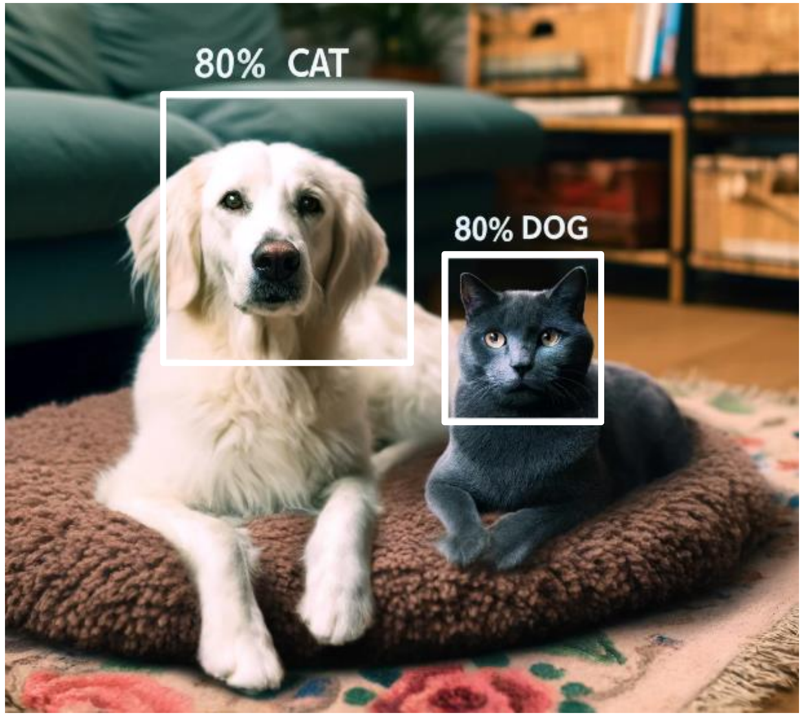
Cost-Sensitive Uncertainty-Based Failure Recognition for Object Detection

Moussa Kassem Sbeyti, Michelle Karg, Christian Wirth, Nadja Klein, and Sahin Albayrak

Motivation



Over/underconfidence

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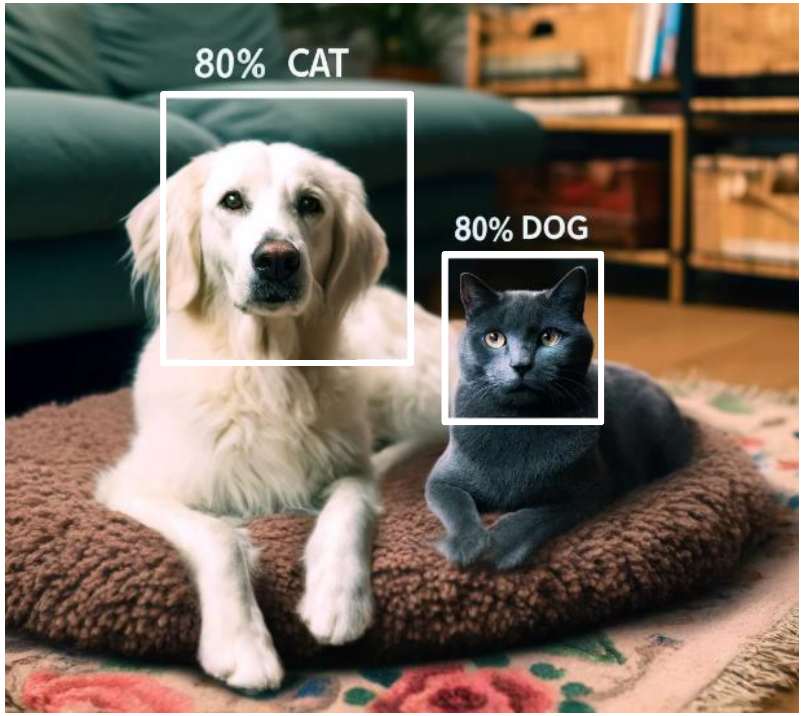

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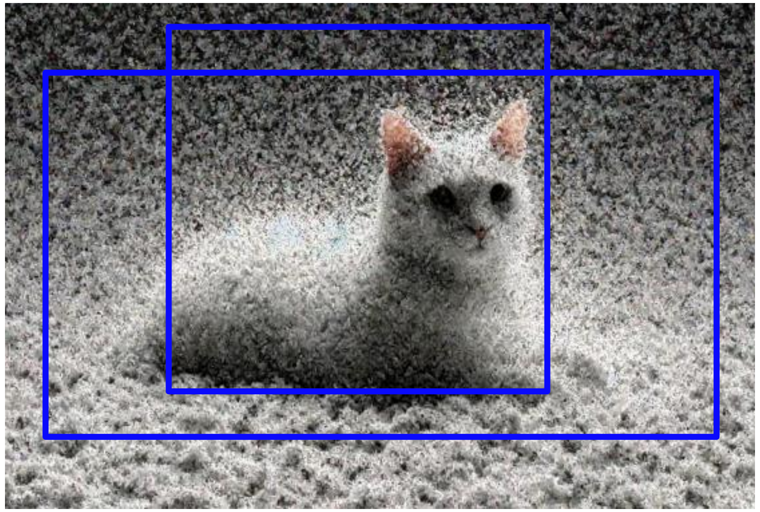

Noisy objects

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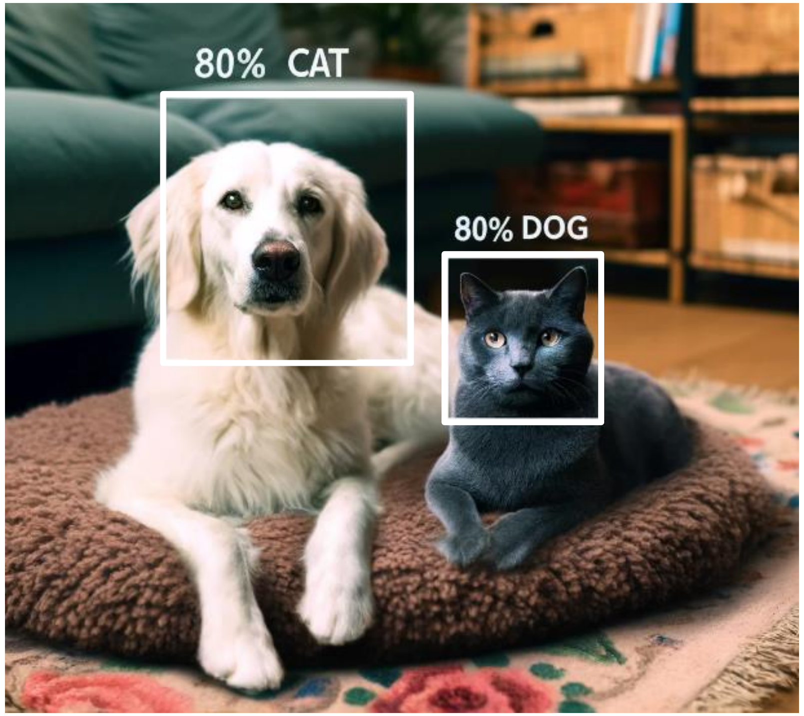

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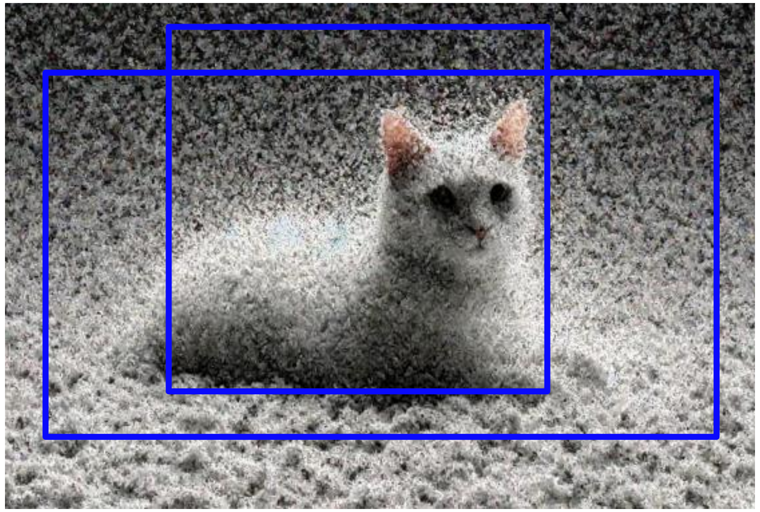

Noisy objects

Unknown objects

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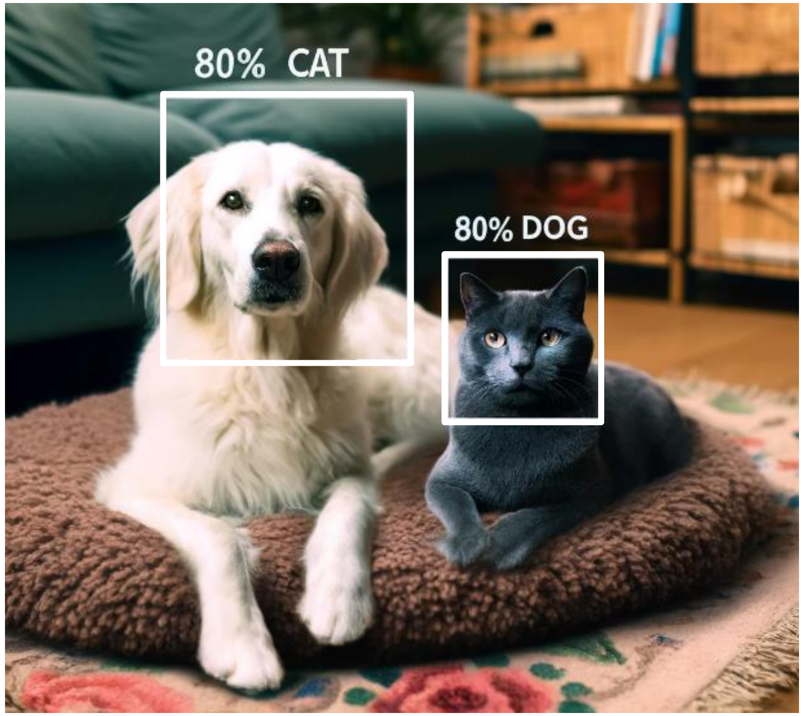

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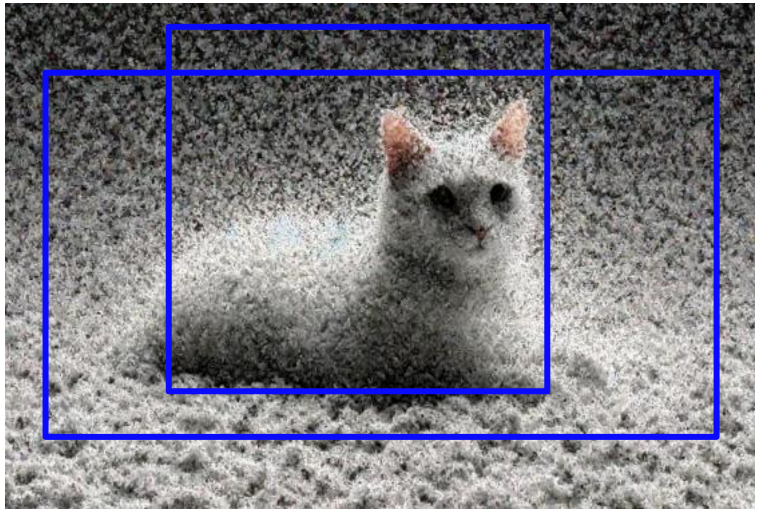


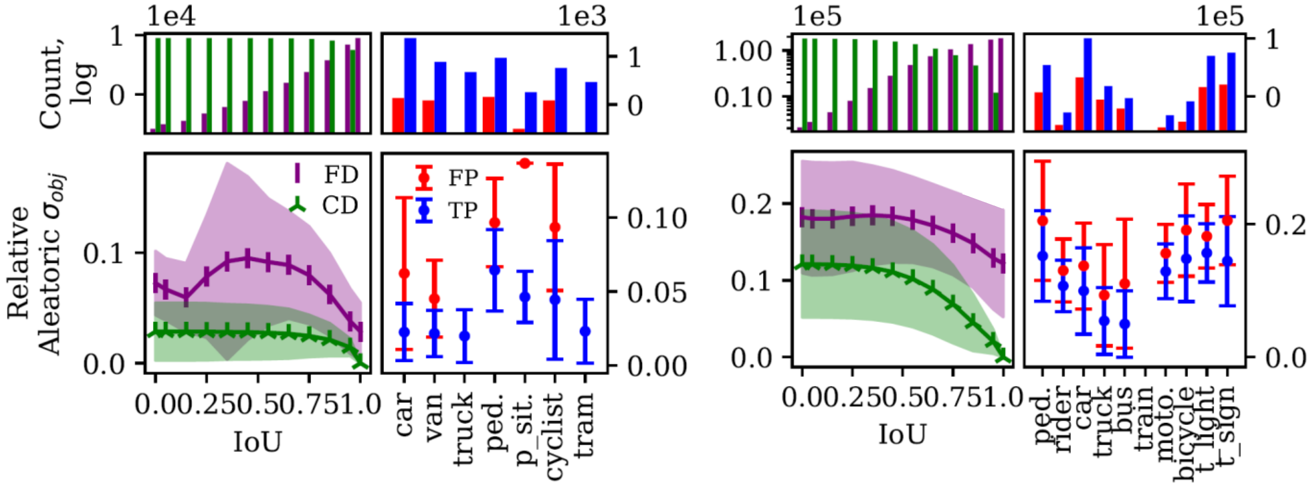
Noisy objects

Unknown objects

Reject option based on different uncertainties is required

I. Cost Sensitivity

Correlation Uncertainty vs Failures



CD: Correct Detection
FD: False Detection
MD: Missing Detection

[1]

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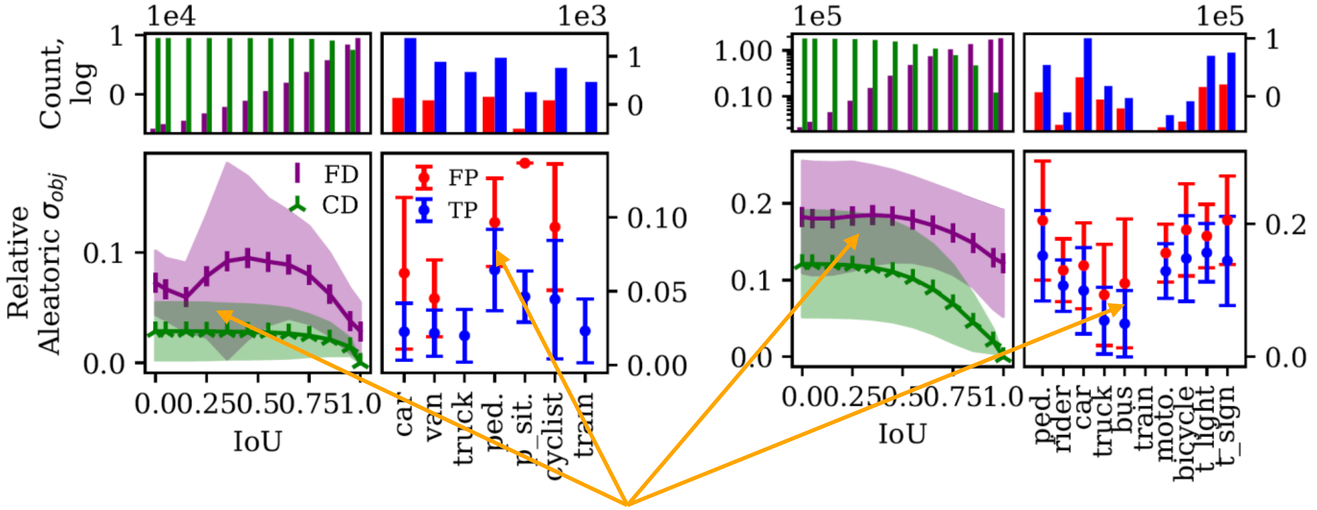

