	Method			Dataset			
		ASCADv1 (fixed)	ASCADv1 (random)	DPAv4 (Zaid version)	AES-HD	OTiAiT	OTP
	Random	112 ± 1	108 ± 4	11.5 ± 0.4	127 ± 1	1.20 ± 0.05	1.048 ± 0.008
First-order	SNR	111.0 ± 0.2	123 ± 2	126 ± 1	128.5 ± 0.3	4.26 ± 0.07	1.33 ± 0.04
parametric	SOSD	111.6 ± 0.2	125.6 ± 0.6	105.7 ± 0.9	128.3 ± 0.3	3.94 ± 0.08	1.34 ± 0.04
methods	CPA	118.2 ± 0.4	114 ± 2	111.5 ± 0.9	128.4 ± 0.3	2.7 ± 0.2	1.32 ± 0.04
	GradVis	124.9 ± 0.3	127 ± 1	121 ± 1	127 ± 1	1.8 ± 0.2	1.31 ± 0.05
Neural net	Saliency	124.8 ± 0.3	127 ± 1	124 ± 1	127 ± 1	2.8 ± 0.2	1.29 ± 0.05
attribution	Input * Grad	124.8 ± 0.3	127 ± 1	$\frac{124 \pm 1}{124 \pm 1}$	127 ± 1	3.1 ± 0.2	1.29 ± 0.05
	LRP	124.8 ± 0.3	127 ± 1	$\frac{124 \pm 1}{124 + 1}$	127 ± 1	3.1 ± 0.2	1.29 ± 0.05
	1-Occlusion 5-Occlusion	124.8 ± 0.3 125.0 ± 0.4	127 ± 1 127.1 ± 0.6	$\frac{124 \pm 1}{124.0 \pm 0.0}$	127 ± 1 128 ± 1	3.2 ± 0.2 4.4 ± 0.1	1.29 ± 0.05 1.27 ± 0.03
				124.9 ± 0.8			
	17-Occlusion	124.5 ± 0.2	127.1 ± 0.7	123.1 ± 0.7	128 ± 1	4.5 ± 0.1	1.23 ± 0.02
	65-Occlusion	122.4 ± 0.3	126 ± 2	119.5 ± 0.8	127 ± 2	4.1 ± 0.1	1.17 ± 0.02
	257-Occlusion 2 nd -order 1-Occlusion	121.4 ± 0.6 124.8 ± 0.3	122 ± 3 127 ± 1	104.4 ± 0.6 125 ± 1	127 ± 2 127 ± 1	3.9 ± 0.1 3.6 ± 0.2	$1/16 \pm 0.02$ 1.29 ± 0.05
	OccPOI	TODO	TODO	$\frac{120 \pm 1}{\text{TODO}}$	TODO	TODO	TODO
	GradVis (ZaidNet)	119 ± 3	n/a	113 ± 2	128.0 ± 0.5	n/a	n/a
	Saliency (ZaidNet)	119 ± 3	n/a	113 ± 2	128.0 ± 0.5	n/a	n/a
	Input * Grad (ZaidNet)	119 ± 2	n/a	113 ± 2	128.0 ± 0.5	n/a	n/a
	1-Occlusion (ZaidNet)	119 ± 2	n/a	113 ± 2	128.0 ± 0.5	n/a	n/a
	5-Occlusion (ZaidNet)	121 ± 2	n/a	120 ± 1	128.3 ± 0.4	n/a	n/a
	17-Occlusion (ZaidNet)	121 ± 2	n/a	119 ± 2	128.3 ± 0.3	n/a	n/a
	65-Occlusion (ZaidNet)	120 ± 1	n/a	114 ± 4	128.3 ± 0.4	n/a	n/a
	257-Occlusion (ZaidNet)	122 ± 1	n/a	101 ± 2	128.4 ± 0.4	n/a	n/a
	2 nd -order 1-Occlusion (ZaidNet)	120 ± 2	n/a	113 ± 2	128.0 ± 0.5	n/a	n/a
	OccPOI (ZaidNet) GradVis (WoutersNet)	TODO	n/a	TODO	TODO 128.1 ± 0.6	n/a	n/a
	Saliency (WoutersNet)	119.2 ± 0.9 119.3 ± 0.9	n/a n/a	112 ± 7 112 ± 7	$\frac{128.1 \pm 0.6}{128.1 \pm 0.5}$	n/a n/a	n/a n/a
	Input * Grad (WoutersNet)	119.3 ± 0.9 119.3 ± 0.9	n/a n/a	112 ± 7 112 ± 7	$\frac{128.1 \pm 0.5}{128.1 \pm 0.6}$	n/a	n/a
	1-Occlusion (WoutersNet)	119.3 ± 0.9	n/a	112 ± 7	128.1 ± 0.6	n/a	n/a
	5-Occlusion (WoutersNet)	120 ± 1	n/a	119 ± 3	128.3 ± 0.4	n/a	n/a
	17-Occlusion (WoutersNet)	121 ± 1	n/a	120 ± 2	$\underline{128.4 \pm 0.3}$	n/a	n/a
	65-Occlusion (WoutersNet)	121.4 ± 0.7	n/a	114 ± 3	128.4 ± 0.3	n/a	n/a
	257-Occlusion (WoutersNet)	122.0 ± 0.7	n/a	104 ± 4	$\underline{128.4\pm0.3}$	n/a	n/a
	2 nd -order 1-Occlusion (WoutersNet)	119.7 ± 0.9	n/a	112 ± 7	128.1 ± 0.6	n/a	n/a
	OccPOI (WoutersNet)	TODO	n/a	TODO	TODO	n/a	n/a
	ALL (ours)	$\underline{125.5\pm0.4}$	$\boxed{127.6 \pm 0.3}$	$\underline{124.5\pm0.8}$	$\underline{128.4 \pm 0.3}$	4.3 ± 0.1	$\underline{1.38 \pm 0.04}$
Table 1: Performance of leakage localization algorithms according to the Rev-DNNO (reverse DNN occlusion)							
test (large	r is better). To compute	this metric.	we first train a	a supervised DN	IN classifie	er to ma	p emission
test (larger is better). To compute this metric, we first train a supervised DNN classifier to map emission traces to the sensitive variable. We then occlude all its inputs and incrementally un-occlude them from least-							
- · · · · · · · · · · · · · · · · · · ·							
to most-leaky as estimated by the leakiness assessment under test, and at each step compute its performance							
(quantified by rank, lower is better) on the test dataset. The Rev-DNNO metric is given by the average value							
of these performance assessments (higher is better, because it indicates that claimed nonleaky features indeed							
had little utility to the classifier). Of the two DNN occlusion metrics, this is more sensitive to true/false							
negative leakiness measurements because the performance of the classifier tends to jump and stay up as soon							
as it sees leaky measurements. Best result is boxed and best deep learning result is <u>underlined</u> . Results are							
reported as mean \pm std. dev. over 5 random seeds. Observe that our method is superior or comparable to							
all deep learning methods on 5 of the 6 datasets and slightly worse on the remaining dataset. Additionally,							
deep learning methods perform better in comparison to parametric methods on the first-ordered datasets							
relative to their performance under the oSNR metric.							
elative to their performance under the object.							