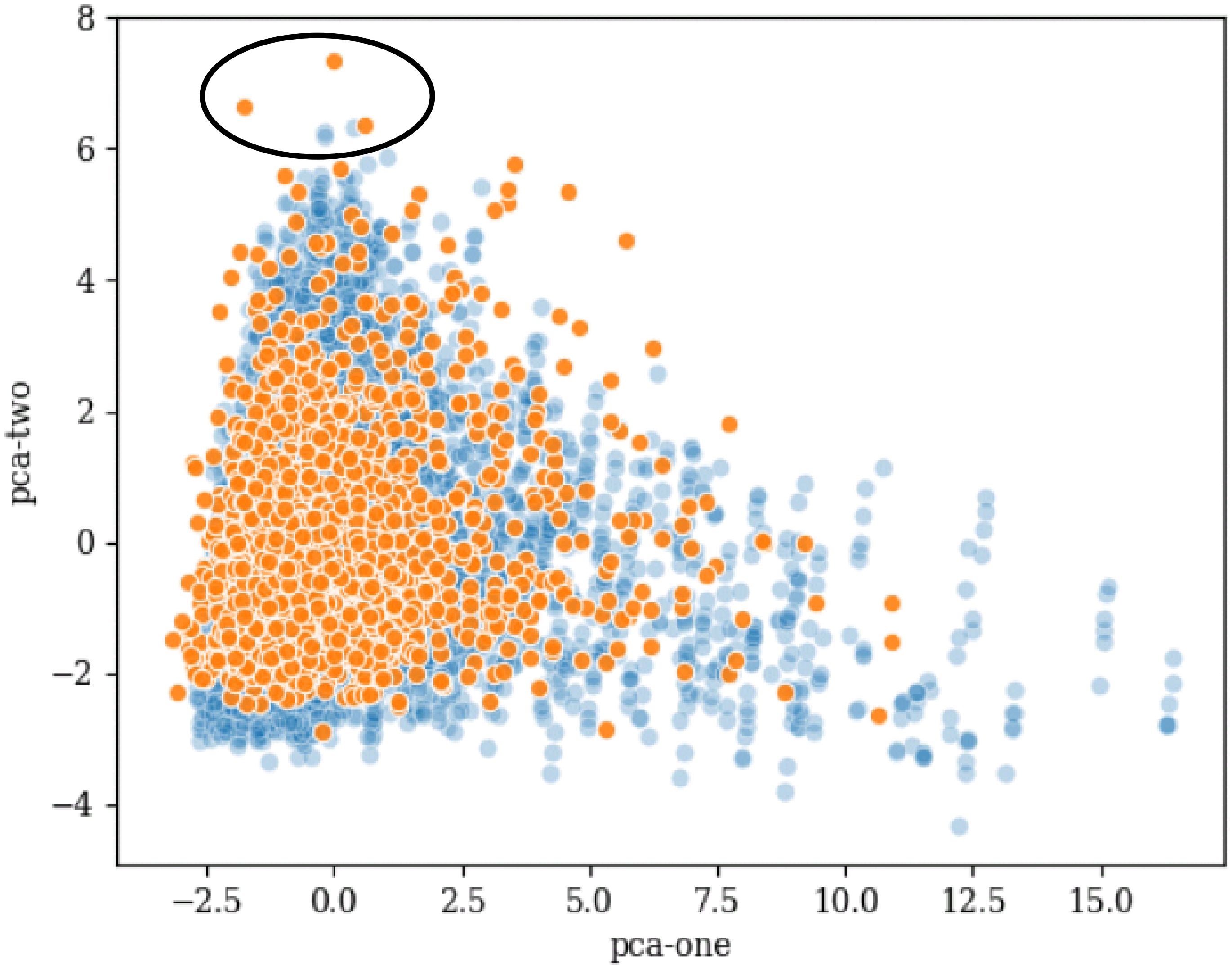


- Investigate Outliers in PCA, i.e., pedestrian instances being outside of the major red (non-detected) PLF area