Challenge I: Overlap ⇔ Cost

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[1]

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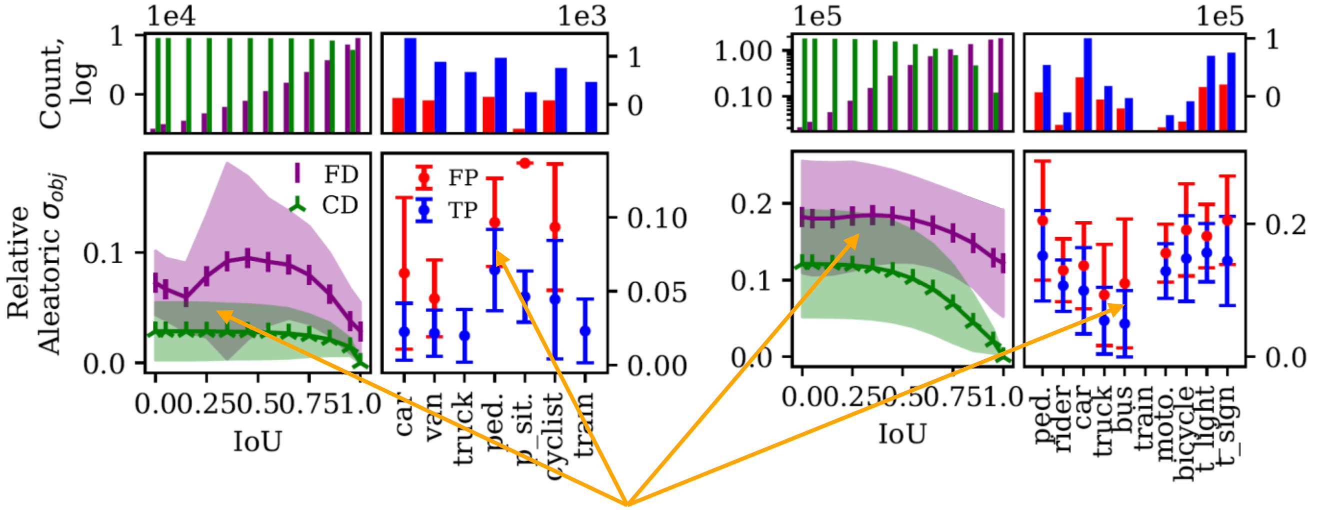

Challenge I: Overlap ⇔ Cost

Cost-Sensitive Approach

Table 1: Cost-matrix for detection thresholding.

	CD	FD
$\mathrm{CD_T}$	$C_{\mathrm{CD}} \cdot \lvert\mathrm{CD}\rvert$	$C_{\mathrm{FD}} \cdot \lvert\mathrm{FD}\rvert$
$\mathrm{FD_T}$	$C_{\mathrm{MD}} \cdot \lvert\mathrm{MD}\rvert$	$C_{\mathrm{BG}} \cdot \lvert\mathrm{BG}\rvert$

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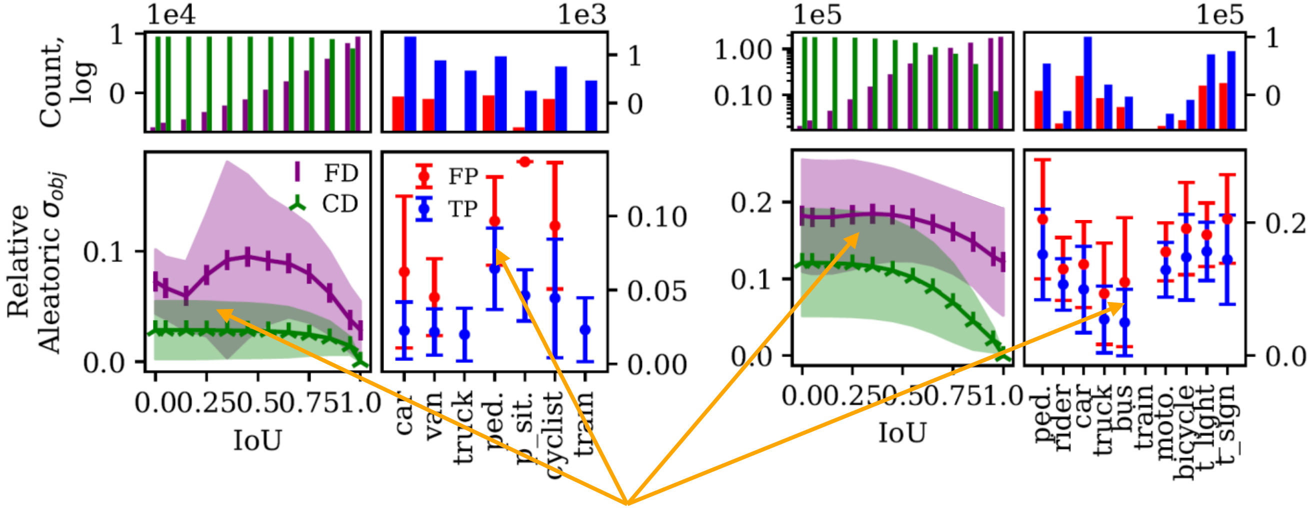

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$$C_{\text{total}} = C_{\mathrm{MD}} \cdot |\mathrm{MD}| + C_{\mathrm{FD}} \cdot |\mathrm{FD}|$$

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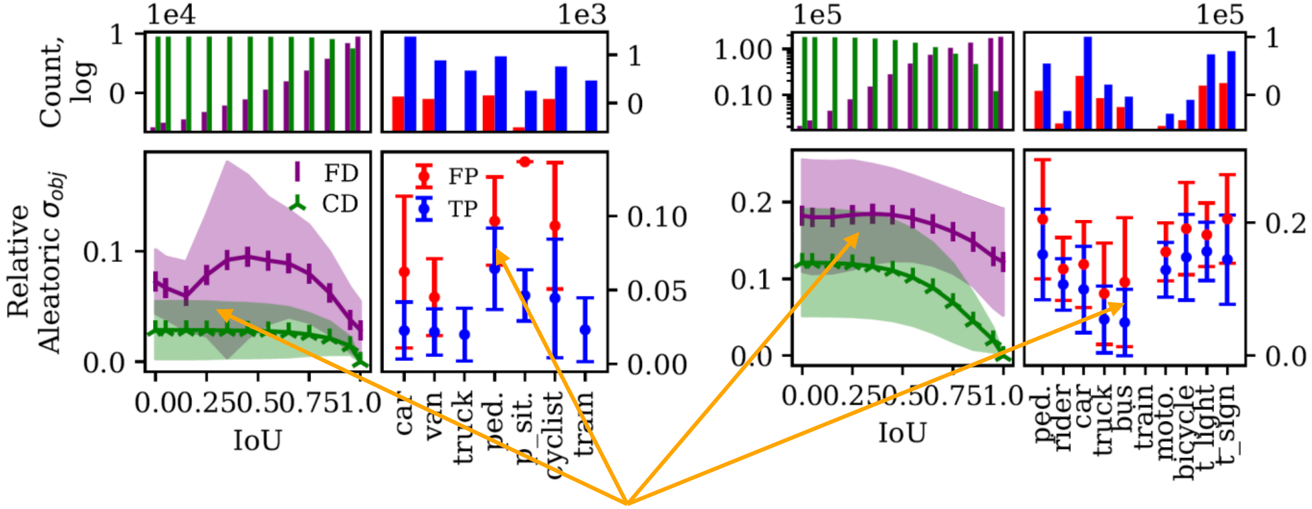

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Thresholding

Budget $b \in [0, 1]$

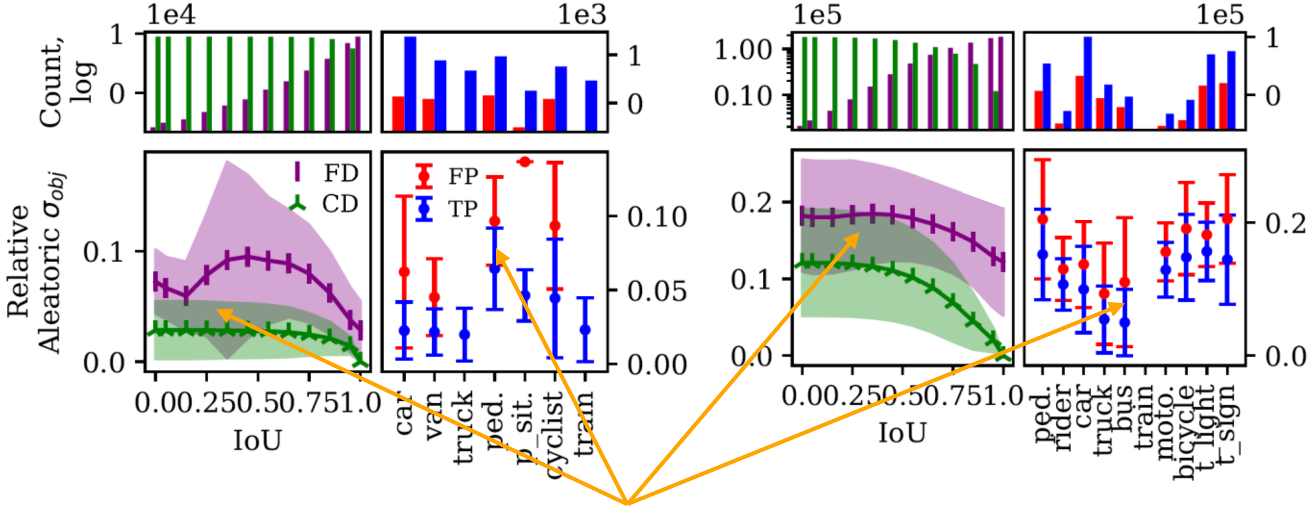
$|\mathrm{CD}|$ Before

$|\mathrm{FD}|$ Before

[1]

I. Cost Sensitivity

Correlation Uncertainty vs Failures



Challenge I: Overlap ⇔ Cost

CD: Correct Detection
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Introduce cost-sensitivity into the detector

Cost-Sensitive Approach

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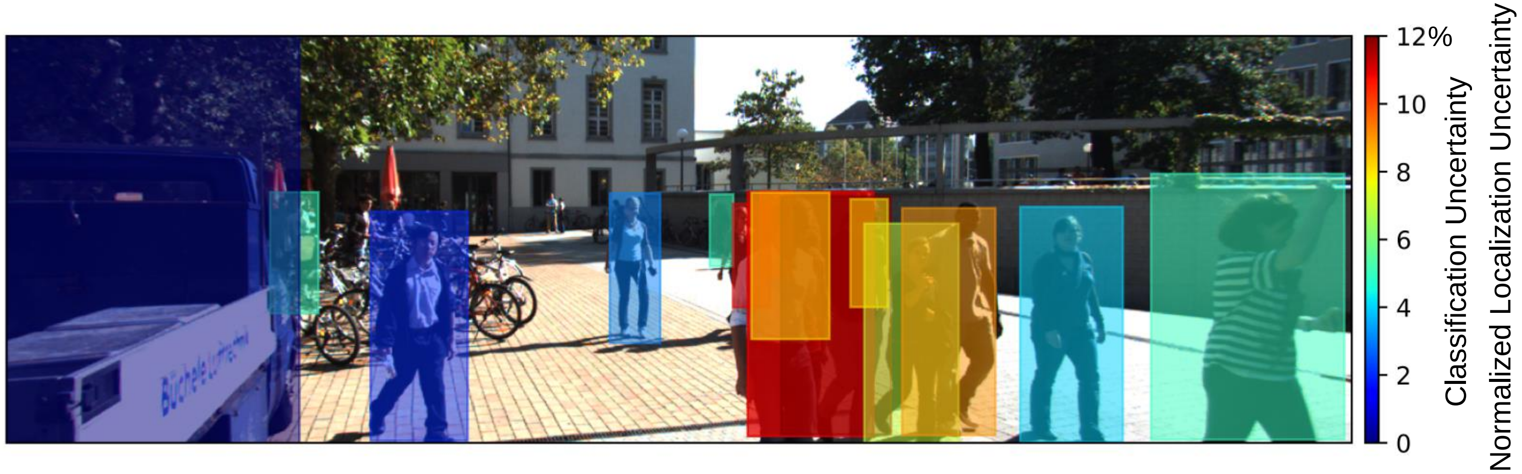
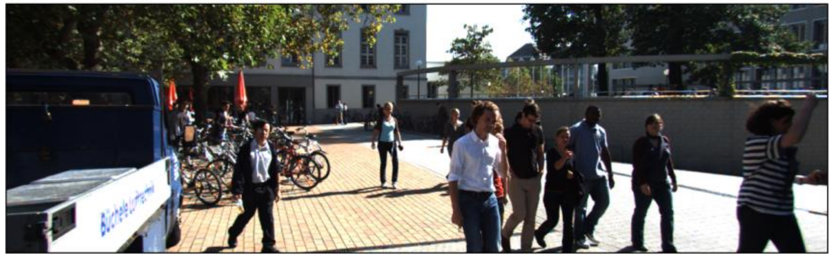
$$C_{\mathrm{total}} = C_{\mathrm{MD}} \cdot |\mathrm{MD}| + C_{\mathrm{FD}} \cdot |\mathrm{FD}|$$

Thresholding	Budget $b \in [0,1]$		
$\lvert\mathrm{CD}\rvert$ Before	$b \cdot \lvert\mathrm{CD}\rvert$ After	$\lvert\mathrm{FD}\rvert$ Before	$b \cdot \lvert\mathrm{FD}\rvert$ After

[1]

