

Classify Me Correctly if You Can: Evaluating Adversarial Machine Learning Threats in NIDS

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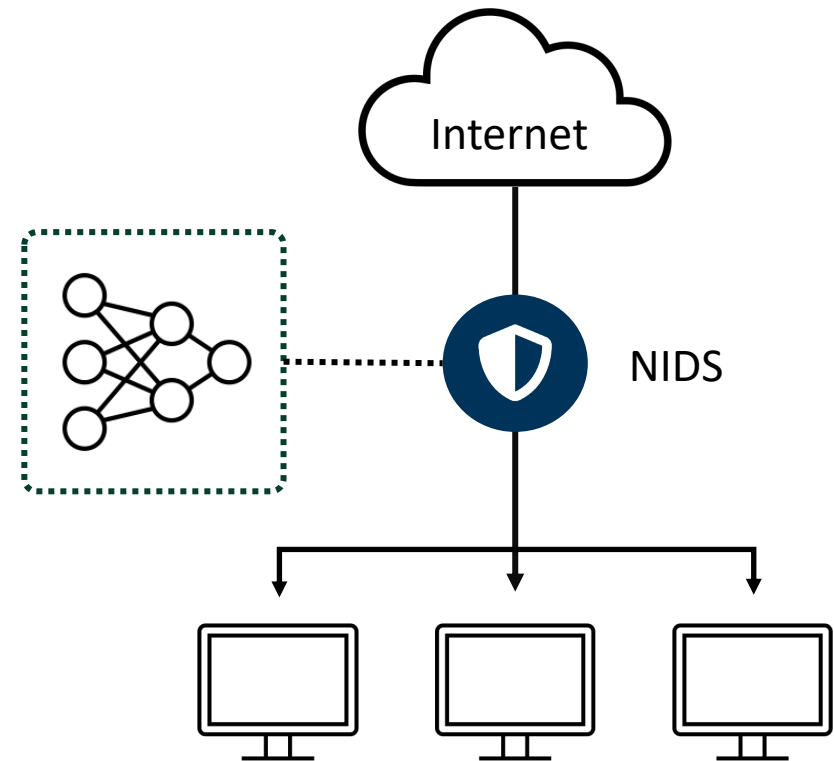
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j.w.w. Asma Jodeiri Akbarfam, Hoda Maleki, Gagan Agrawal and Gokila Dorai

Network Intrusion Detection Systems (NIDS) detect and protect against network attacks.

- Defend against different network attacks
- Deployed in various kinds of networks

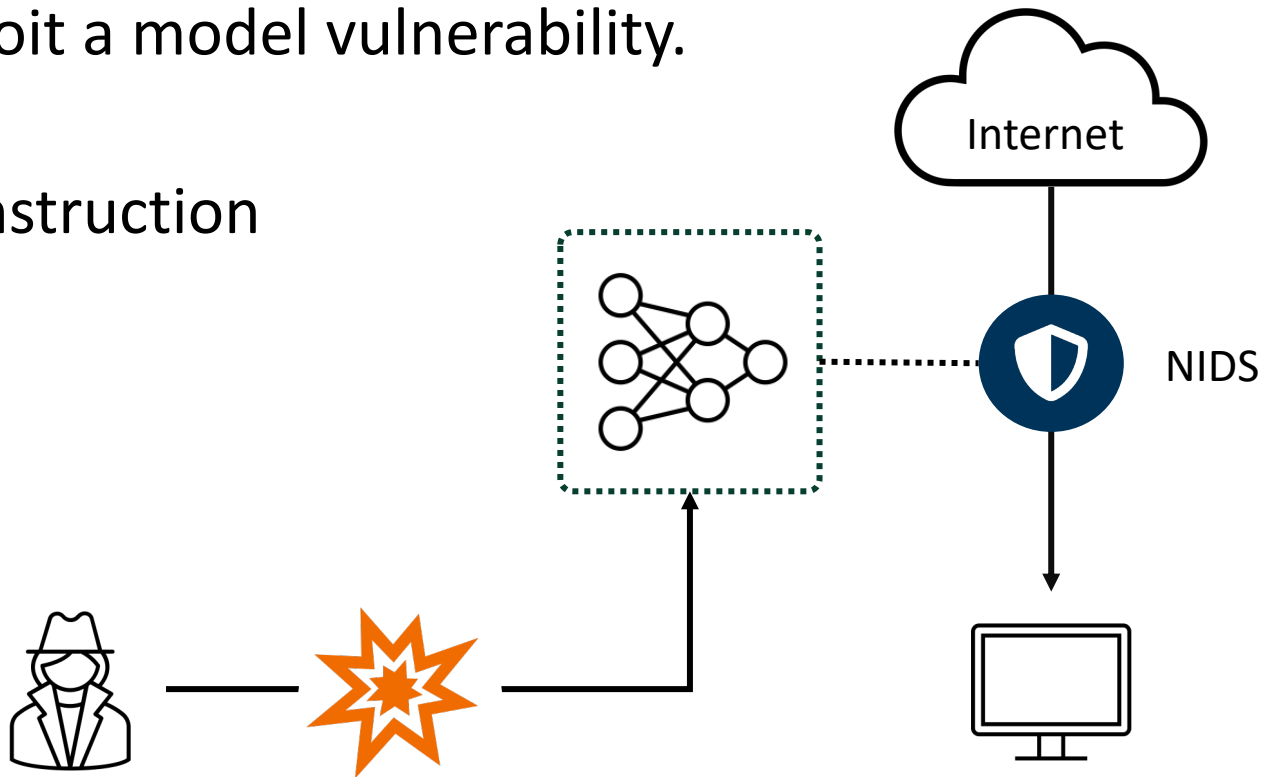
Modern NIDS use **machine learning**.



