KIDELTA LEARNING
Scalable AI for Automated Driving

Final Event | March 09, 2023

Activation-based Domain Shift Quantification for Semantic Segmentation

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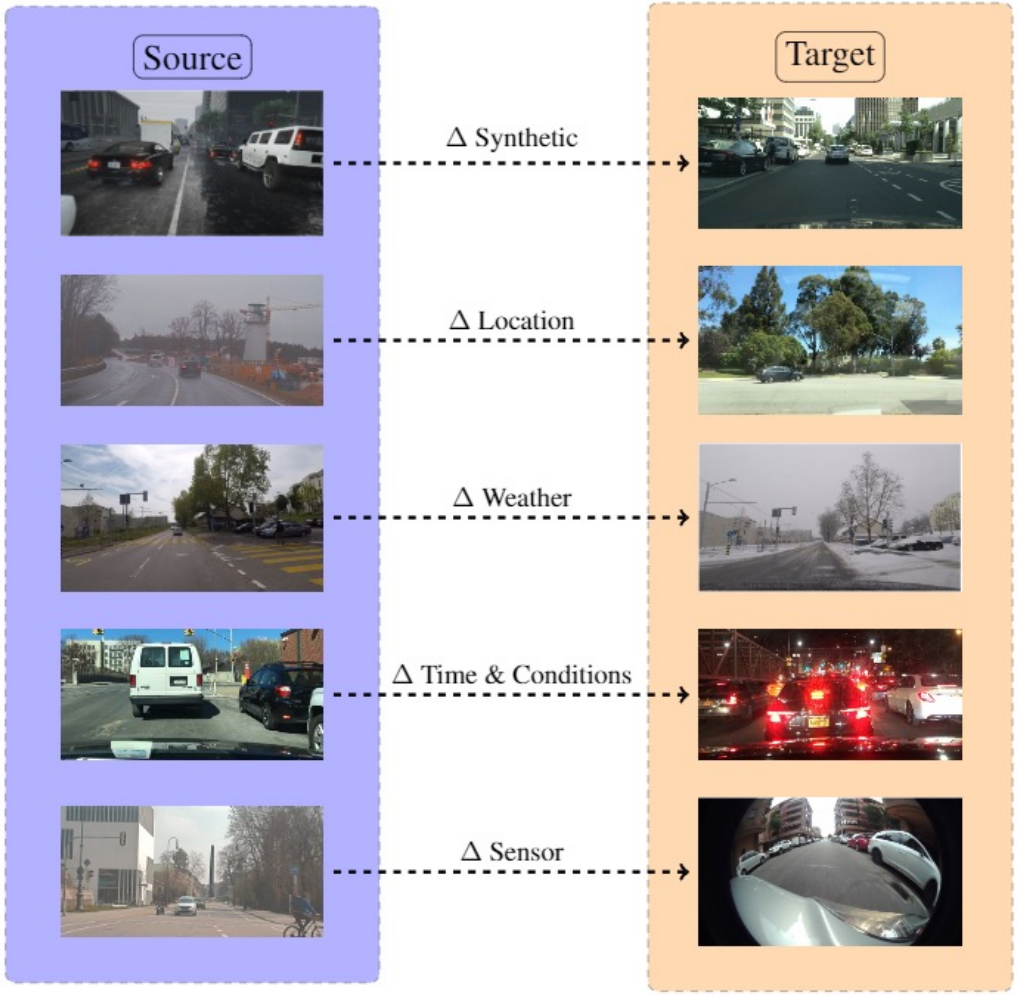
Domain Shifts



- Several different domain shifts challenge DNNs in real applications
- Performance drop, e.g. mean intersection over union (mIoU), used as a proxy for the strength of the domain shift
- No to little understanding of the behaviour of DNNs under domain shift

Our Approach

Develop a method to quantify the domain shift within a DNN

Applications of a Domain Shift Metric

Multi-Purpose Domain Shift Metric

- Out-of-Domain Detec.
- AI Safety
- Performance Metric
- Behaviour Analysis
- Active Learning
- Domain Adaptation