II. Uncertainty-Based Thresholding





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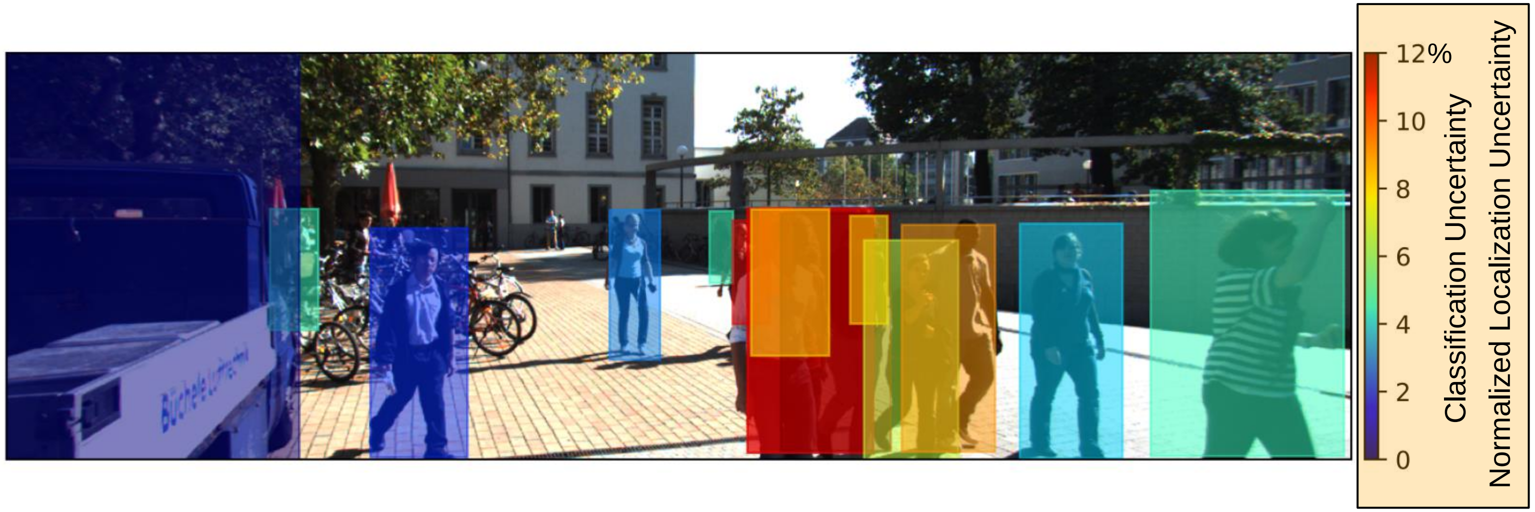
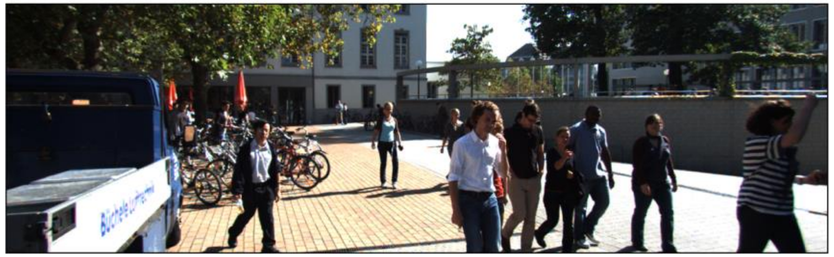
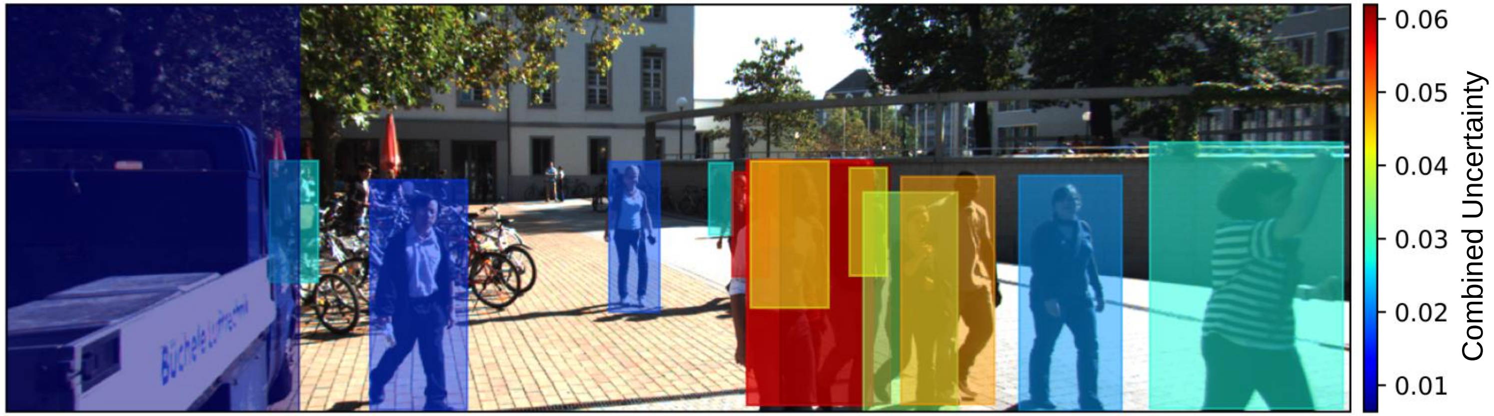




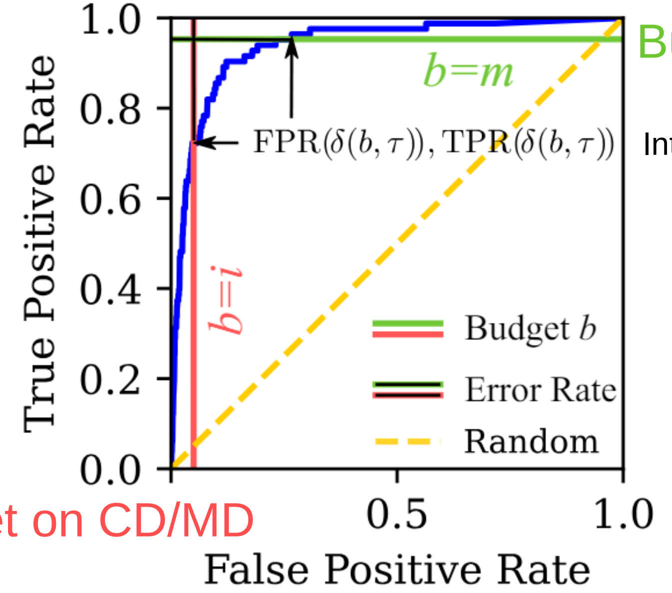


Challenge II:

Selecting a threshold on uncertainty $\in [0, \infty)$

II. Uncertainty-Based Thresholding

Automation via ROC Curve



Budget on FD

Intersection over Union (IoU) Threshold τ

Budget on CD/MD

[2]

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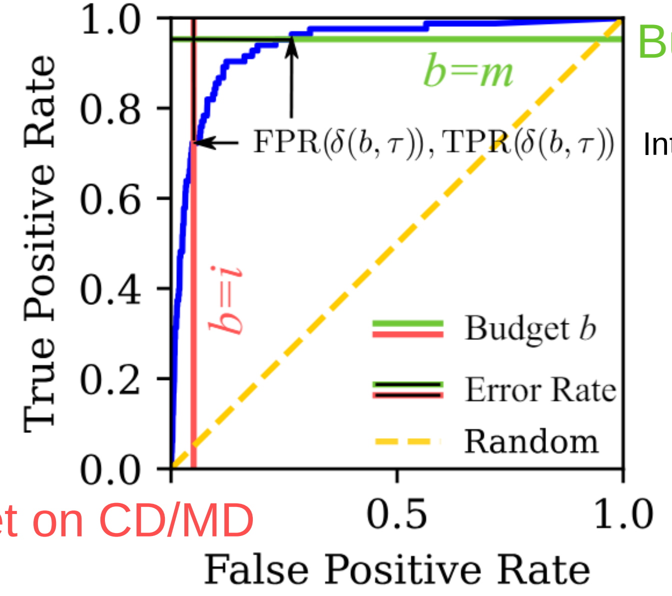

Budget on FD

Intersection over Union (IoU) Threshold τ

Budget on CD/MD

Thresholding Performance

$$\mathrm{CD@FD}(b) = \sum_{\tau=0.5}^{0.75} \mathrm{TNR}(\mathrm{TPR}(\delta(b,\tau)))$$

$$\mathrm{FD@CD}(b) = \sum_{\tau=0.5}^{0.75} \mathrm{TPR}(\mathrm{FPR}(\delta(b,\tau)))$$

[2]

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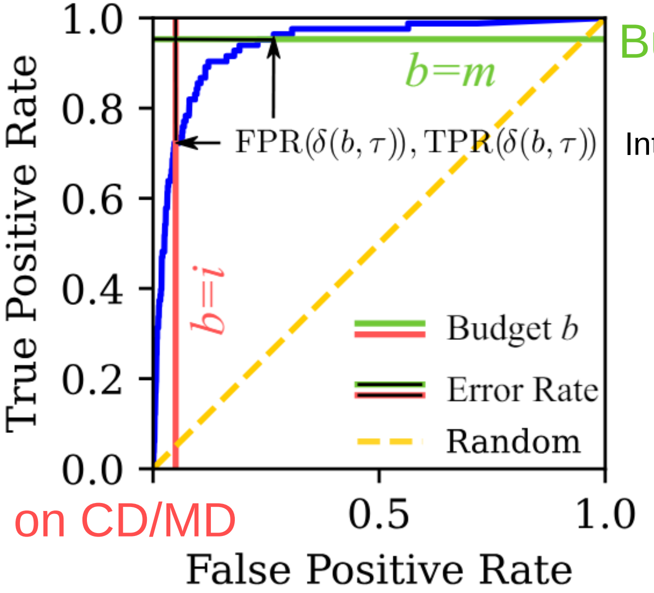

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Detector Performance

$$\frac{|\mathrm{CD}|}{|\mathrm{CD}| + |\mathrm{FD}|} \leq \frac{i|\mathrm{CD}|}{i|\mathrm{CD}| + (1-m)|\mathrm{FD}|}$$

Recall, Precision, Accuracy, F1-Score

[2]

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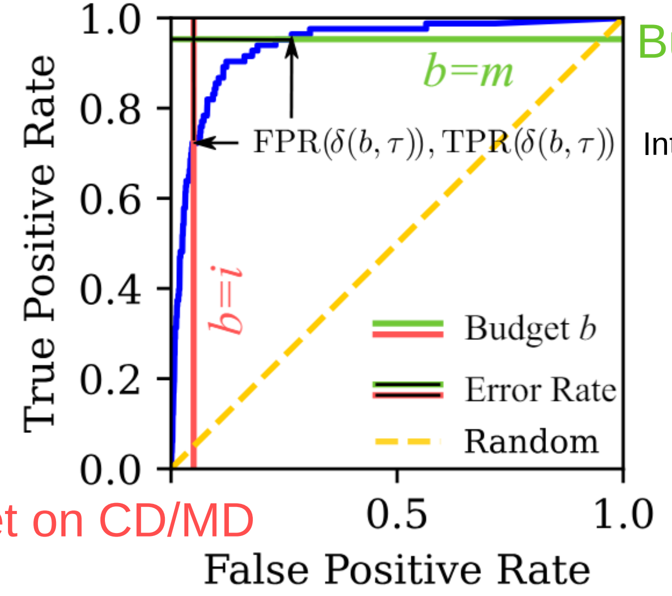
Automation via ROC Curve



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Recall, Precision, Accuracy, F1-Score

Requirements

$$\text{minimize}\,\{(1-i), 0\}$$

$$1 - i \leq m$$

$$(1-i)(|\mathrm{FD}| + |\mathrm{CD}| + |\mathrm{MD}|) \leq m|\mathrm{FD}|$$

Automate thresholding and its evaluation

[2]

III. Optimal Uncertainty Combination

Weights

$$\mathbf{w}^\top \times (\sigma_{\text{cls}}, \sigma_{\text{loc}})^\top, \mathbf{w} = (w_1, w_2)^\top \in [0, 1]^2$$

Challenge III: Optimal Combination

III. Optimal Uncertainty Combination

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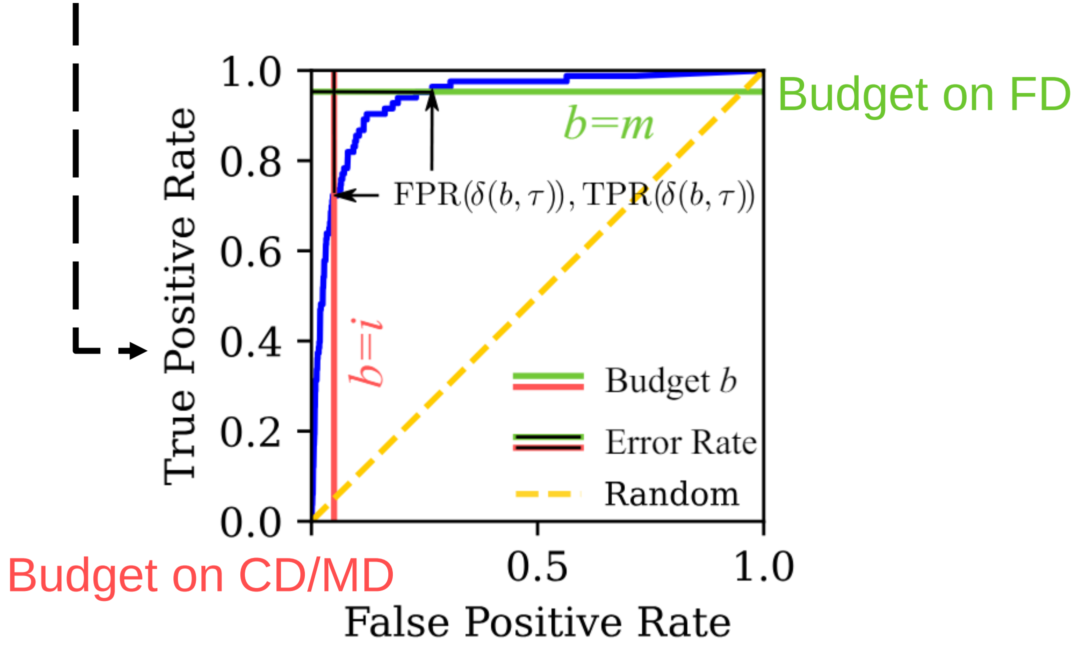

Challenge III: *Optimal Combination*

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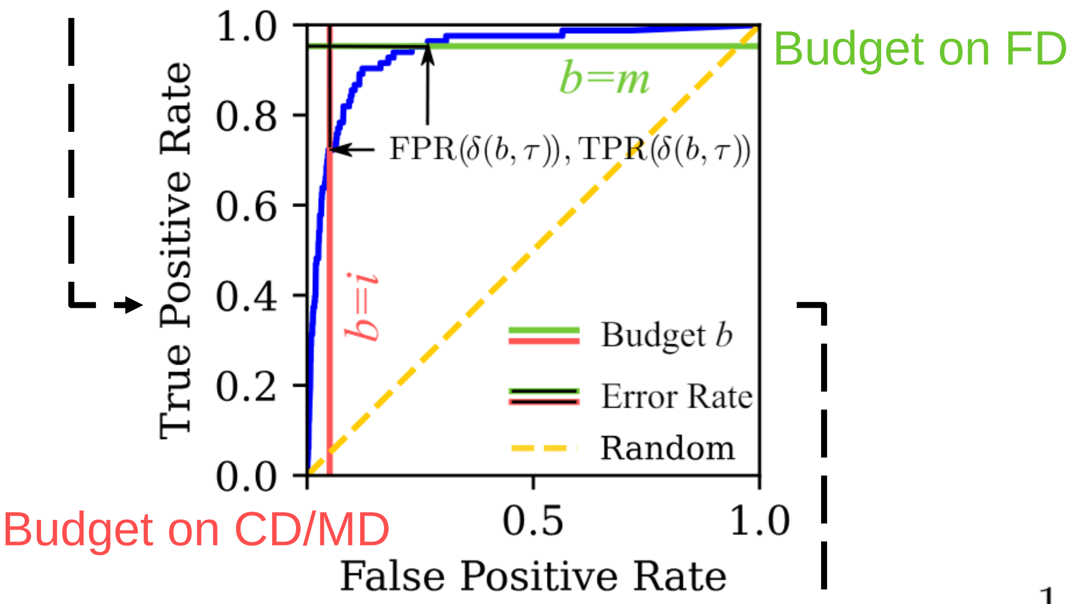

$$\mathcal{L}_{opt} = \frac{1}{6}\sum_{\tau\in\mathcal{T}} \begin{cases} \mathcal{L}_{step} = FNR(\delta_{opt}(b,\tau)) & if\, b = i \\ \mathcal{L}_{step} = FPR(\delta_{opt}(b,\tau)) & if\, b = m \end{cases}$$

$$\mathcal{T} = \{0.5, 0.55, 0.6, 0.65, 0.7, 0.75\}$$

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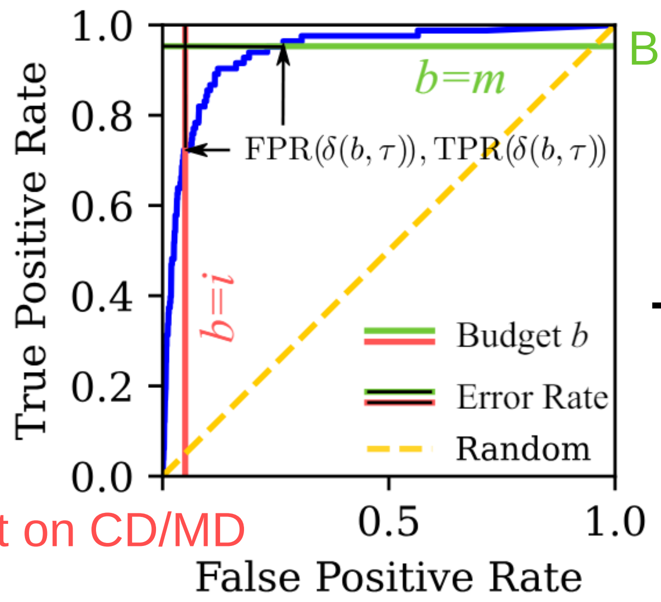