Problem: machine learning models are susceptible to adversarial attacks.

In **Adversarial Machine Learning (AML)**
adversary attempts to exploit a model vulnerability.

- obtain information of construction
- alter behavior



Adversarial Strategies

Training-phase attacks

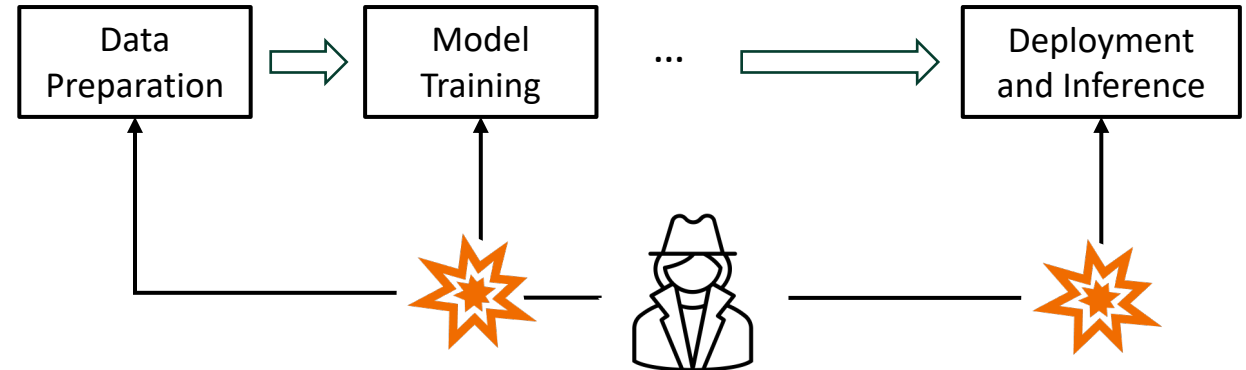
- Contaminate or alter data
- Cause learning bias