Research Objectives

- Different metrics
- Layers
- Architecture
- UDA Approaches
- Classes
- Correlation w.r.t mIoU

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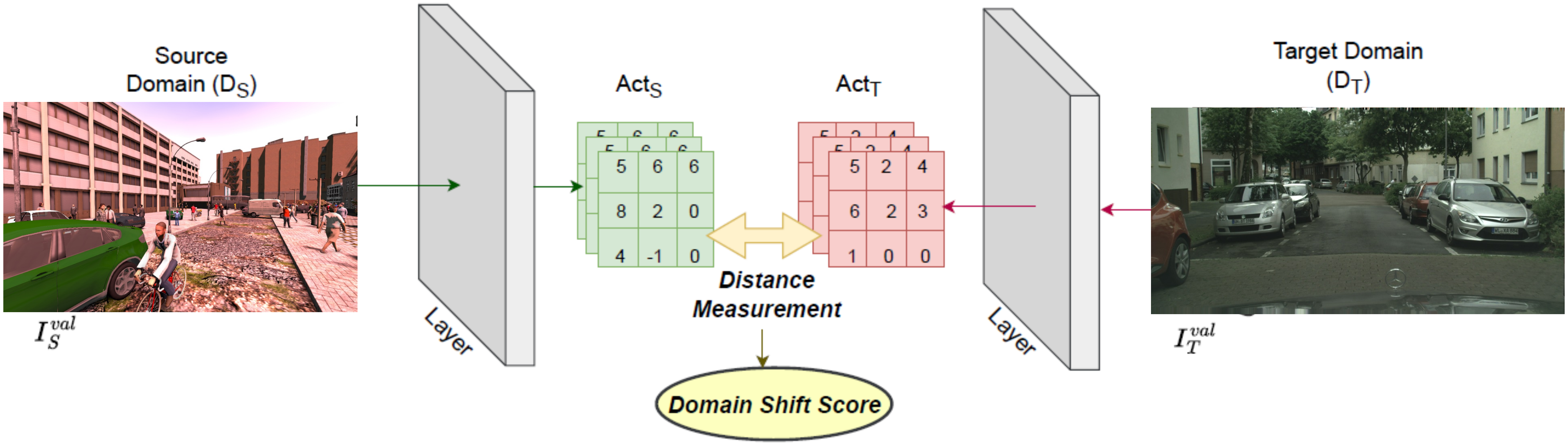
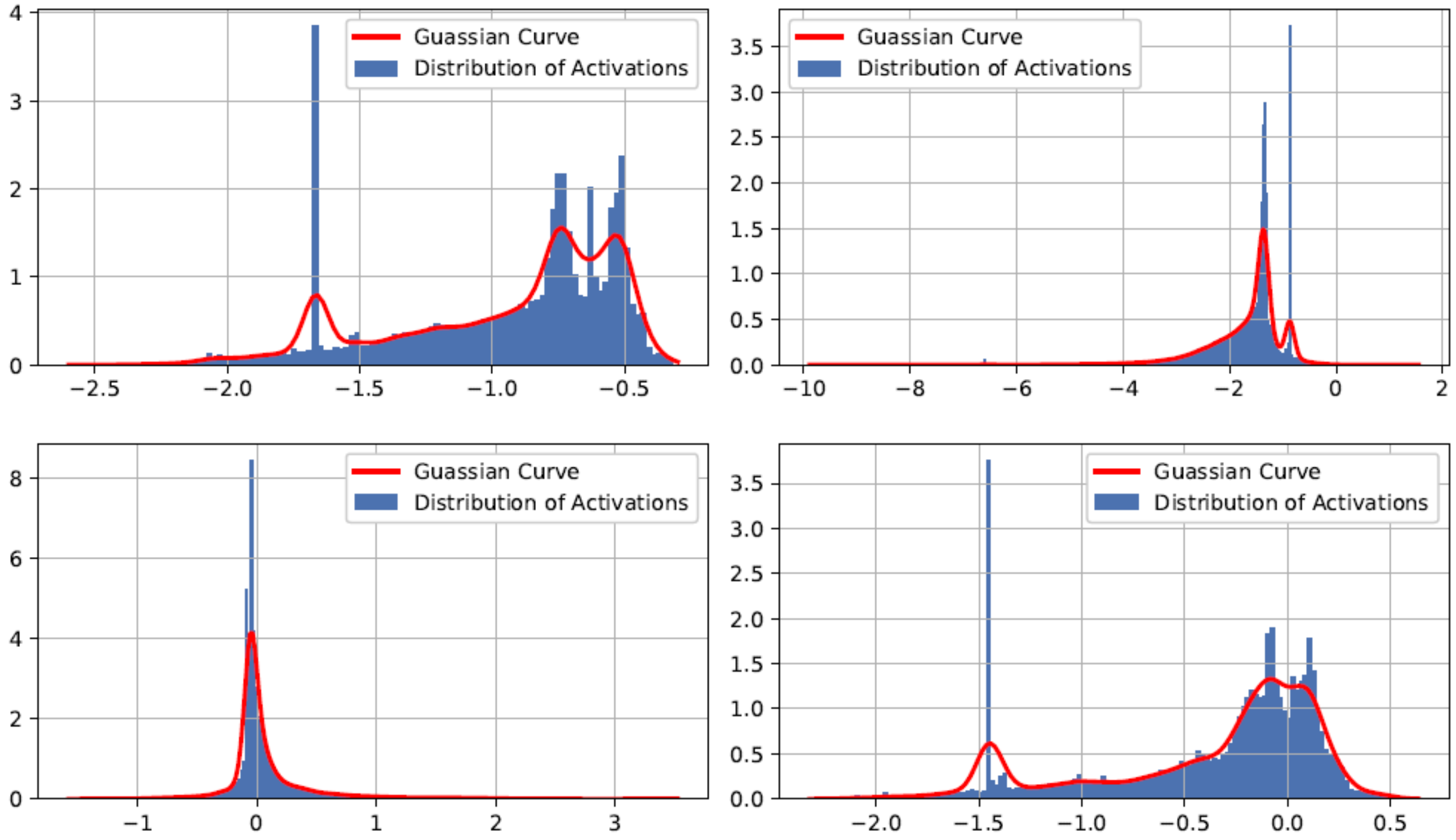
Concept