Budget on FD

Budget on CD/MD

Challenge III: *Optimal Combination*

Black-Box Optimization

For a given **budget**:

Optimize the threshold and weights for the combined sum of the uncertainties

over multiple IoU Thresholds

$$\mathcal{L}_{opt} = \frac{1}{6} \sum_{\tau \in \mathcal{T}} \begin{cases} \mathcal{L}_{step} = FNR(\delta_{opt}(b,\tau)) & if\, b = i \\ \mathcal{L}_{step} = FPR(\delta_{opt}(b,\tau)) & if\, b = m \end{cases}$$

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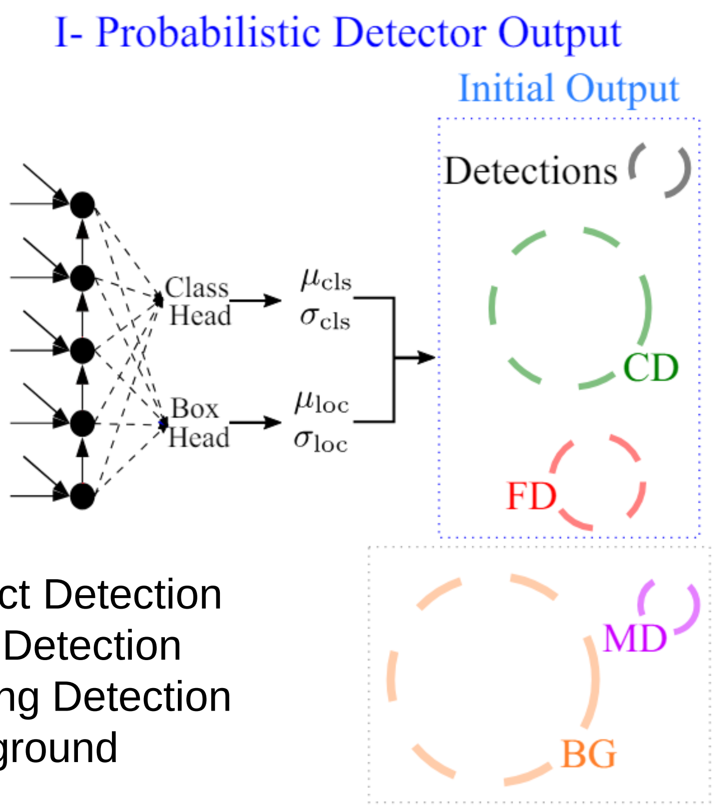
Cost-Sensitive Uncertainty-Based Failure Recognition for Object Detection



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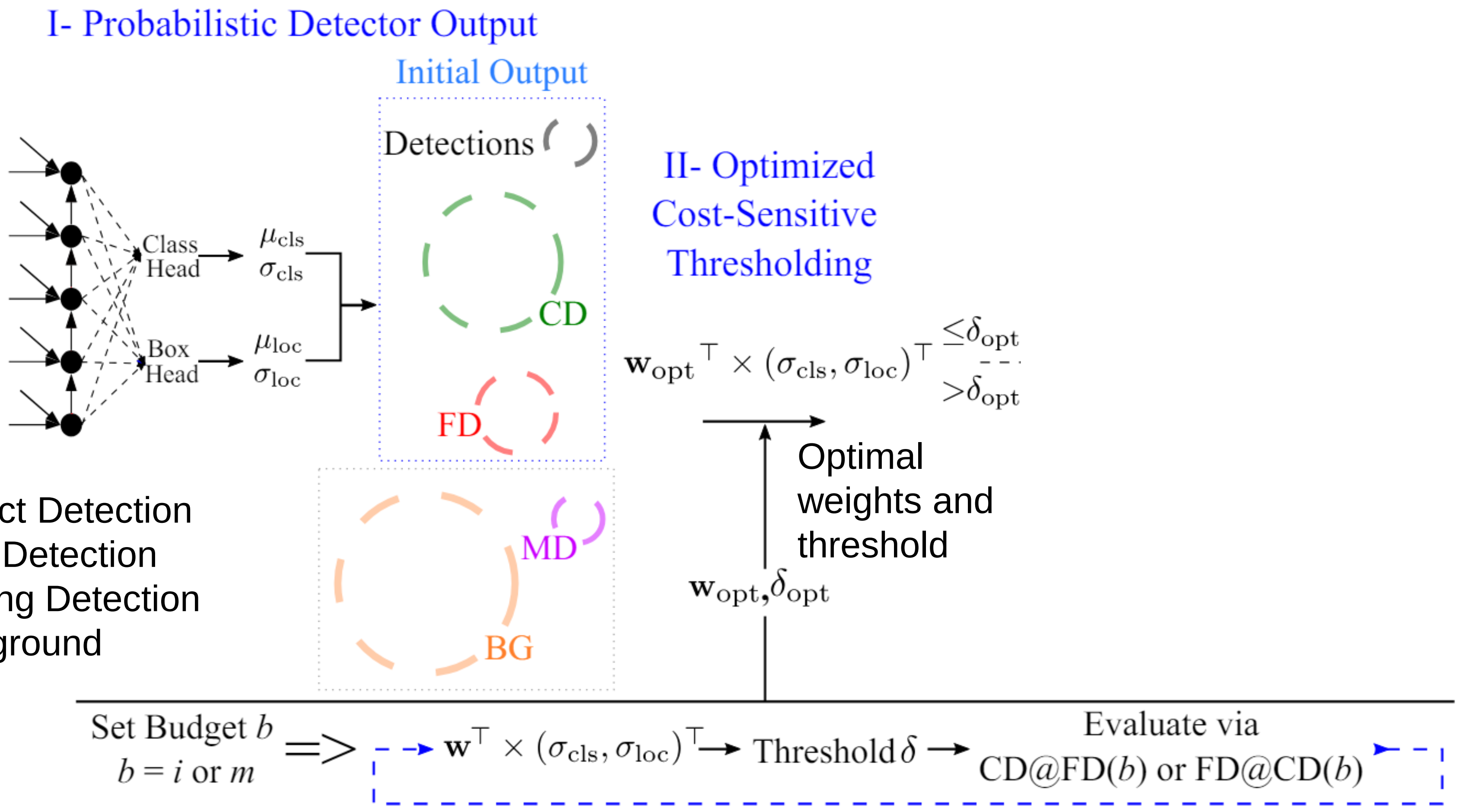

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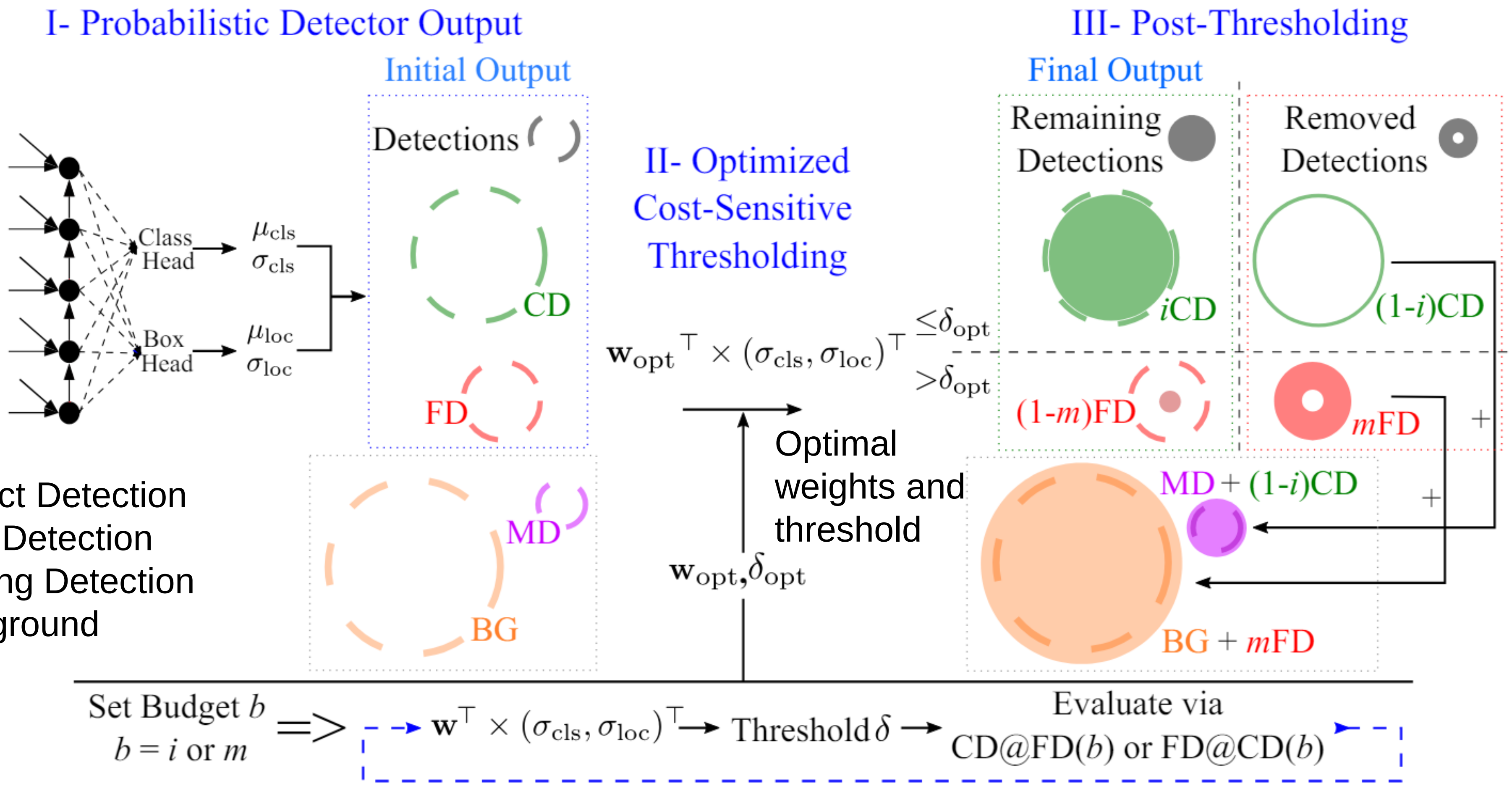

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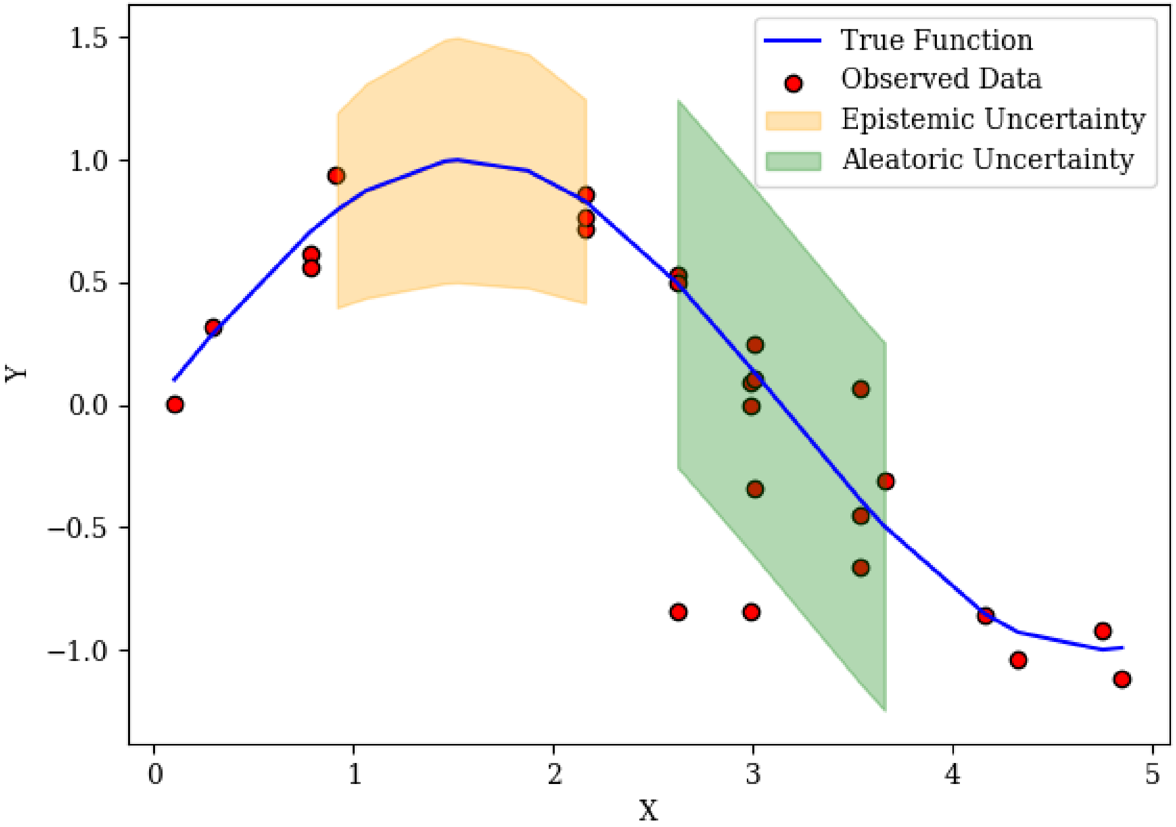
Uncertainty Estimation

Classification and Regression – Epistemic and Aleatoric

Epistemic
Model Uncertainty



Aleatoric
Data Uncertainty

[3]

Uncertainty Estimation

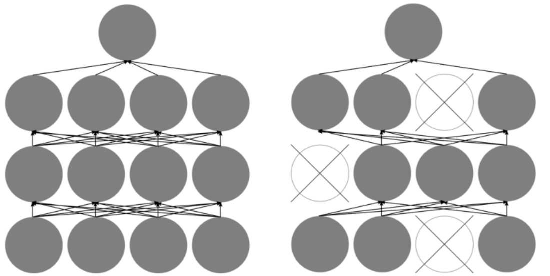
Classification and Regression – Epistemic and Aleatoric