Investigate Outliers in PCA

PLF PCA for comparison of datasets

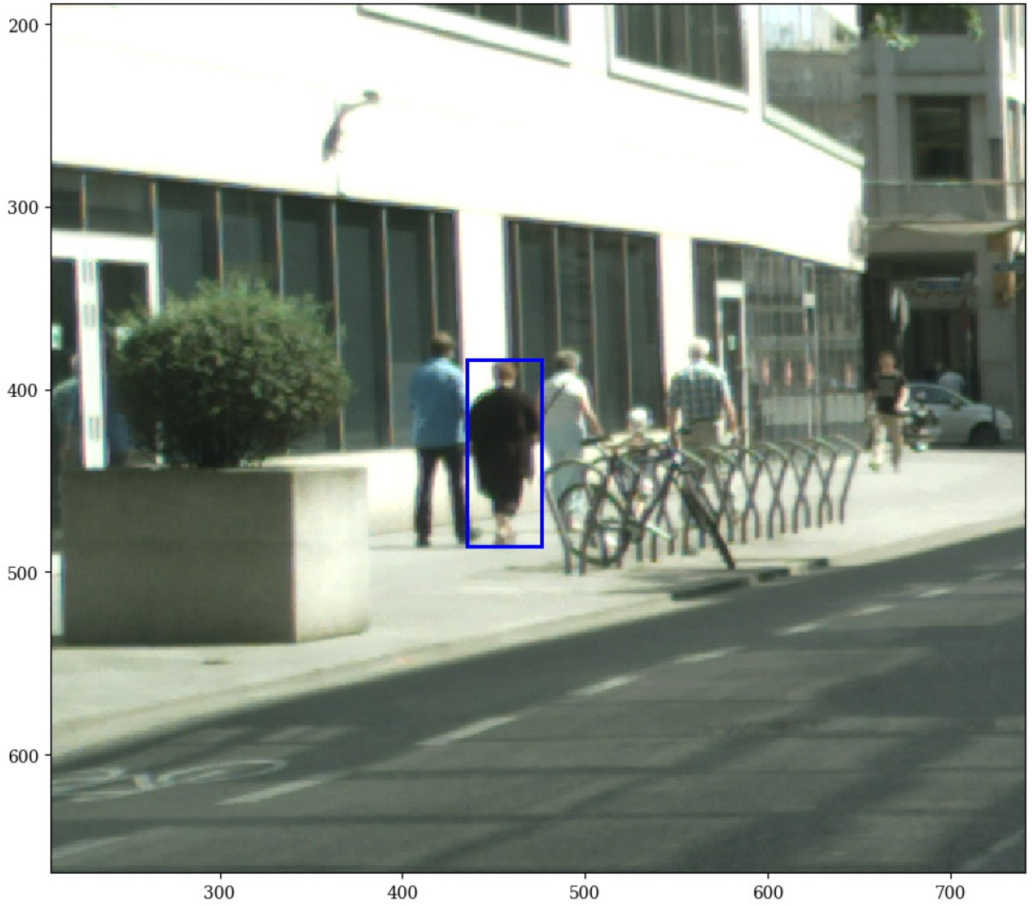
- The PLF PCA can also be used to compare different datasets
- Here:
  - Blue is our synthetic dataset
  - Orange are cityscapes pedestrians
- Interesting Instances in these analysis are pedestrian points of Cityscapes that do not overlap with our synthetic dataset
- These outliers indicate a very high contrast