Domain Shift Quantification in Feature Space



Preliminiary Insights: Activation Distribution Analysis



Activation Distribution of four different filters in Conv-Layer 2

- Multimodal Gaussian distribution in the earlier layers, unimodal in the deeper layers
- Averaging over filters does not represent the distribution accurately

Metrics for Domain Shift Quantification

Core Question

Which metric is most suitable and how to assess it?

Mean Squared Error (MSE)

$$D_{\mathrm{MSE}}(\phi_L^a, \phi_L^b) = ||\phi_L^a - \phi_L^b||^2$$

Multivariate Frechet Distance

$$\|\mu_X - \mu_Y\|^2 + Tr(cov_X + cov_Y - 2\sqrt{cov_X cov_Y})$$

Wasserstein Distance

$$W_p(a,b) = (inf_{\gamma\in\pi(a,b)} \int_{\omega*\omega} c(m1,m2)^p d\gamma(m1,m2))^{\frac{1}{p}}$$

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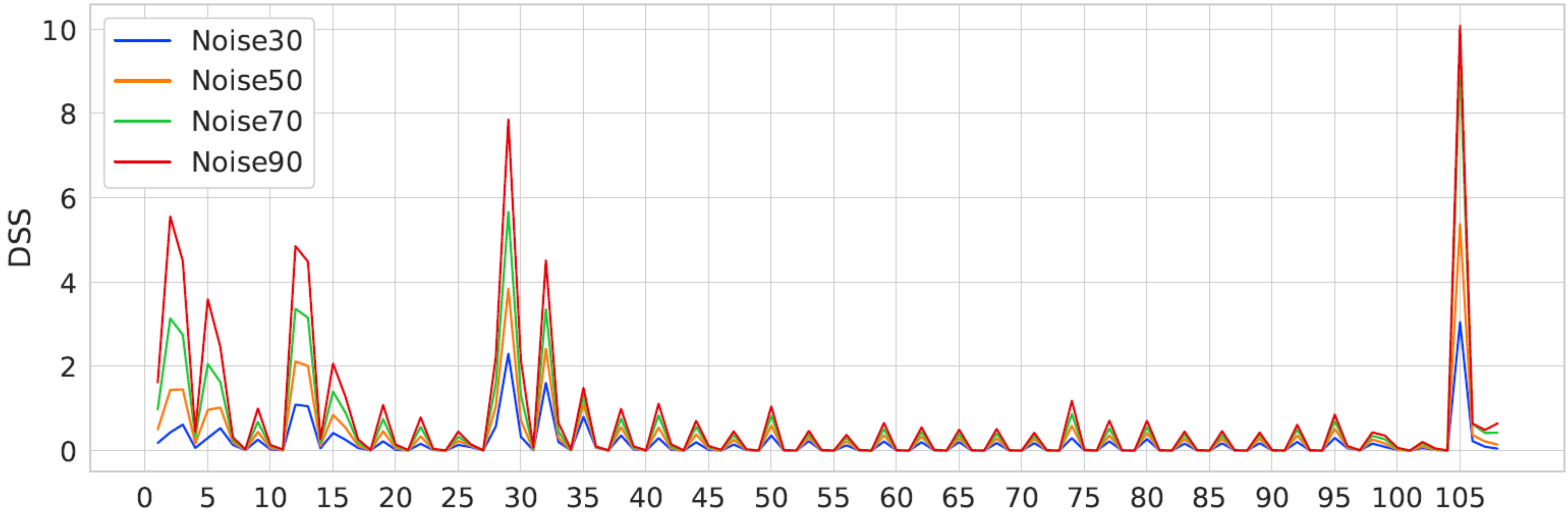
Results

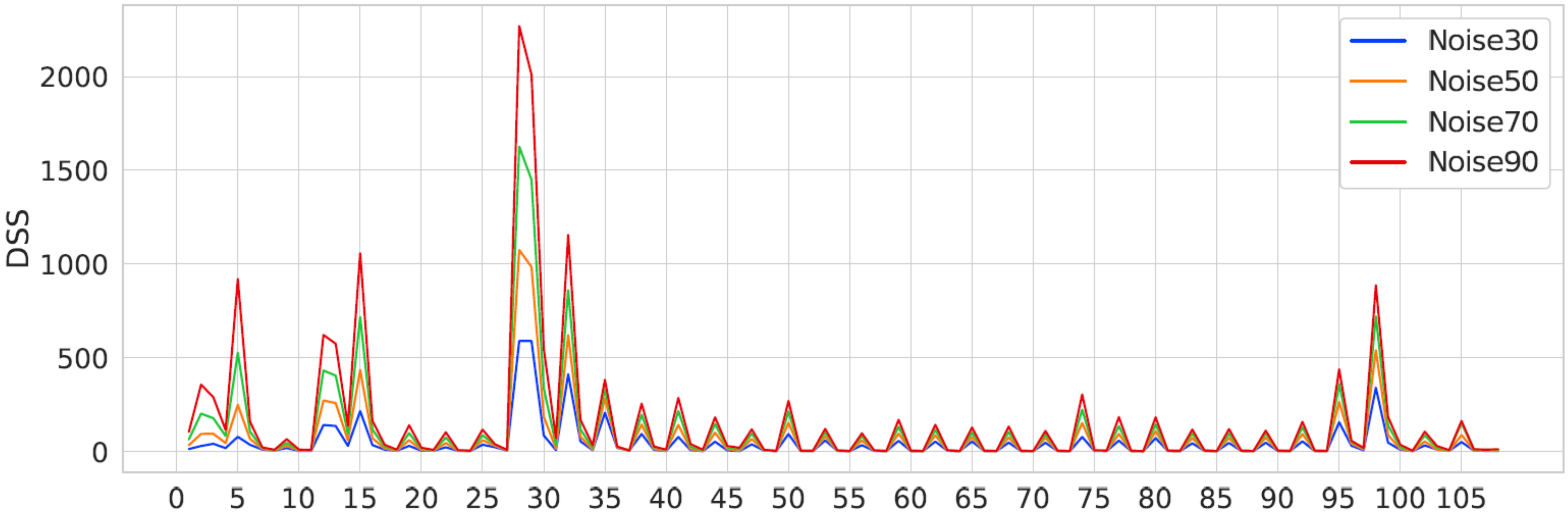
Artificial Domain Shift under Noise (MSE)