Epistemic

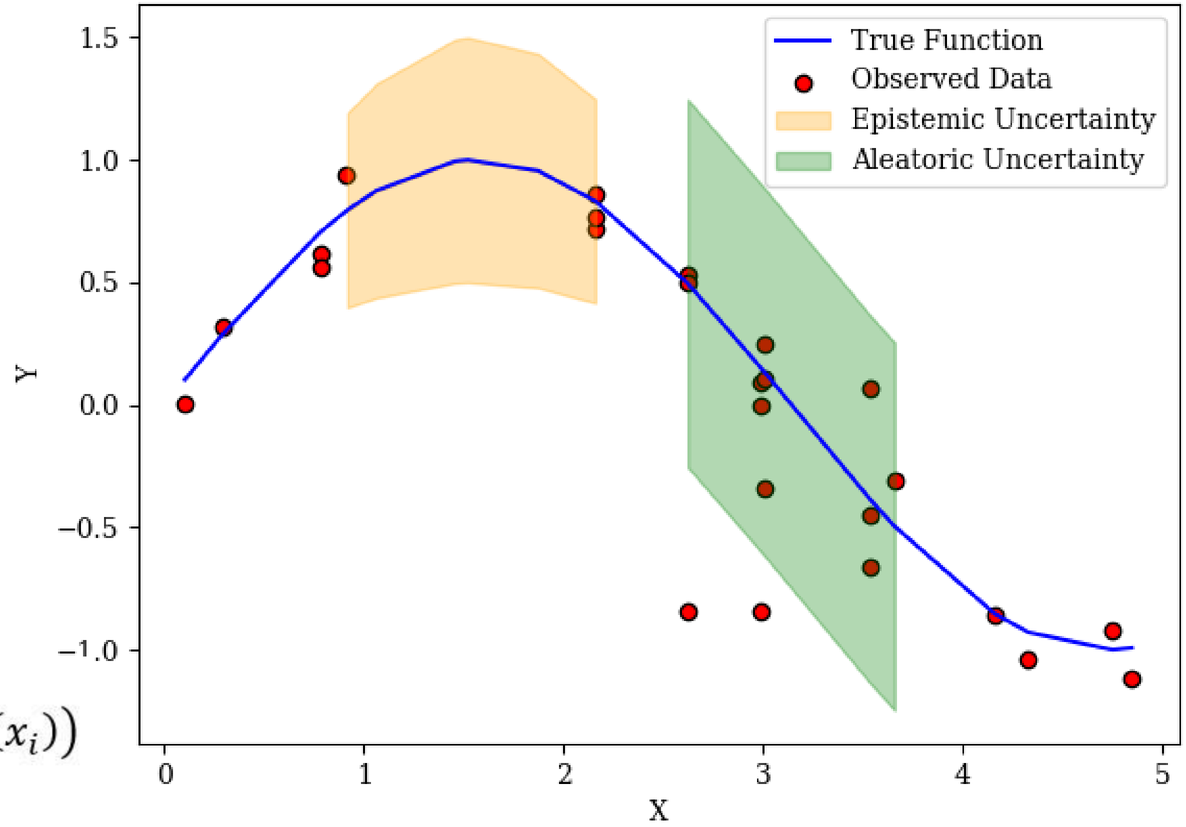
Model Uncertainty

- MC Dropout
- Entropy

Standard With Dropout



$$H(X) = -\sum_{x_i \in X} P(x_i) * Log_2(P(x_i))$$



Aleatoric

Data Uncertainty

[3,4]

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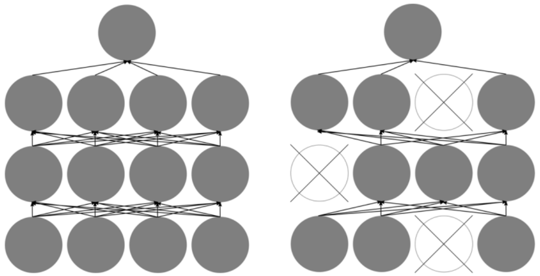

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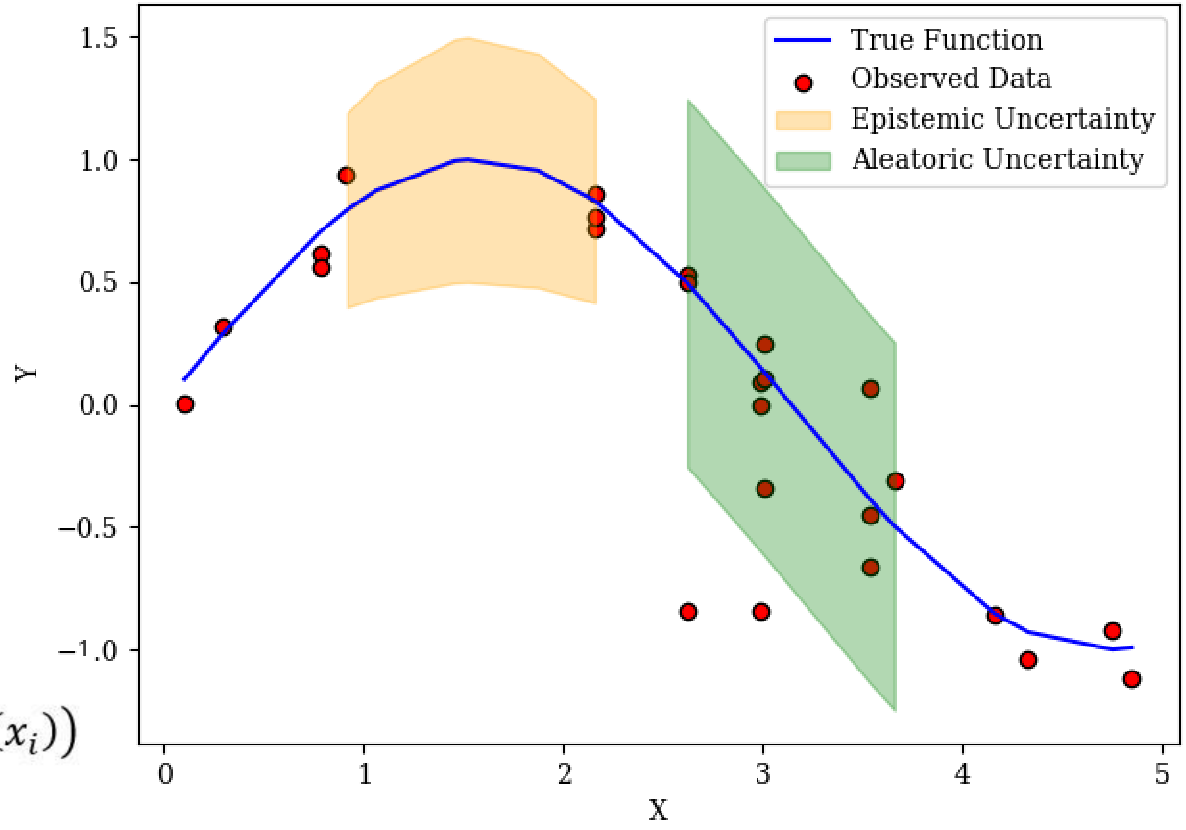
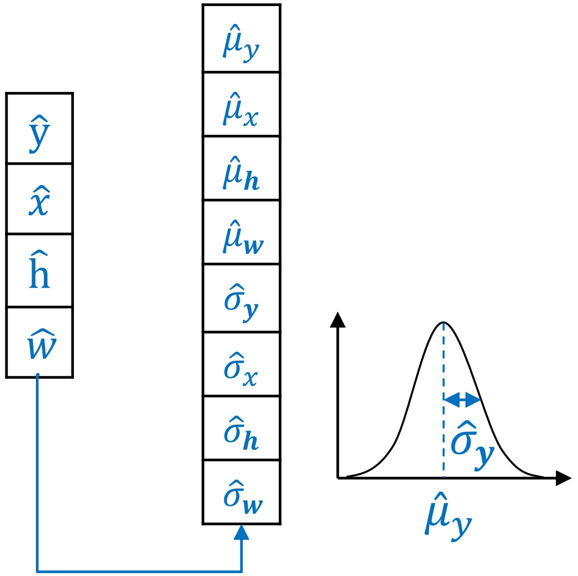


Aleatoric

Data Uncertainty

Loss Attenuation



[3,4]

Datasets

BDD100K, KITTI and CODA

BDD100K:

- Relatively large
- Many difficult scenarios:
  - Night/crowded images
  - Tiny objects

[5,6,7]

Datasets

BDD100K, KITTI and CODA

BDD100K:
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- Many difficult scenarios:
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KITTI:
- Relatively small
- High fidelity dataset with daylight only

[5,6,7]

Datasets

BDD100K, KITTI and CODA

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- Many difficult scenarios:
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KITTI:

- Relatively small
- High fidelity dataset with daylight only

CODA:
Real-World Road Corner Case Dataset for Object Detection in Autonomous Driving

Evaluation Set
Model pre-trained on BDD100K

[5,6,7]

Results

Uncertainty Estimation Methods

EfficientDet-D0 pre-trained on **COCO**
Input resolution: **1024x512**
Batch size: **8**

Inference time:
Baseline: ~35ms
LA: ~30ms
MC: ~185ms

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AP: Average precision
Acc: Classification accuracy
mIoU: Average intersection over union

	Method	AP↑	Acc↑	mIoU↑
KITTI	Baseline	72.83±0.12	**0.99±0.00**	90.06±0.05
	LA	**73.26±0.50**	**0.99±0.00**	**90.34±0.03**
	MC	70.88±0.17	**0.99±0.00**	89.10±0.02
	MC+LA	70.15±0.09	**0.99±0.00**	89.03±0.05
BDD	Baseline	24.69±0.09	**0.94±0.00**	**67.74±0.07**
	LA	24.38±0.12	**0.94±0.00**	67.69±0.05
	MC	**25.55±0.02**	**0.94±0.00**	67.30±0.02
	MC+LA	24.78±0.01	0.93±0.00	66.60±0.02
CODA	Baseline	16.09±0.07	**0.89±0.00**	72.23±0.03
	LA	15.53±0.25	**0.89±0.00**	72.06±0.14
	MC	**16.97±0.04**	**0.89±0.00**	**73.30±0.08**
	MC+LA	16.05±0.25	**0.89±0.00**	72.19±0.03

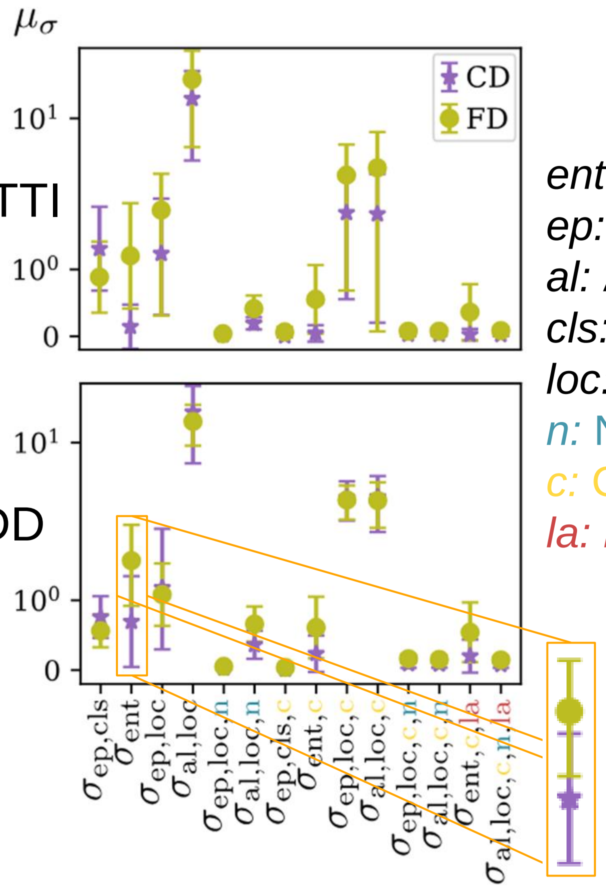
- *Correlation between estimation method and dataset characteristics*
- *Better performance than baseline*

Results

Comparison Uncertainty Types

KITTI

BDD

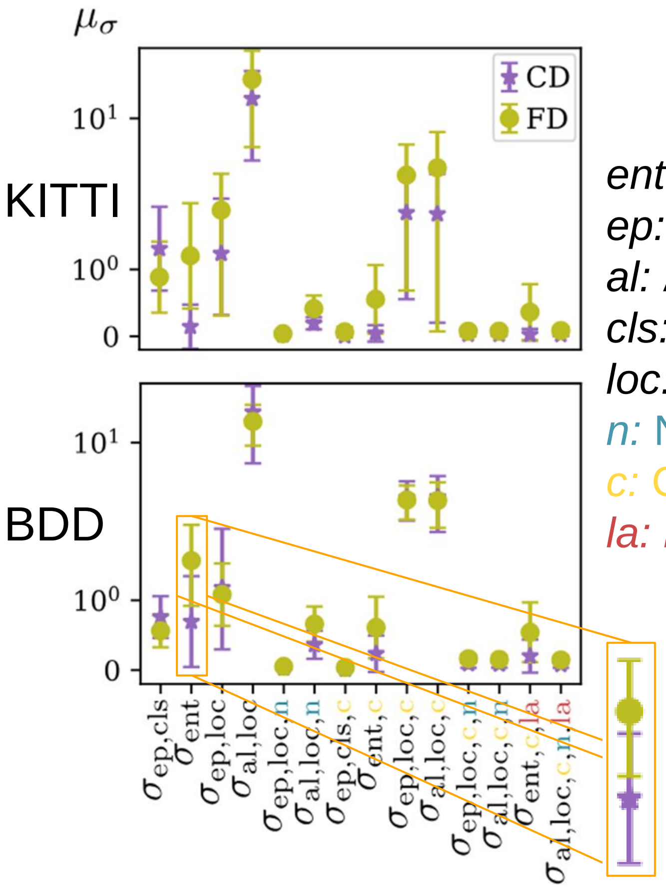


Overlap

ent: Entropy
ep: Epistemic
al: Aleatoric
cls: Classification
loc: Localization
n: Normalized
c: Calibrated
la: *L*oss attenuation only

Results

Comparison Uncertainty Types



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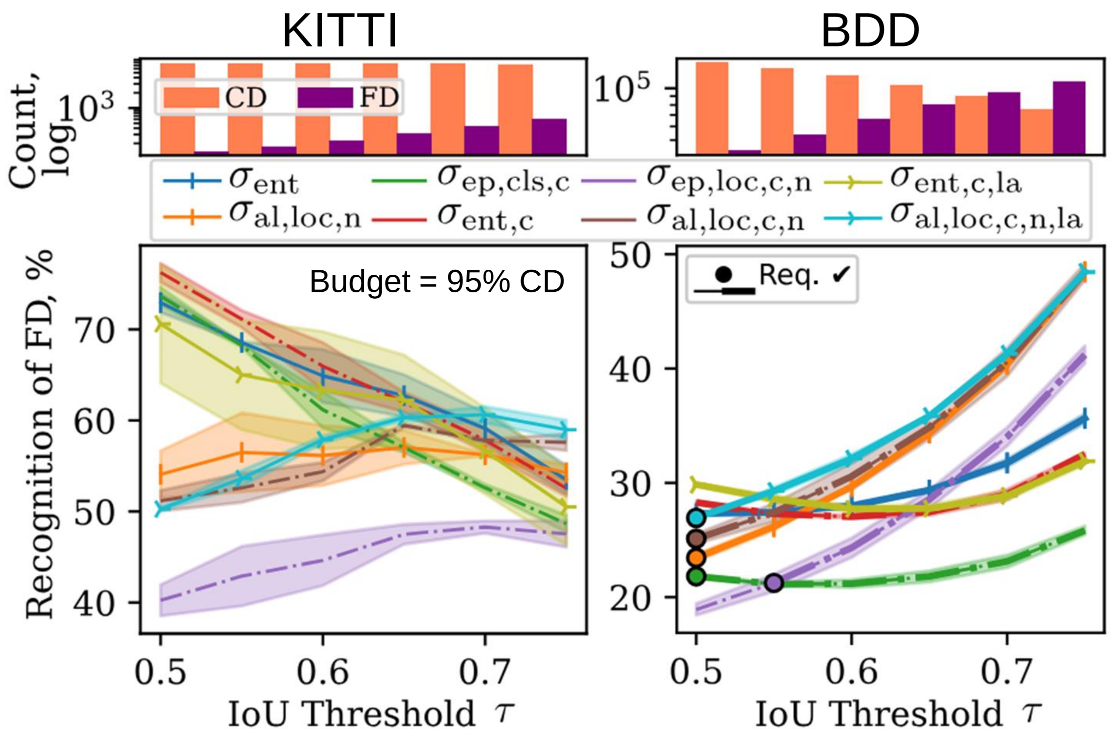
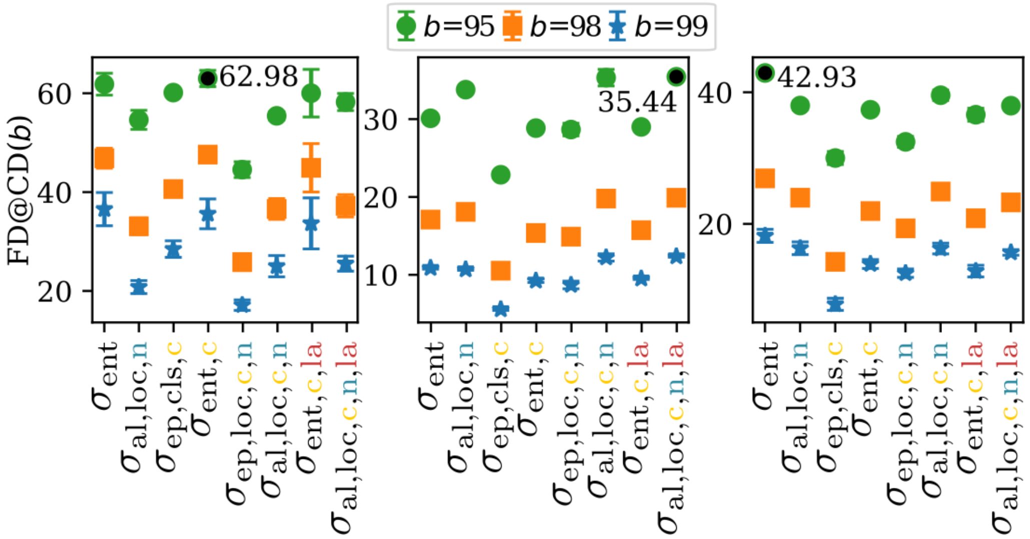