Defenses

- Numerous mechanisms
- Applied at different model deployment stages

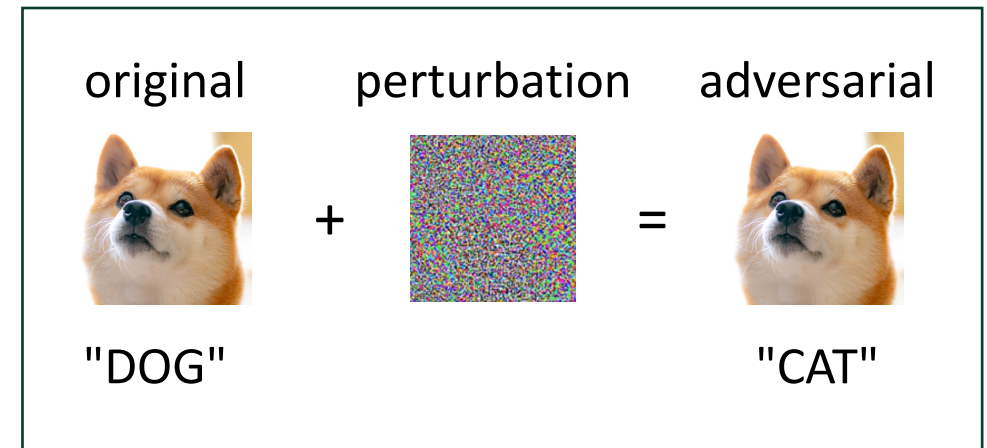
Exploits on trained models

- Alter inputs to avoid detection
- Attempt to recover the model



Evaluating AML Threats in NIDS

Adversarial machine learning techniques have been studied primarily in **unconstrained** domains.



Network intrusion detection models are trained on network data, with correlation and **constraints** between attributes.

A **constrained domain** adds many new considerations

Acceptable perturbations are restricted.

Misclassification is class sensitive.

Traditional evaluation metrics are inapplicable.

Model invocations must be limited.

TCP	UDP	OTHER	ORIG_PKTS	BYTES	CONN_S0	CONN_SF	RESP_PKTS	DURATION	LABEL
1	0	0	1	32	1	0	0	0.0722	benign
0	1	0	1	128	0	1	1	0.0047	malicious

