It's Not All About Size: On the Role of Data Properties in Pedestrian Detection

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Pedestrian detection is challenging Weather conditions and performance Pedestrian attributes and performance The performance of pedestrian detection algorithms in the presence of individual attributes. The results are • JAAD is divided into four subsets: reported as MR_4 metric **Localization errors:** • *Clear:* Data collected under clear conditions Attributes presence of • *Cloudy:* Data collected under cloudy conditions Due the to Algorithms male pose_back pose_front pose_left pose_right child female backpack cap/hood umbrella bag • *Cloudy + Clear (c + c):* Data from clear and cloudy subsets attributes bags, such as ACF+ 38.96 34.66 38.28 34.70 33.91 60.92 38.88 36.00 39.71 40.21 69.18 backpacks and umbrellas that • *Mix:* All weather conditions including extreme weather such as LDCF+ 37.24 37.02 33.84 35.27 32.90 30.94 28.27 55.02 33.50 33.94 68.16 are associated with pedestrians rain/snow



False positives:

Caused by various factors such as wet surfaces, over-exposure as well as the presence of objects resembling pedestrians

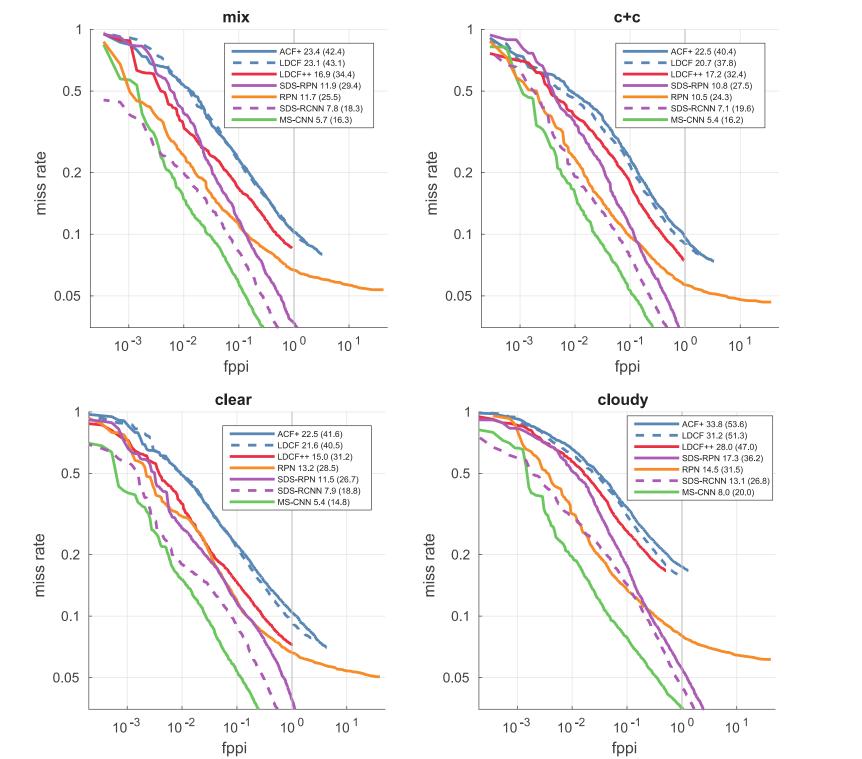


False negatives: Due to the variation in shape appearance (e.g. and pedestrians wearing hooded

jackets, holding umbrellas).

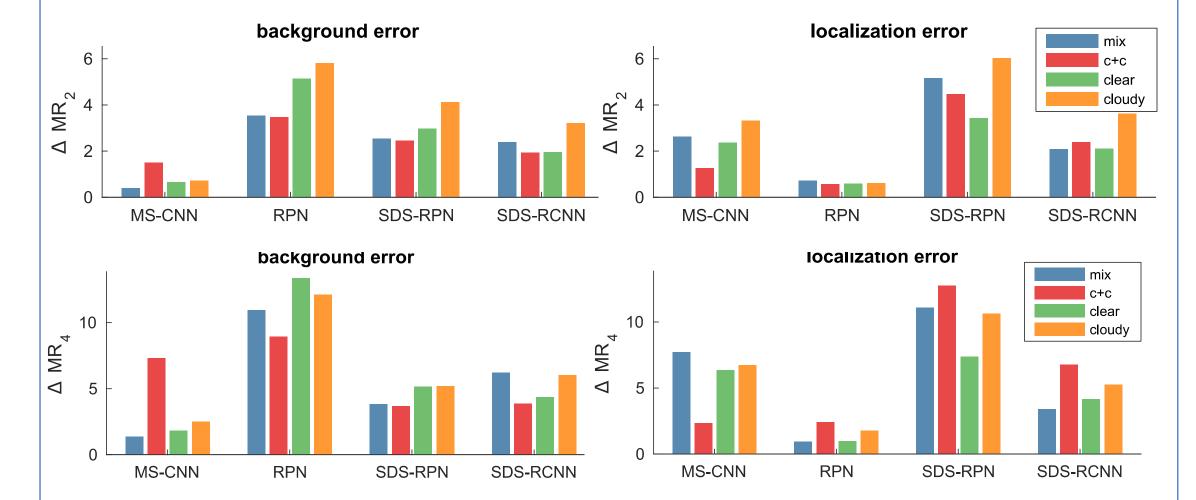
Pedestrian detection, benchmarks and evaluation