Shift: Synthia → Synthia-Noise
Network: ResNet-101-DeeplabV2

(a) $M_{AVG-MSE}$

Artificial Domain Shift under Noise (Frechet Distance)



(b) M_{FD}

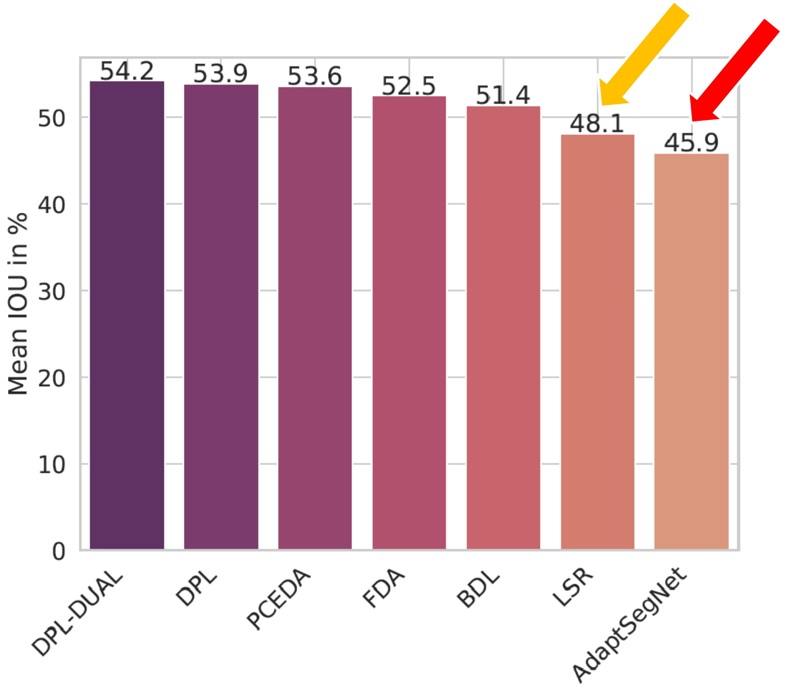
Artificial Domain Shift under Noise - Metric Comparison

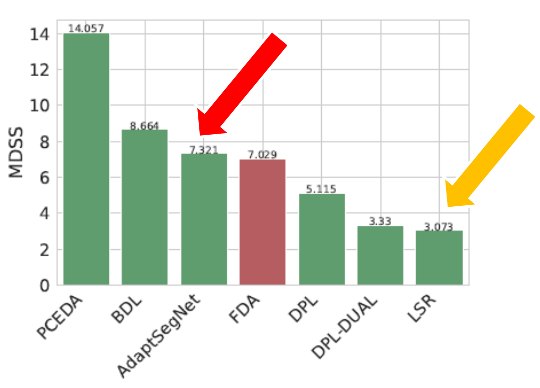
- All metrics show similar and expected behaviour for noise and color jitter
- Only SVD-processing of channels negatively affects the measurement
- Also layer-wise behaviour across the metrics is similar
- SVD dropped for future research