High-level Motivation

Take the state-of-the-art unconstrained AML attacks and defenses



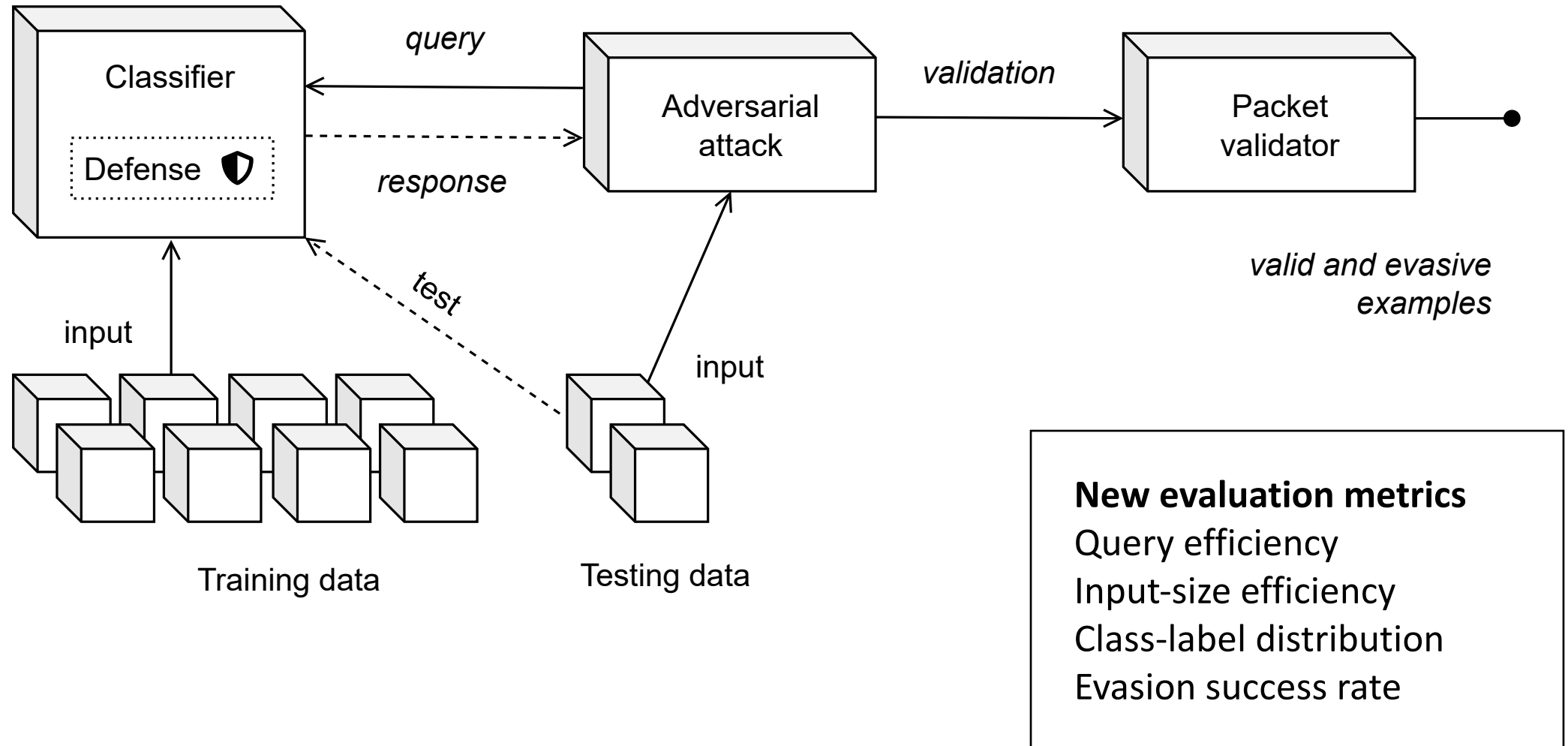
Adapt to constrained domains



Measure impact of attacks and defenses in NIDS

Concrete approach

- 1) Design an **evaluation system** — includes choice input data, classifier, defense, and attack.
- 2) Capture domain constraints as **rules** — adversarially generated record must satisfy all applicable rules.
- 3) Add to the evaluation system a post-hoc packet **validator** — identifies adversarial examples that satisfy domain constraints.



Experimental evaluation

The implementation enabled to evaluate classifiers, attacks, and defenses. By varying different parameters, we can study their impact on NIDS security.

Data sets	2×	IoT-23, UNSW-NB15
Classifiers	2×	XGBoost, Deep Neural Network
Defenses	2×	Robust Trees, Adversarial Training
Attacks	2×	HopSkipJump Attack, Zeroth Order Optimization
Validator	1×	Validates TCP, UDP and other traffic flows







github.com/aucad/aml-networks

Limited model queries

Adversarial attack success rate for 48 attack configurations, as *fractions*.





"Valid" represents the fraction of evasive records that also pass validation.

Model/ Iterations	HopSkipJumpAttack						Zeroth Order Optimization					
	Evasions			Valid			Evasions			Valid		
	2	5	10	2	5	10	2	5	80	2	5	80
IoT-23												
DNN	.34	.27	.31	0	0	.01	0	0	0	0	0	0
DNN- 	0	0	0	0	0	0	0	0	0	0	0	0
XGB	.43	.39	.41	.06	.07	.18	.47	.49	.49	.05	.05	.04
XGB- 	.38	.38	.38	.01	.01	.03	.03	.07	.07	.03	.06	.07
UNSW-NB15												
DNN	.79	.68	.81	.41	.39	.42	.28	.36	.29	.25	.30	.24
DNN- 	.02	.11	.07	.02	.11	.07	0	0	0	0	0	0
XGB	.93	.92	.91	.47	.46	.47	.50	.69	.78	.49	.65	.69
XGB- 	.64	.65	.65	.38	.38	.38	.09	.31	.32	.09	.30	.31

Limited model queries

Adversarial success rate
by transmission protocol
on UNSW-NB15 data.

Benign—Malicious
column shows
class-label distribution
of evasive and valid
records.

Model/ Protocol	Evasions			Valid			Benign- Malicious
	TCP	UDP	other	TCP	UDP	other	
HopSkipJumpAttack							
DNN	.79	.85	.81	.78	.02	.03	27-73
DNN- 	.14	0	0	.14	0	0	0-100
XGB	.91	.94	.88	.89	.02	.01	30-70
XGB- 	.75	.43	.78	.73	0	0	17-83
Zeroth Order Optimization							
DNN	.35	.23	.22	.34	.13	.14	52-48
DNN- 	0	0	0	0	0	0	-
XGB	.89	.70	.55	.88	.50	.43	34-66
XGB- 	.54	.11	.01	.53	.11	.01	24-76

Summary



An evaluation system with a post-hoc constraint validator — added constraints to unconstrained state-of-the-art attacks.

Experimentally measured attacks and defenses — despite constraints, AML attacks pose challenges to NIDS.



Many possible future directions — e.g., performing validation during an adversarial search and using the validator feedback to improve attack success.