- Data diversity is necessary: Pedestrian datasets should be diverse to highlight the true performance of detection algorithms
- Benchmark datasets lack variability: The widely used benchmark datasets, such as Caltech and KITTI, lack variability:
 - Collected under sunny clear weather conditions
 - Recorded in similar geographical locations



ROC curves for all algorithms trained and tested on different JAAD subsets with detection threshold set to 0.5 *IoU*.

- MS-CNN (outside top-5 on Caltech) outperforms SDS-RCNN (best on *Caltech*) on JAAD
- Weak-segmentation in SDS-RPN is only effective under clear conditions (similar to Caltech)



LDCF++	30.09	28.30	34.41	31.79	26.44	26.71	55.16	32.76	26.69	33.29	56.64
MS-CNN	13.49	14.03	17.77	14.00	15.20	11.19	45.37	16.01	10.77	14.08	31.06
RPN	21.99	25.79	28.03	26.82	22.72	21.34	53.59	24.59	19.48	28.97	37.35
SDS-RPN	24.31	22.57	26.58	23.67	21.51	22.74	52.54	19.50	20.12	24.61	31.68
SDS-RCNN	14.30	15.77	17.72	15.29	14.46	13.60	43.14	15.85	12.25	15.68	25.57
FP background				FP localization				FN			
50 40 30 5 20				IS-CNN				MS-CNN SDS-RCNN			MS-CNN SDS-RCN
10	affic light bike	hydrant kne	ster stroller billoos	d other	oroup child p	ag stroller ation	bike back	hbrella parts othe	occiusio	t child group m	unbrell ² other
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Data properties and generalizability

The performance detection algorithms on the Caltech and JAAD subsets. Left, the results for algorithms trained and tested on the same dataset. Right, trained and tested on different datasets (J = JAAD, C = Caltech). MR^{o} and MR^N refer to old and new Caltech annotations. The best and second best results are highlighted with blue and green color respectively

Algorithms	$C \rightarrow C$ $MR_2^N (MR_2^0)$	$mix \rightarrow mix$ MR_2	$\begin{array}{c} C \rightarrow mix\\ MR_2 \end{array}$	$J \rightarrow C$ $MR_2^N (MR_2^0)$				
		MAX		mix	c + c	cloudy	clear	
ACF+	26.27 (30.55)	23.36	77.94	46.97 (53.63)	49.52 (55.06)	70.79 (74.06)	49.99 (55.23)	
LDCF+	23.07 (25,79)	23.07	54.82	43.61 (49.93)	44.89 (50.85)	59.18 (64.11)	47.29 (52.54)	
LDCF++	13.66 (16.10)	16.90	47.94	37.66 (46.04)	40.41 (48.54)	54.86 (60.72)	44.77 (51.93	
RPN	11.71 (14.33)	11.71	40.15	27.80 (41.19)	25.74 (38.18)	34.67 (47.34)	28.75 (40.05	
MS-CNN	9.47 (11.21)	5.70	35.09	22.87 (34.83)	26.30 (38.11)	31.55 (46.35)	29.49 (41.64	
SDS-RPN	8.15 (9.27)	11.89	43.40	24.24 (30.84)	26.64 (33.61)	35.62 (42.90)	30.85 (38.52	
SDS-RCNN	6.58 (7.59)	7.78	25.45	21.47 (27.73)	25.29 (32.69)	35.20 (42.35)	23.81 (31.75	