Measures	Noise30	Noise50	Noise70	Noise90
$M_{AVG-MSE}$	20.51	37.34	59.39	81.49
$M_{AVG-Wass}$	8.77	14.50	21.02	27.02
M_{FD}	4671.30	8199.21	12326.91	17015.25
M_{IMSE}	89.89	119.48	148.86	176.20
$M_{SVD-MSE}$	1.17E-07	1.26E-07	1.43E-07	1.53E-07
$M_{SVD-Wass}$	1.02E-04	1.24E-04	1.25E-04	1.26E-04

Measures	ColorJitter30	ColorJitter50
$M_{AVG-MSE}$	0.01	0.03
$M_{AVG-Wass}$	0.03	0.04
M_{FD}	0.16	0.23
M_{IMSE}	2.75	3.74

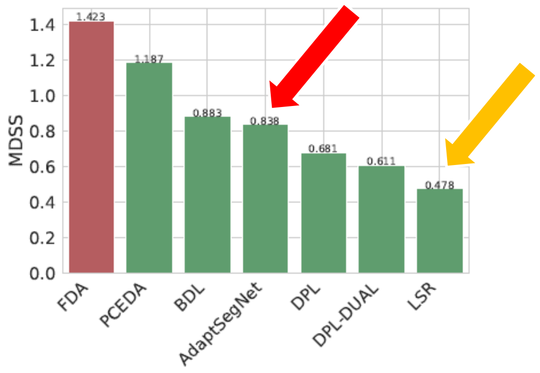
Evaluation of Domain Adaptation Approaches