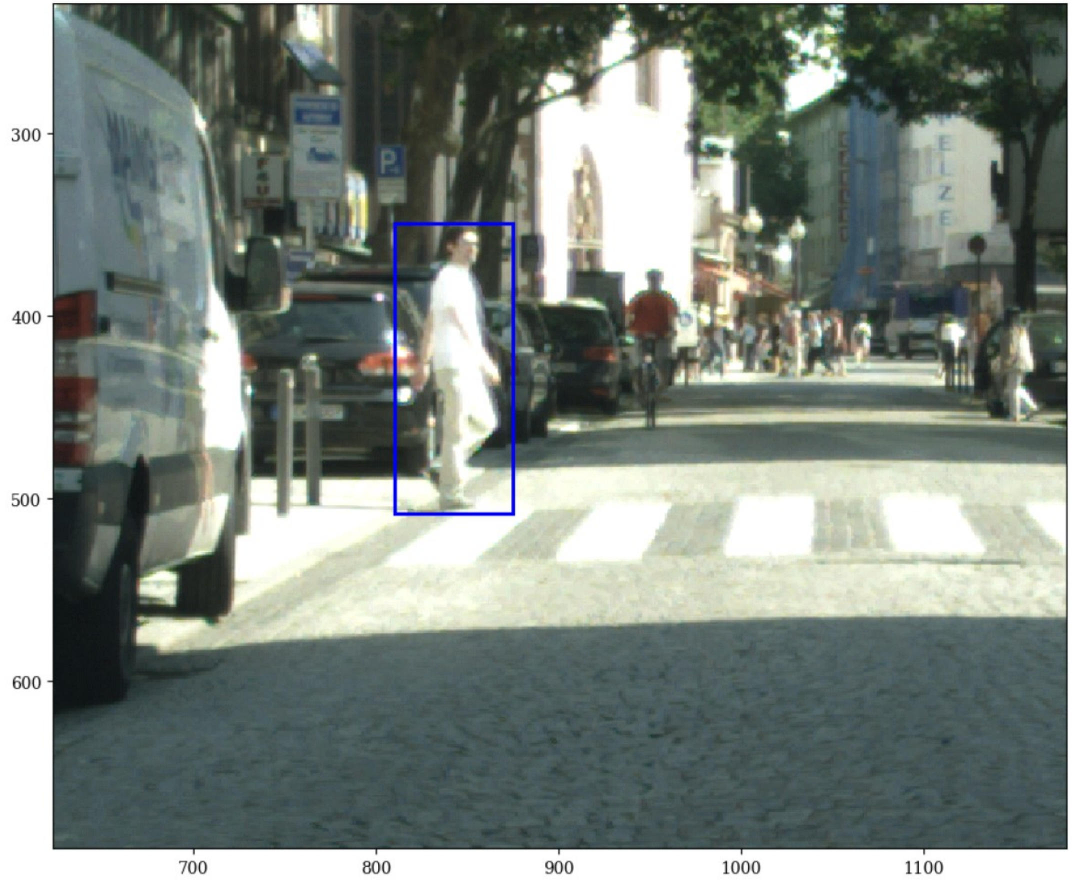


Date, Occasion

PLF PCA for comparison of datasets

High Contrast examples



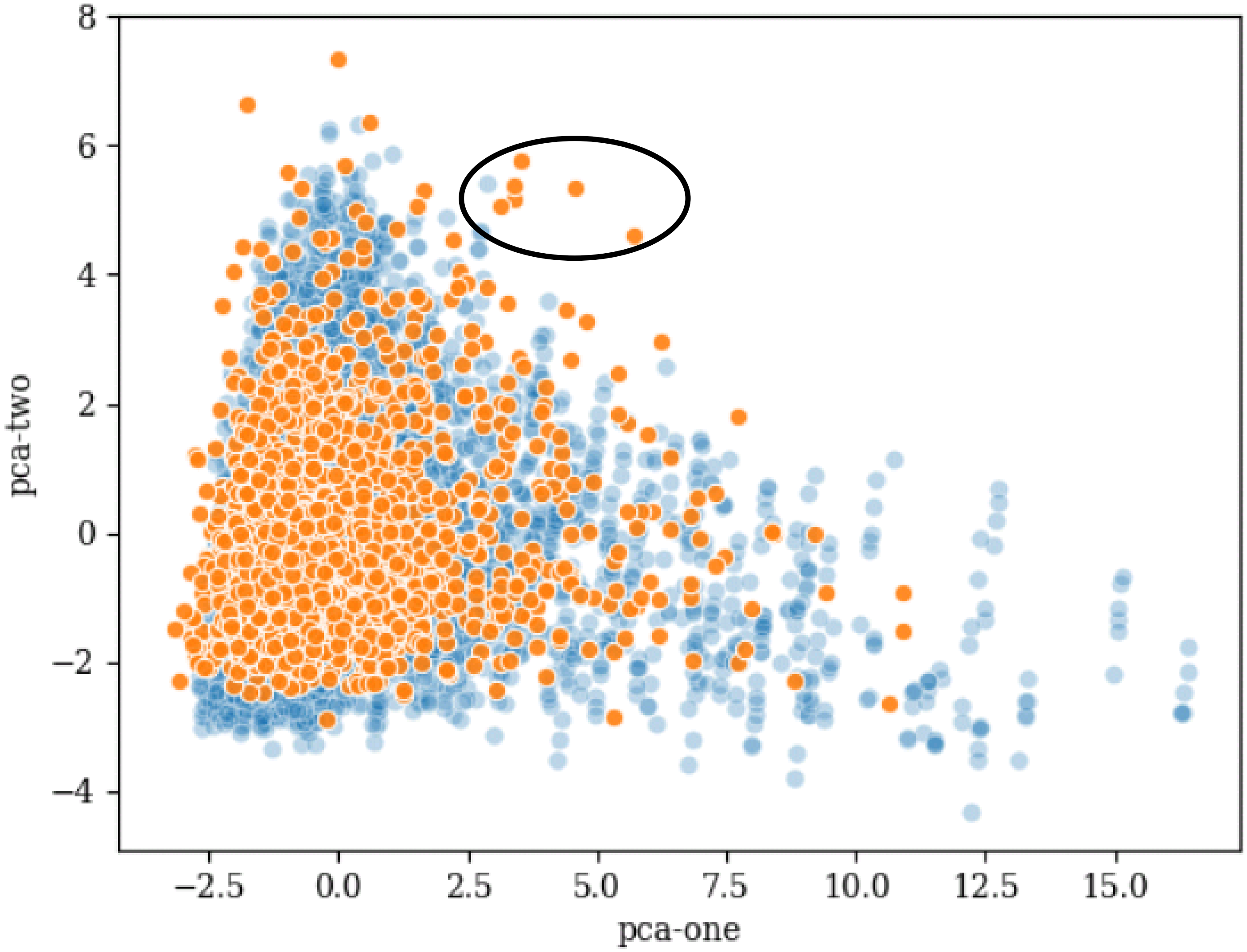


PLF PCA for comparison of datasets

High Contrast examples

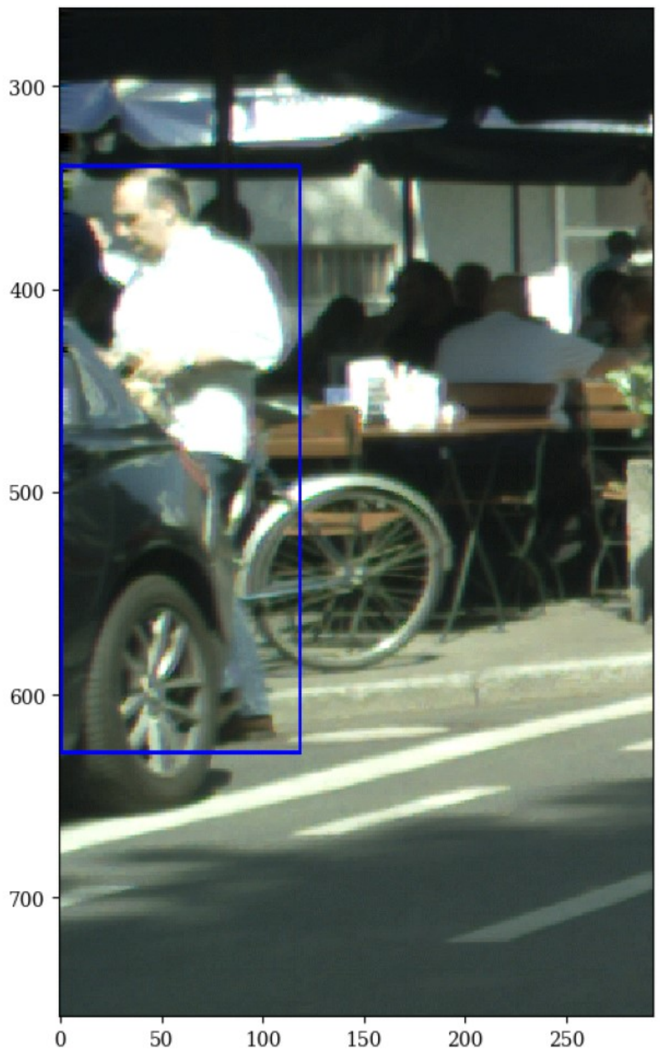
Use PLF PCA for comparison of datasets

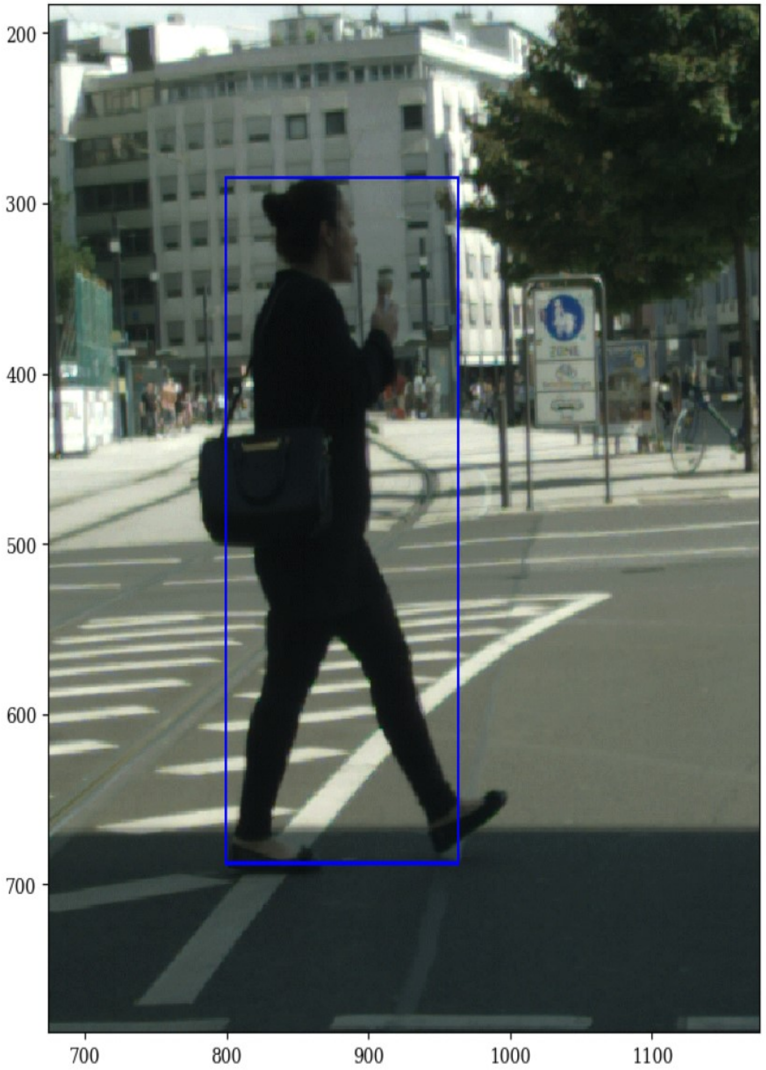
- Here:
  - Blue is our synthetic dataset
  - Orange are cityscapes pedestrians
- The outliers indicate high contrast, low occlusion and high visible pixels count



PLF PCA for comparison of datasets

High contrast, low occlusion, high number of visible pixels





PLF PCA for comparison of datasets

High contrast, low occlusion, high number of visible pixels

Summary

- Automated data generation pipeline produces unbiases distributions and steerable scene complexity
- produce synthetic data to 'match' real data on
  - Scene complexity
  - Spatial distribution
  - Sensor characteristics → Deep Variational Data Synthesis
- The PCA of PLFs allows for a visual inspection of differences in datasets and comparisons of synthetic & real data sets

KI ABSICHERUNG

Safe AI for Automated Driving

KI Absicherung

Project : https://www.ki-absicherung-projekt.de/

German collaborative project: 24 partners, 41 Mio € budget, 36 m duration