Lack variability in pedestrian appearance



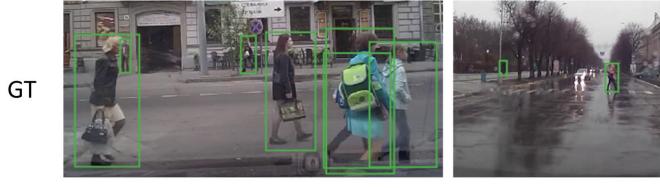
Contributions

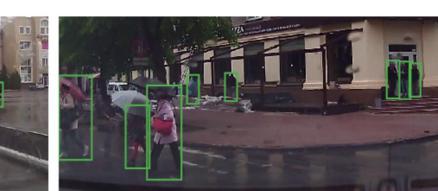
- A large dataset of attributes: Augmented JAAD dataset with more than 900k attributes
- Evaluate state of the art: Highlight the performance of pedestrian detection algorithms under different conditions
- Cross-evaluation of datasets: Measure generalizability of datasets according to data properties
- A software framework for experimentation: with 10 \bullet detection algorithms and 8 common datasets

The relative contribution of background and localization errors to the performance of state-of-theart pedestrian detection algorithms.

- There are two sources of error:
 - Background error: Ignoring all false positives resulting from poor localization
 - Localization error: Ignoring all false positives resulting from background misdetections
- Different algorithms are prone to different sources of error:
 - Adding weak-segmentation to *RPN* reverses the contribution of error from background to localization
 - SDS-RCNN has a more balanced performance compared to MS-CNN which has poorer localization error vs background error
- Under different weather conditions sources of error differ:
 - MS-CNN is more prone to background error under c+c conditions

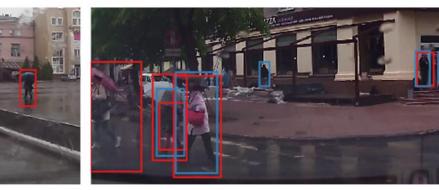
Conclusions

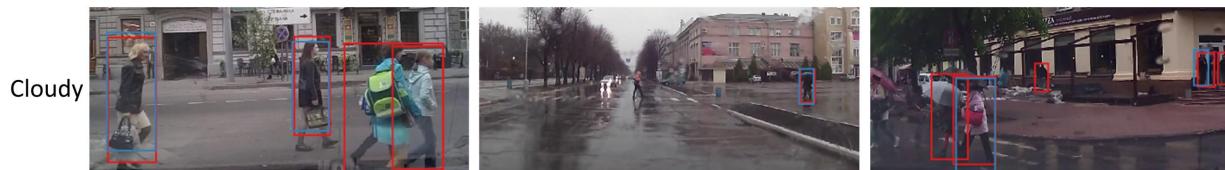






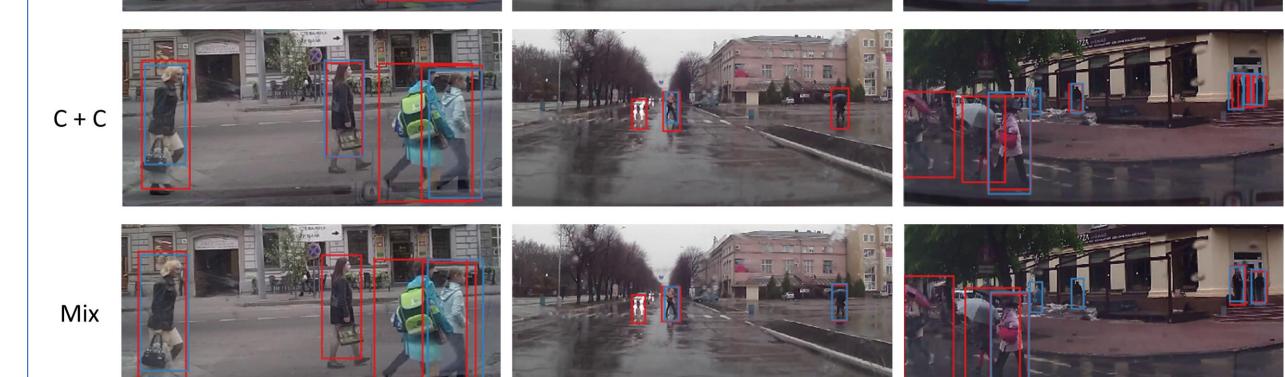
Clear





JAAD-Attributes: A dataset of pedestrian attributes and poses





The performance of state of the art on different subsets of JAAD. Colors green, red and blue correspond to the ground truth, MS-CNN and SDS-RCNN respectively.

- Data properties influence the performance of algorithms differently \bullet
- Diverse benchmark datasets give an unbiased estimate of pedestrian detection algorithms performance
- Diversity of data increases algorithms' generalizability even with fewer samples
- Benchmark datasets should be designed following protocols to minimize any unevenness in the statistical distribution of different aspects of the driving task