- *Positive impact of calibration and normalization*
- *Correlation type vs. IoU Threshold*
- *Entropy and aleatoric localization uncertainty*

Results

Budget and Optimization

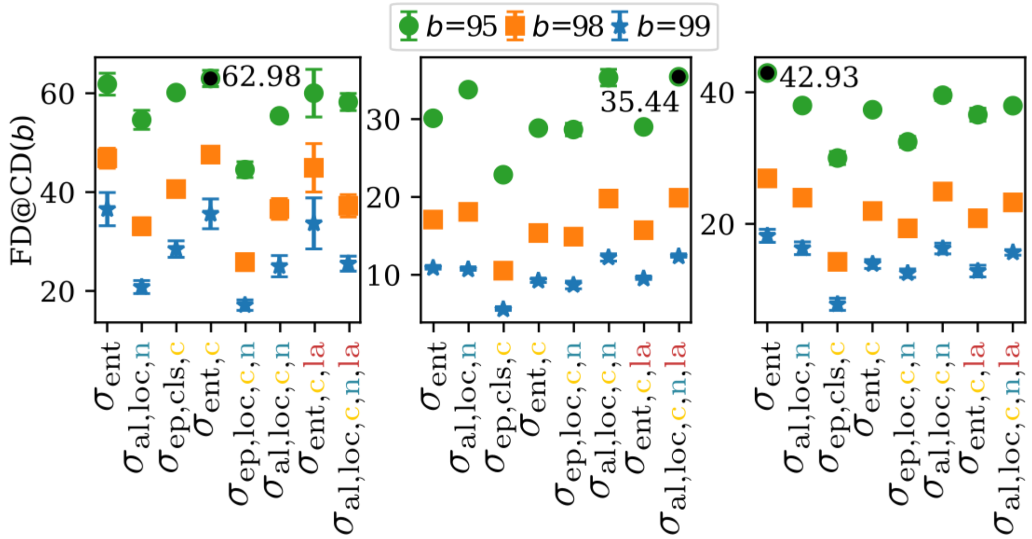


KITTI BDD CODA

Controllable thresholding performance

Results

Budget and Optimization



KITTI BDD CODA

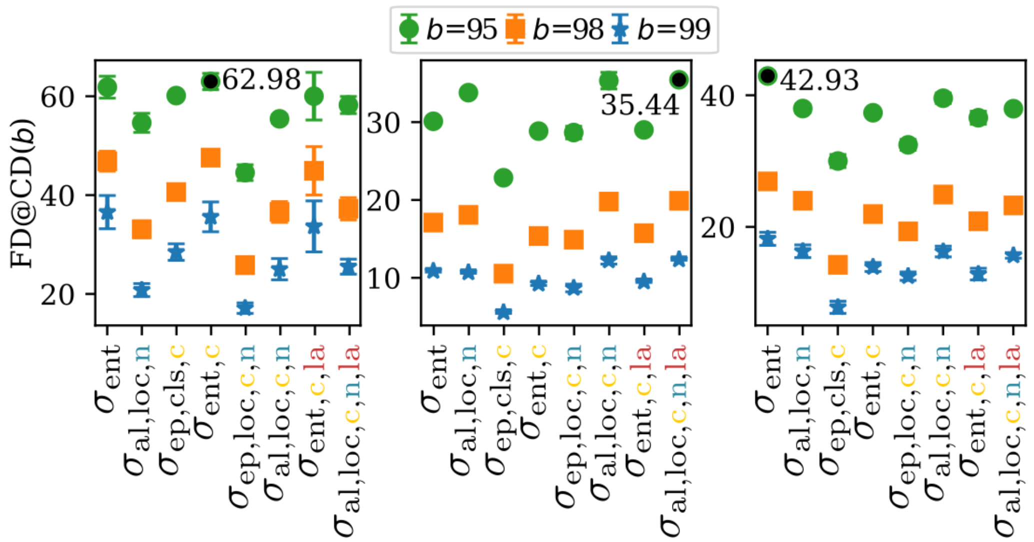
Controllable thresholding performance

		Weights σ_{ent}	Weights $\sigma_{\text{ep,loc}}$	Weights σ_{al}	FD@CD95↑	BAcc↑
Standard Sum (KITTI)	$\sum \sigma_{\text{mc+la}}$	1.00±0.00	1.00±0.00	1.00±0.00	68.02±1.97	0.81±0.01
Optimized Sum (KITTI)	$\sum * \sigma_{\text{mc+la}}$	0.16±0.03	0.03±0.04	1.0±0.00	**72.36±2.72**	**0.83±0.01**
KITTI	$\sum \sigma_{\text{la}}$	1.00±0.00	-	1.00±0.00	65.86±3.43	0.80±0.02
KITTI	$\sum * \sigma_{\text{la}}$	0.14±0.06	-	0.72±0.21	**70.93±1.47**	**0.83±0.01**
BDD	$\sum \sigma_{\text{mc+la}}$	1.00±0.00	1.00±0.00	1.00±0.00	32.03±0.24	0.63±0.00
BDD	$\sum * \sigma_{\text{mc+la}}$	0.06±0.03	0.00±0.00	0.72±0.32	**37.98±0.90**	**0.67±0.00**
BDD	$\sum \sigma_{\text{la}}$	1.00±0.00	-	1.00±0.00	30.65±0.23	0.63±0.00
BDD	$\sum * \sigma_{\text{la}}$	0.05±0.02	-	0.72±0.36	**38.11±0.21**	**0.67±0.00**
CODA	$\sum \sigma_{\text{mc+la}}$	1.00±0.00	1.00±0.00	1.00±0.00	40.60±0.21	0.68±0.00
CODA	$\sum * \sigma_{\text{mc+la}}$	0.07±0.02	0.00±0.00	0.82±0.25	**45.68±0.53**	**0.70±0.00**
CODA	$\sum \sigma_{\text{la}}$	1.00±0.00	-	1.00±0.00	38.49±0.96	0.67±0.00
CODA	$\sum * \sigma_{\text{la}}$	0.10±0.01	-	0.99±0.00	**43.95±0.43**	**0.69±0.00**

Using only entropy and aleatoric uncertainty:

Results

Budget and Optimization



KITTI BDD CODA

Controllable thresholding performance

			Weights			FD@CD95↑	BAcc↑
			σ_{ent}	$\sigma_{\mathrm{ep,loc}}$	σ_{al}		
KITTI	Standard Sum	$\sum \sigma_{\mathrm{mc+la}}$	1.00±0.00	1.00±0.00	1.00±0.00	68.02±1.97	0.81±0.01
	Optimized Sum	$\sum * \sigma_{\mathrm{mc+la}}$	0.16±0.03	0.03±0.04	1.0±0.00	**72.36±2.72**	**0.83±0.01**
		$\sum \sigma_{\mathrm{la}}$	1.00±0.00	-	1.00±0.00	65.86±3.43	0.80±0.02
		$\sum * \sigma_{\mathrm{la}}$	0.14±0.06	-	0.72±0.21	**70.93±1.47**	**0.83±0.01**
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Using only entropy and aleatoric uncertainty:

- *+2–11% via optimized combination*
- *+36–60% over conventional methods*

Results

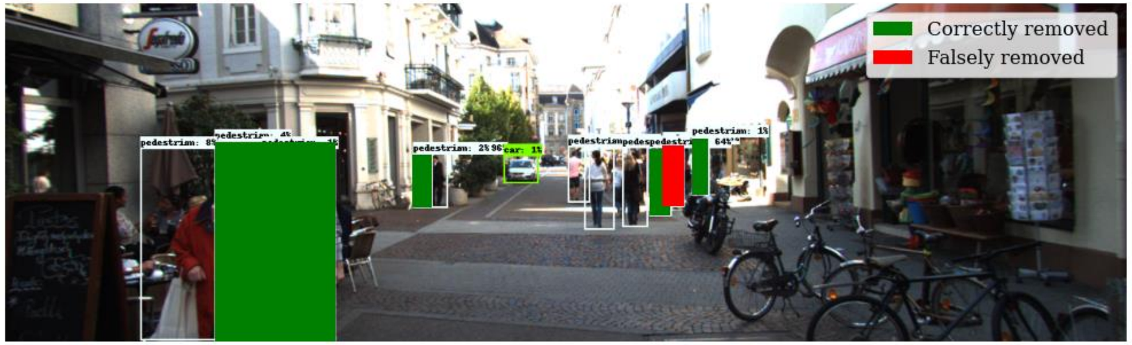
Qualitative – Failure Recognition and Auto-Labeling