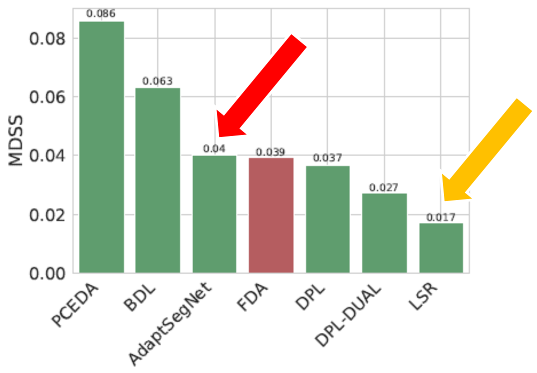


(a) M_{FD}

(b) $M_{AVG-Wass}$



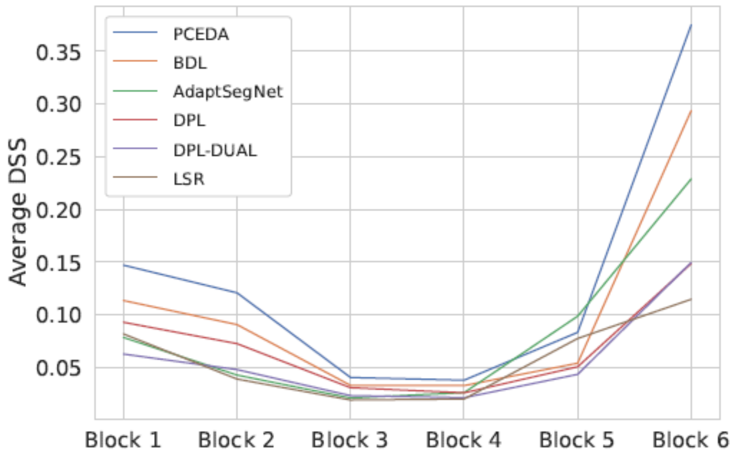
(c) M_{IMSE}



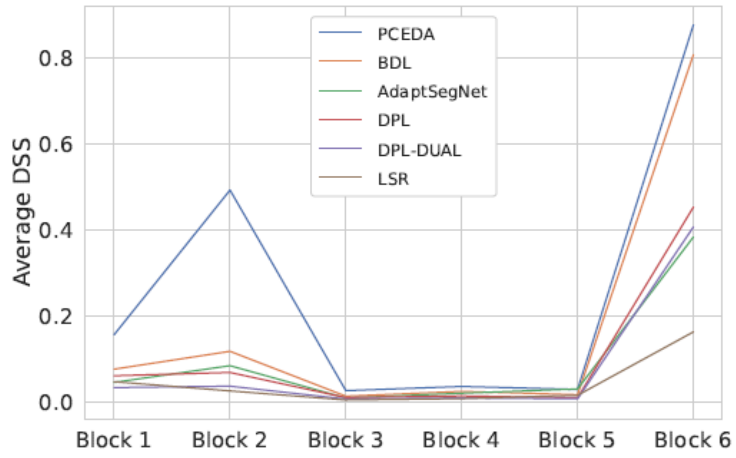
(d) $M_{AVG-MSE}$

→ No correlation between mIoU and domain shift score

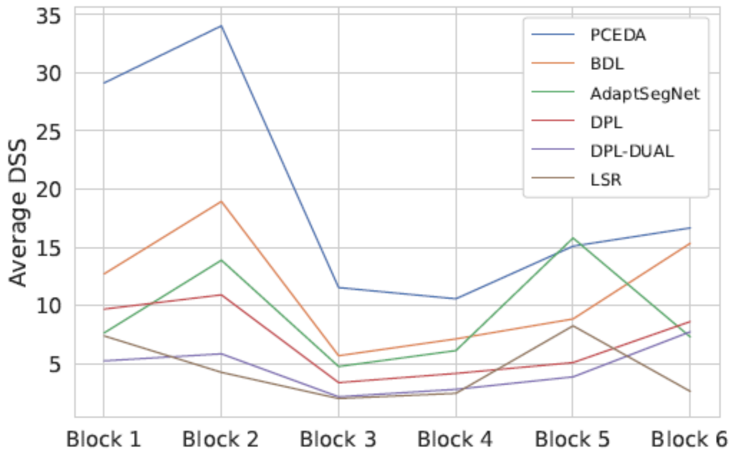
Block-wise Analysis



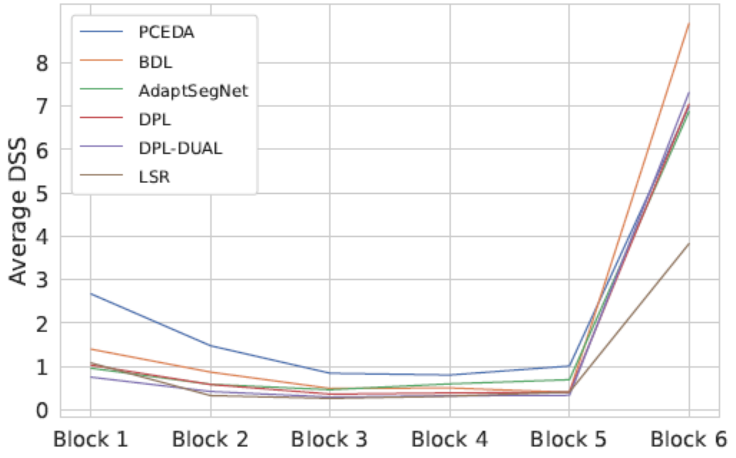
Frechet



Wasserstein



Element-wise MSE



Average MSE

Conclusions

1 Domain shift within DNNs is layer-dependent

2 Dimensionality reduction on activations did not work as expected

3 Different metrics showed both consistent but also different results under domain shift

4 No direct correlation of domain shift score and mIoU→ source domain handling might be reason

5 Adressed a new important research area with the potential to have a fundamental impact on the generalization of DNNs

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KI Delta Learning ist ein Projekt der KI Familie. Es wurde aus der VDA Leitinitiative autonomes und vernetztes Fahren initiiert und entwickelt und wird vom Bundesministerium für Wirtschaft und Klimaschutz gefördert.

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