Ground Truth

Failure Recognition

Post-Thresholding

Eval on IoU 0.75



Results

Qualitative – Failure Recognition and Auto-Labeling

Ground Truth

Failure Recognition

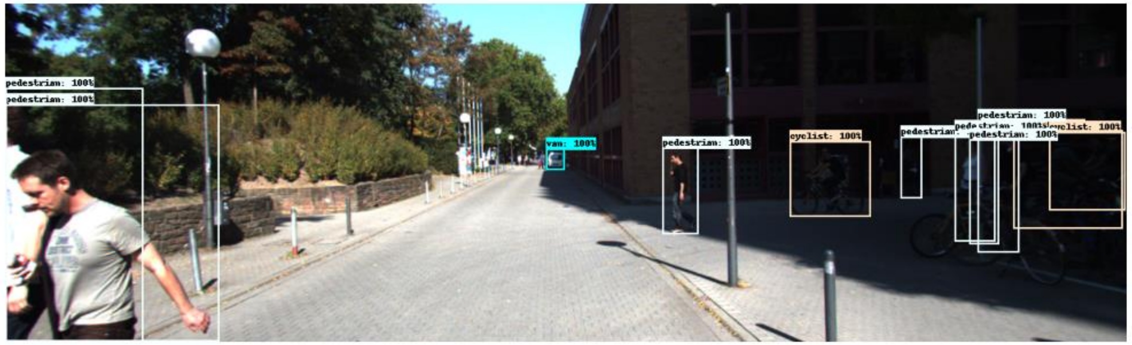
Post-Thresholding

Eval on IoU 0.75

Results

Qualitative – Failure Recognition and Auto-Labeling

Ground Truth



Failure Recognition

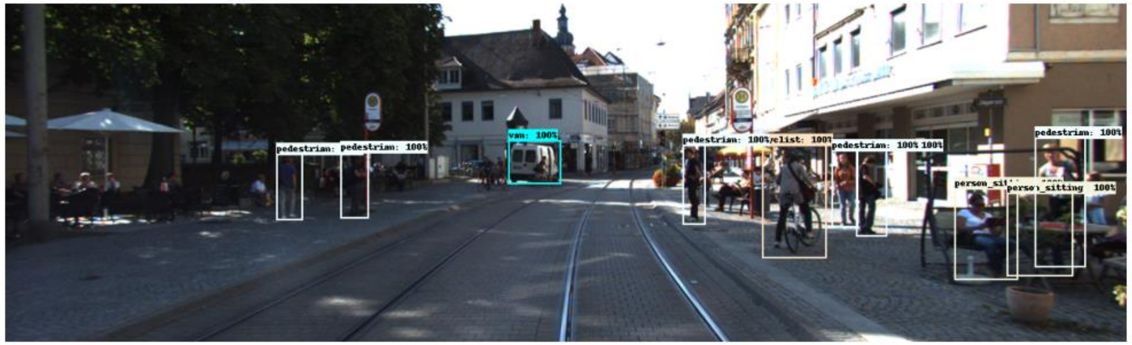
Post-Thresholding

Eval on IoU 0.75

Results

Qualitative – Failure Recognition and Auto-Labeling

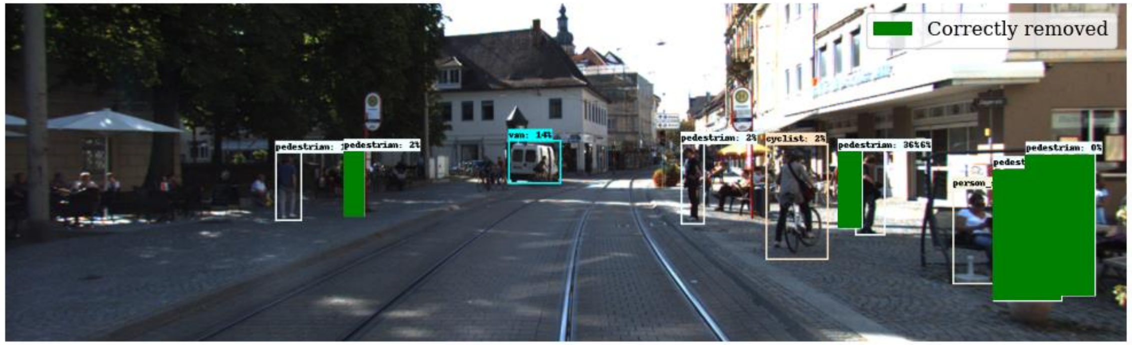
Ground Truth



Failure Recognition

Post-Thresholding

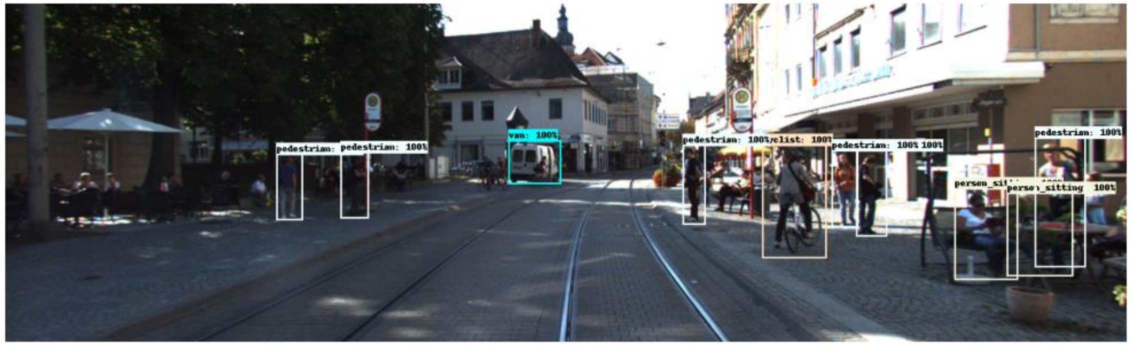
Eval on IoU 0.75



Results

Qualitative – Failure Recognition and Auto-Labeling

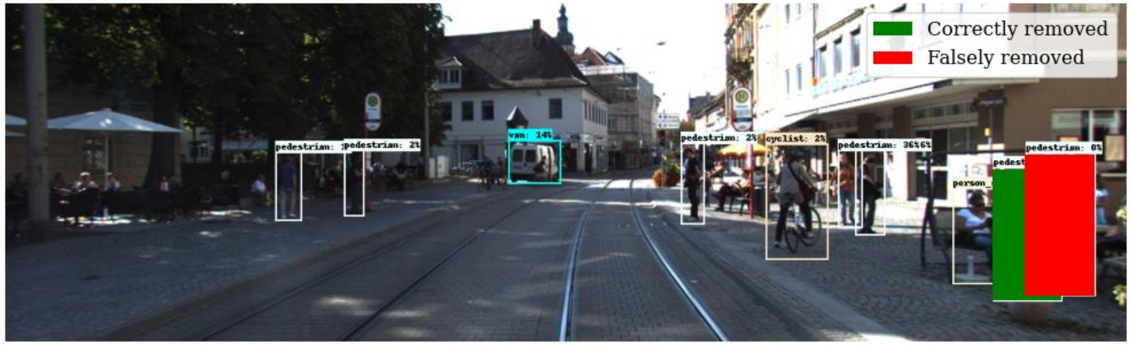
Ground Truth



Failure Recognition

Post-Thresholding

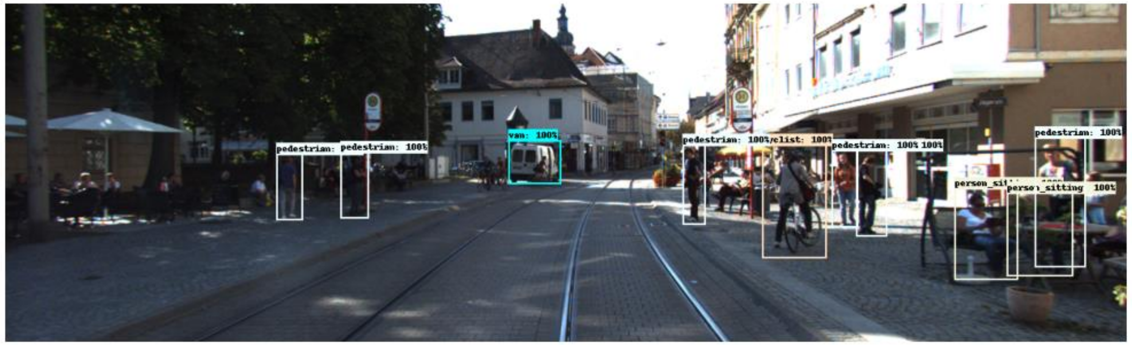
Eval on IoU 0.50



Results

Qualitative – Failure Recognition and Auto-Labeling

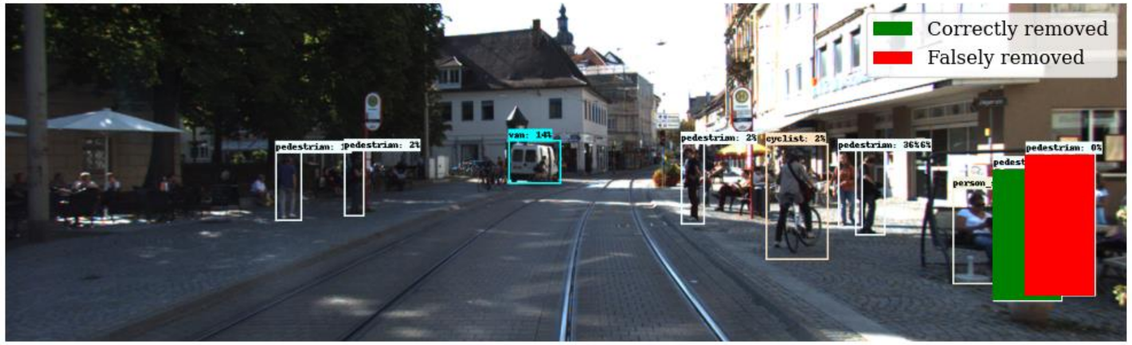
Ground Truth



Failure Recognition

Post-Thresholding

Eval on IoU 0.50



Ground Truth

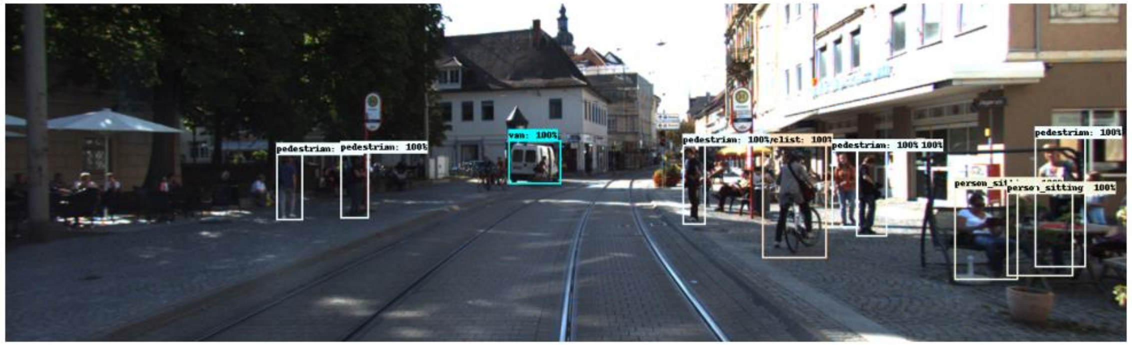
Auto-Labeling

Post-Thresholding

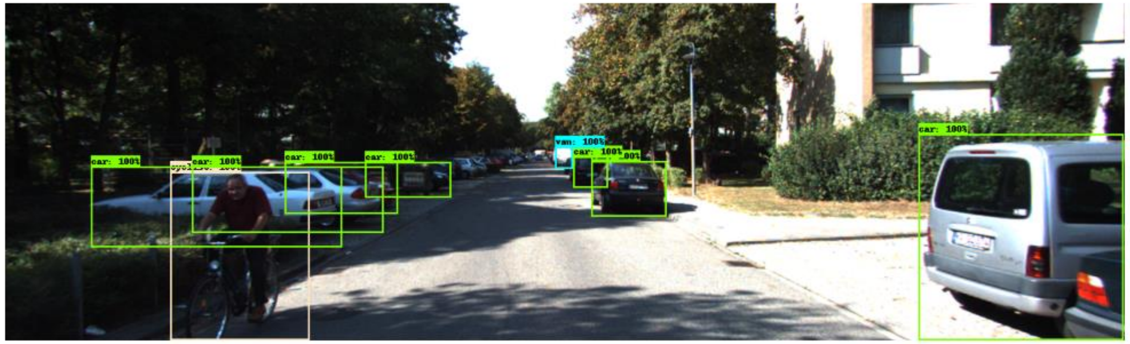
Results

Qualitative – Failure Recognition and Auto-Labeling

Ground Truth



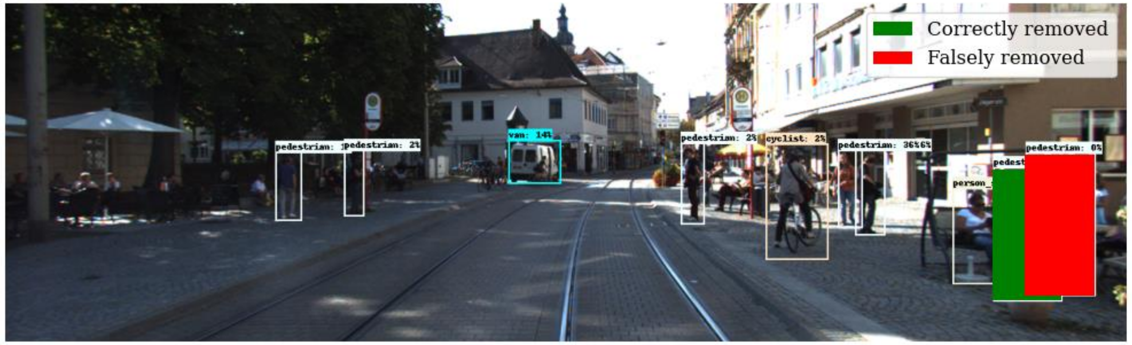
Ground Truth



Failure Recognition

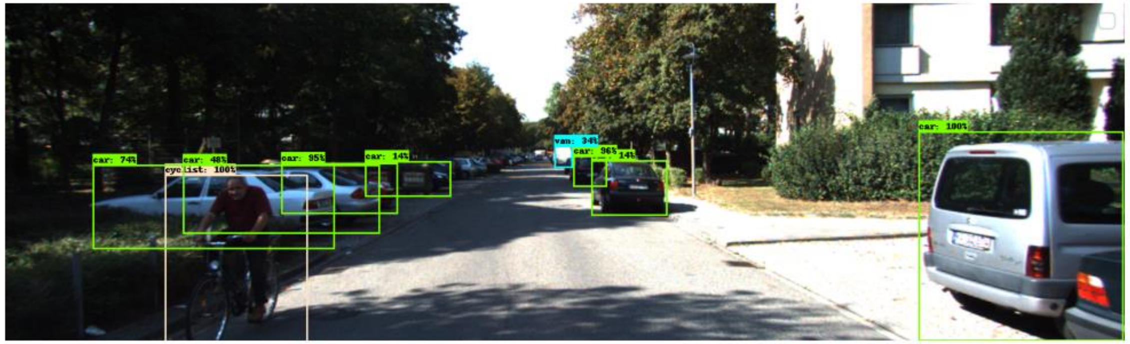
Post-Thresholding

Eval on IoU 0.50



Auto-Labeling

Post-Thresholding



Summary

In this work, we:

- **Define cost-sensitivity** for object detection
- **Automate** the thresholding process
- **Investigate** and **Optimize** the combination of different uncertainties
- **Introduce metrics** and **requirements**

Paper #176

Summary

In this work, we:
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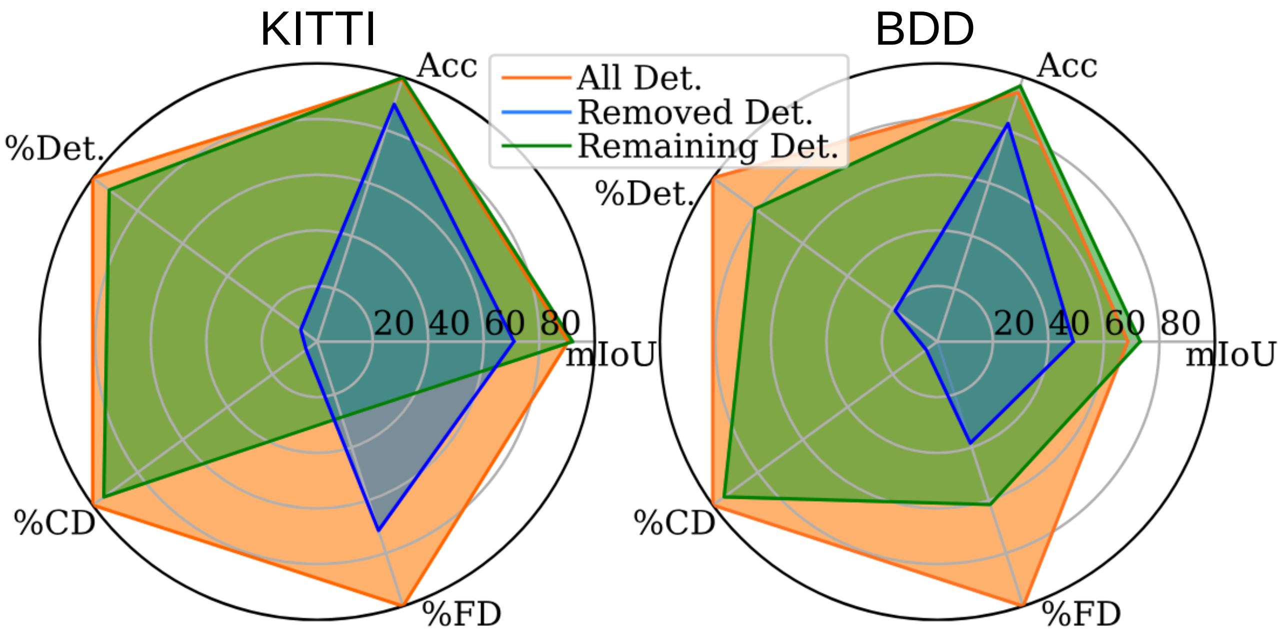
- **Automate** the thresholding process
- **Investigate** and **Optimize** the combination of different uncertainties
- **Introduce metrics** and **requirements**



Key advantages:
- **Model-Agnostic** Failure Recognition
- **Application-Agnostic** Budget-Based Thresholding
- **Efficient Uncertainty Estimation** via Loss Attenuation
- **Minimal Model Expansion** with 0.07% Increase in Parameters
- **Considerable Decrease** in False Detections **Enhancing** Overall **Performance**

Paper #176

Appendix

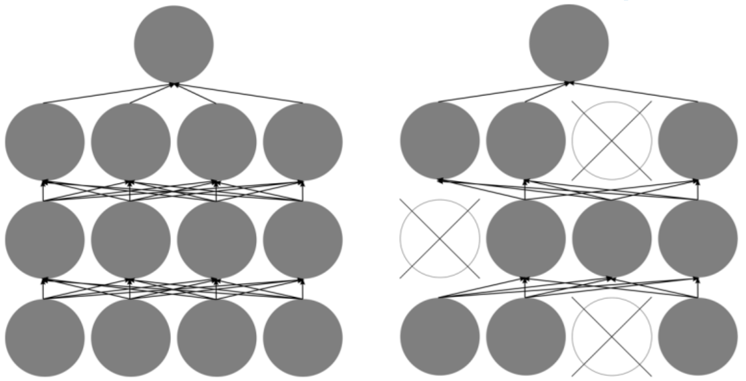
References

1. Moussa Kassem Sbeyti, Michelle Karg, Christian Wirth, Azarm Nowzad, and Sahin Albayrak. Overcoming the limitations of localization uncertainty: Efficient and exact non-linear post-processing and calibration. In Machine Learning and Knowledge Discovery in Databases: Research Track. ECML PKDD 2023., pages 52–68. Springer Nature Switzerland, 2023.
2. Tom Fawcett. An introduction to roc analysis. Pattern recognition letters, 27(8):861–874, 2006.
3. Alex Kendall and Yarin Gal. What uncertainties do we need in bayesian deep learning for computer vision? Advances in Neural Information Processing Systems, 30, 2017.
4. Yarin Gal and Zoubin Ghahramani. Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. In 33rd International Conference on Machine Learning, pages 1050–1059, 2016.
5. Andreas Geiger, Philip Lenz, and Raquel Urtasun. Are we ready for autonomous driving? The kitti vision benchmark suite. In IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3354–3361, 2012.
6. Kaican Li, Kai Chen, Haoyu Wang, Lanqing Hong, Chaoqiang Ye, Jianhua Han, Yukuai Chen, Wei Zhang, Chunjing Xu, Dit-Yan Yeung, Xiaodan Liang, Zhenguo Li, and Hang Xu. Coda: A real-world road corner case dataset for object detection in autonomous driving, 2022.
7. Fisher Yu, Haofeng Chen, Xin Wang, Wenqi Xian, Yingying Chen, Fangchen Liu, Vashisht Madhavan, and Trevor Darrell. Bdd100k: A diverse driving dataset for heterogeneous multitask learning. In IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2633–2642, 2020.

Uncertainty Estimation

Classification and Regression – Epistemic

Standard Network With Dropout



Monte Carlo Dropout

Dropout on during Training

Dropout on during Inference

Sample during Inference

[4]

Uncertainty Estimation

Classification and Regression – Epistemic

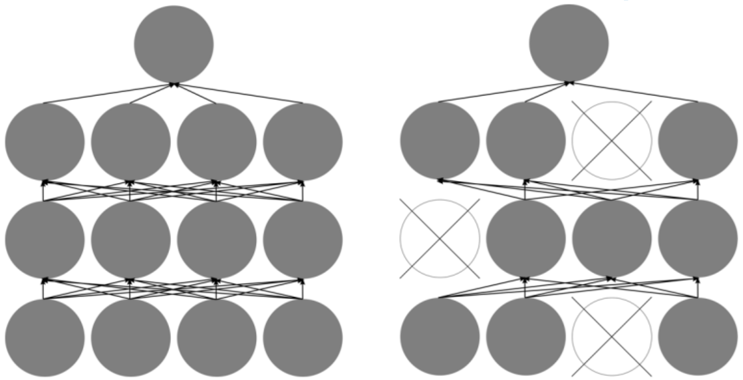
Monte Carlo Dropout

Dropout on during Training

Dropout on during Inference

Sample during Inference

Standard Network | With Dropout



$\hat{\mu}_{car}$
$\hat{\mu}_{pedestrian}$
$\hat{\mu}_{cyclist}$
$\hat{\mu}_{traffic\_light}$
$\hat{\sigma}_{car}$
$\hat{\sigma}_{pedestrian}$
$\hat{\sigma}_{cyclist}$
$\hat{\sigma}_{traffic\_light}$

$\hat{\mu}_{y}$
$\hat{\mu}_{x}$
$\hat{\mu}_{h}$
$\hat{\mu}_{w}$
$\hat{\sigma}_{y}$
$\hat{\sigma}_{x}$
$\hat{\sigma}_{h}$
$\hat{\sigma}_{w}$

[4]

Uncertainty Estimation

Classification and Regression – Epistemic

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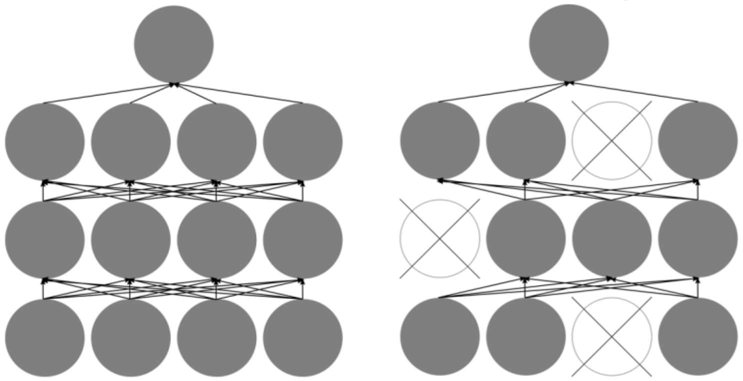


$\hat{\mu}_{car}$
$\hat{\mu}_{pedestrian}$
$\hat{\mu}_{cyclist}$
$\hat{\mu}_{traffic\_light}$
$\hat{\sigma}_{car}$
$\hat{\sigma}_{pedestrian}$
$\hat{\sigma}_{cyclist}$
$\hat{\sigma}_{traffic\_light}$

$\hat{\mu}_{y}$
$\hat{\mu}_{x}$
$\hat{\mu}_{h}$
$\hat{\mu}_{w}$
$\hat{\sigma}_{y}$
$\hat{\sigma}_{x}$
$\hat{\sigma}_{h}$
$\hat{\sigma}_{w}$

Entropy represents the separation capabilities of the model between the classes

$$H(X) = -\sum_{x_i \in X} P(x_i) * Log_2(P(x_i))$$

Cat	0.8	0.2	0.3
Dog	0.1	0.5	0.4
Goat	0.1	0.3	0.3
	Low	Medium	High

[4]

Uncertainty Estimation
Regression – Aleatoric

Observation noise,
weather conditions,
misleading situations

Input

[1,3]

Uncertainty Estimation

Regression – Aleatoric

Observation noise,
weather conditions,
misleading situations

Input → Network

Rewrite box loss with loss attenuation

Negative log-likelihood $\mathcal{L}_{\mathrm{NN}} = \frac{1}{2N}\sum_{i=1}^{N}\frac{\|\mathrm{y}_i^* - \mathrm{f}(\mathrm{x}_i)\|^2}{\sigma(\mathrm{x}_i)^2} + \log\sigma(\mathrm{x}_i)^2$

[1,3]

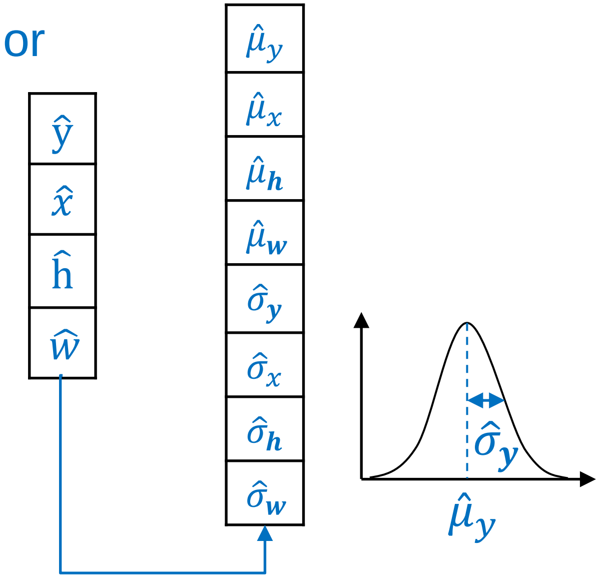
Uncertainty Estimation

Regression – Aleatoric

Observation noise,
weather conditions,
misleading situations

Extend output to 8
values per anchor

Input → Network → Output



Rewrite box loss with loss
attenuation

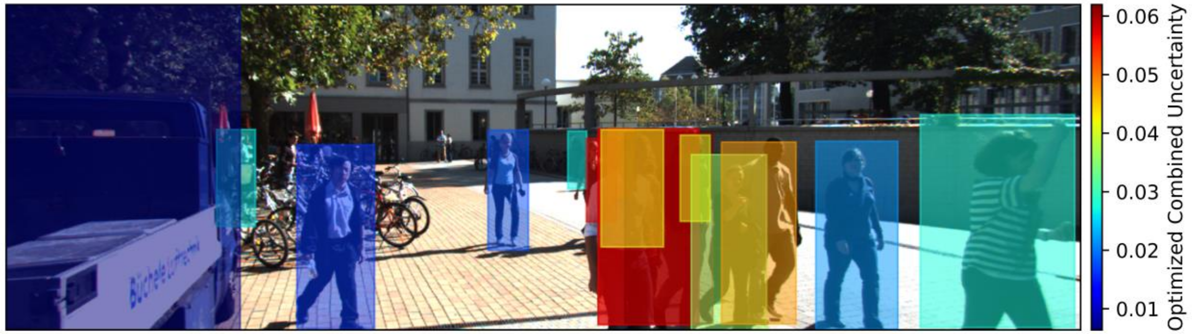
Negative log-likelihood $\mathcal{L}_{\mathrm{NN}} = \frac{1}{2N}\sum_{i=1}^{N}\frac{\|\mathrm{y}_i^* - \mathrm{f}(\mathrm{x}_i)\|^2}{\sigma(\mathrm{x}_i)^2} + \log\sigma(\mathrm{x}_i)^2$

The uncertainty is learned as a function of the data

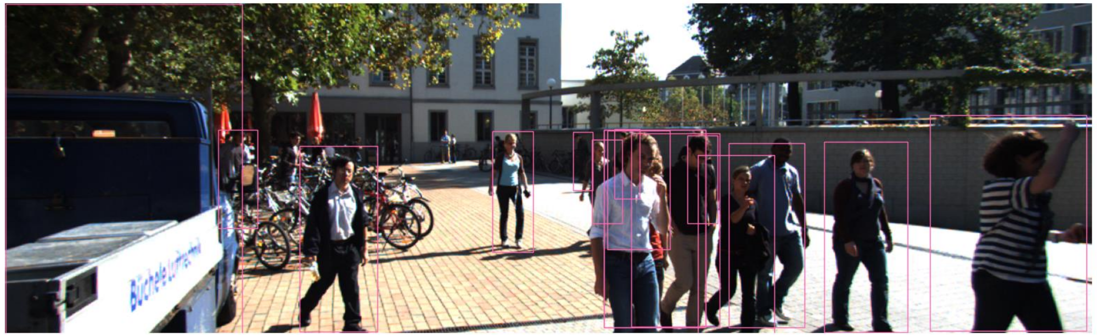
[1,3]

Results

Example



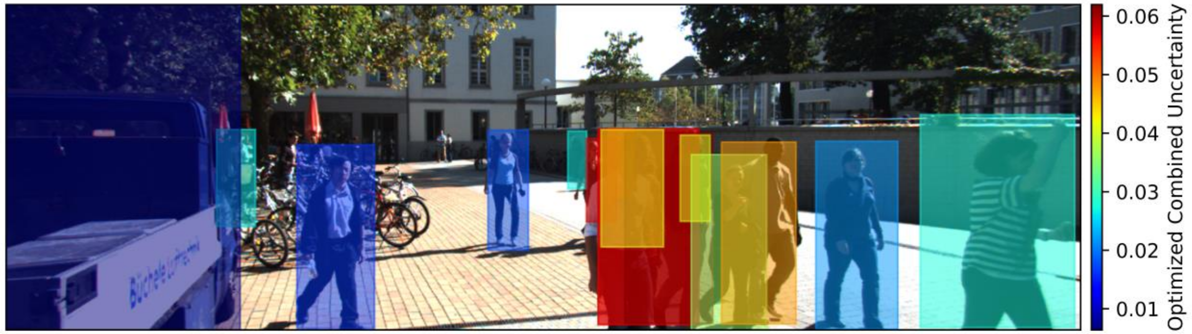
Pre-
thresholding



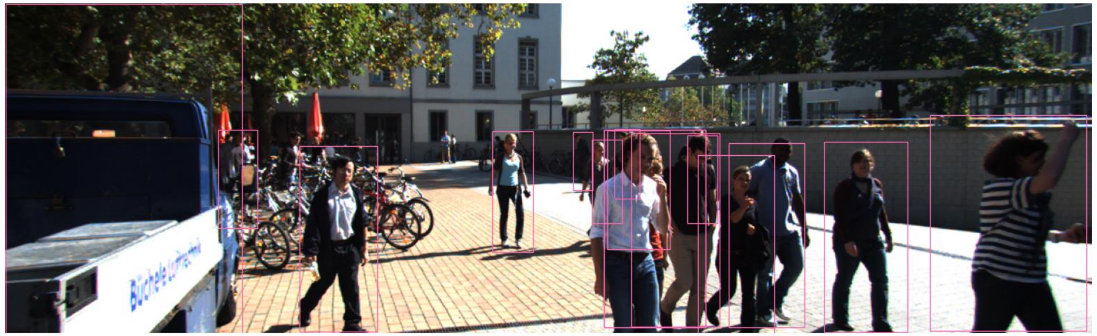
Results

Example

Optimal Threshold = 0.028
Optimization for a budget of 95% CDs over the IoU thresholds 0.5-0.75



Pre-thresholding



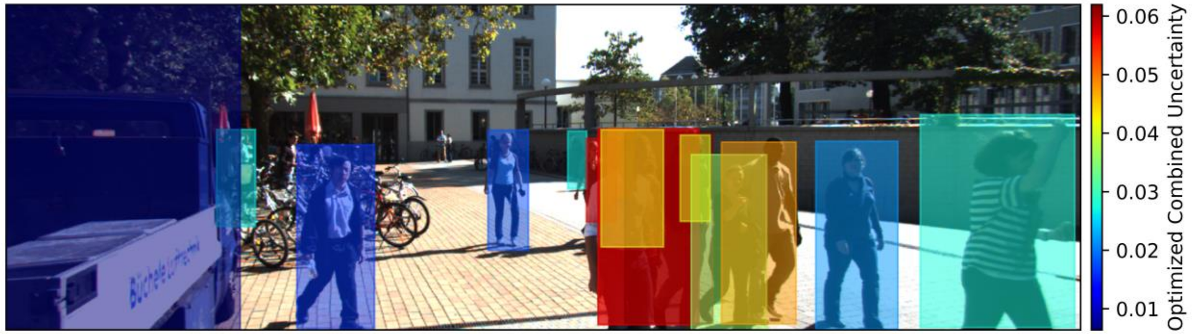
Results

Example

Optimal Threshold = 0.028
Optimization for a budget of 95% CDs over the IoU thresholds 0.5-0.75

All classes correct

#	IoU
1	0.66
2	0.70
3	0.77
4	0.66
5	0.59
6	0.73
7	0.63
8	0.77
9	0.69
10	0.93
11	0.88
12	0.78
13	0.54
14	0.83
15	0.36
16	0.99



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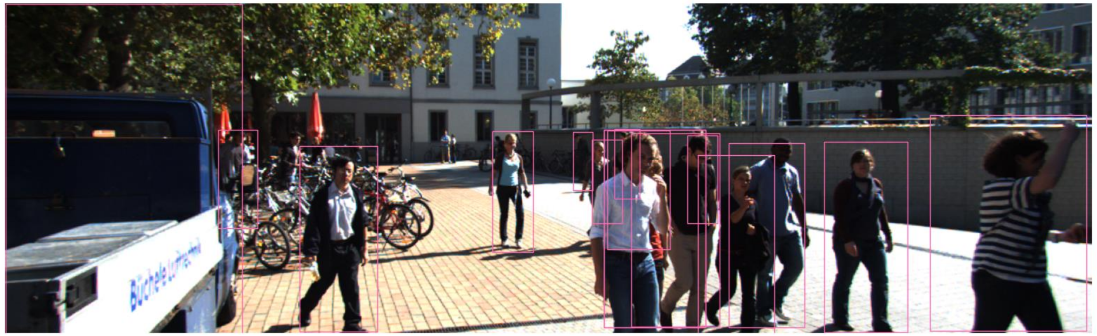

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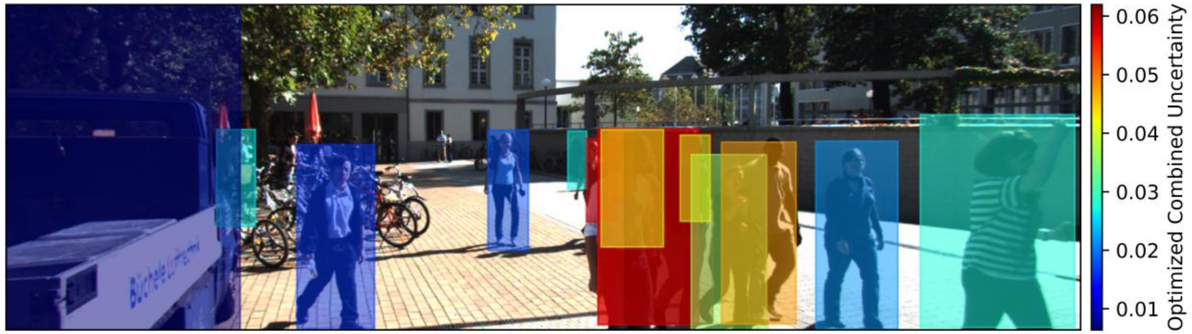
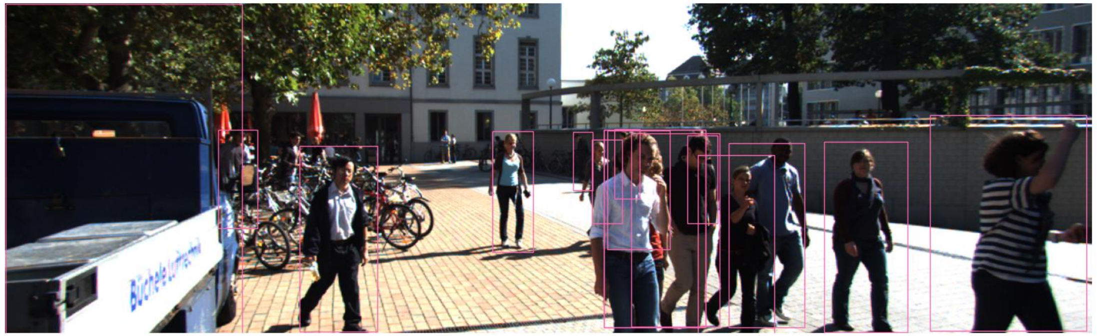
13	0.54
14	0.83
15	0.36
16	0.99

Removed



Pre-thresholding



Post-thresholding