Meta concerns in ML security/privacy

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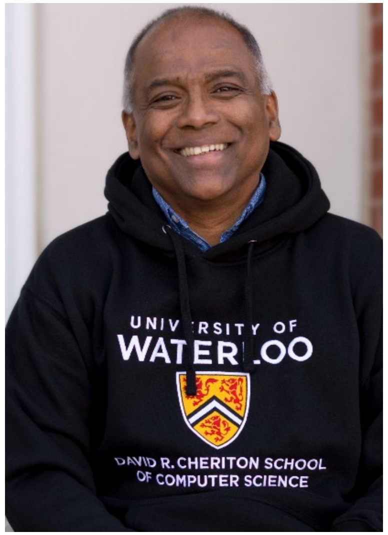
(Joint work with Vasisht Duddu, Jian Liu, Sebastian Szyller, Asim Waheed, Rui Zhang)

UNIVERSITY OF WATERLOO

Who am I?



Executive Director, [Cybersecurity and Privacy Institute (CPI)](#) (on leave)
Professor of Computer Science, University of Waterloo

Fellow of the Royal Society of Canada (2023), IEEE Fellow (2017), ACM Fellow (2019)

Previously: Professor, Aalto University (2013-2019), **Nokia** (14 y; built up Nokia security research team), **IBM Research** (3 y)

Industry collaborations: Private-AI Institute, ICRI-CARS, Google Awards
https://asokan.org/asokan/ for more background

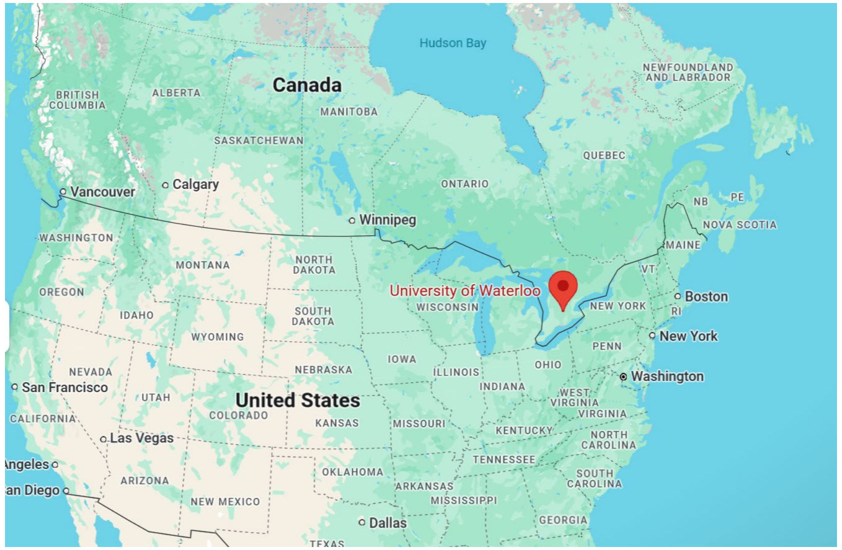
University of Waterloo

#1 in cybersecurity/privacy technology research in Canada; top-15 in the world
https://csrankings.org/

100+ professors in computer science

60+ professors (across the university) working on different aspects of cybersecurity/privacy

#1 Engineering school in Canada



https://uwaterloo.ca/bioinformatics-group/about

My research interests

Systems Security and Privacy

AI and Security/Privacy

- How to use AI to improve security/privacy solutions
- How to improve security/privacy of AI-based systems

Platform security

- How to design/use hardware assistance to secure software?

https://ssg-research.github.io/

Platform security research

https://ssg-research.github.io/platsec/

Hardware assisted trusted execution environments (TEEs)

CCS 2019 keynote[1] https://youtu.be/hHYoGn5PSl4

2022 book https://ssg.aalto.fi/publications/hardware-platform-security-for-mobile-devices/

Novel hardware security mechanisms

- HardScope (DAC 2019, https://arxiv.org/abs/1705.10295) , BliMe (NDSS 2024, HOST 2024, https://ssg-research.github.io/platsec/blime)

Novel uses of deployed hardware security mechanisms

- PACStack (Usenix SEC 2021, https://arxiv.org/abs/1905.10242) and PARTS (Usenix SEC 2019, https://arxiv.org/abs/1811.09189), Deterministic MTE tagging (https://arxiv.org/abs/2204.03781)

Outline

The big picture: studying ML security/privacy — why and how?

What can be done to counter “model stealing”?

Are we using the right adversary models?

(How) can we simultaneously deploy defenses against multiple concerns?

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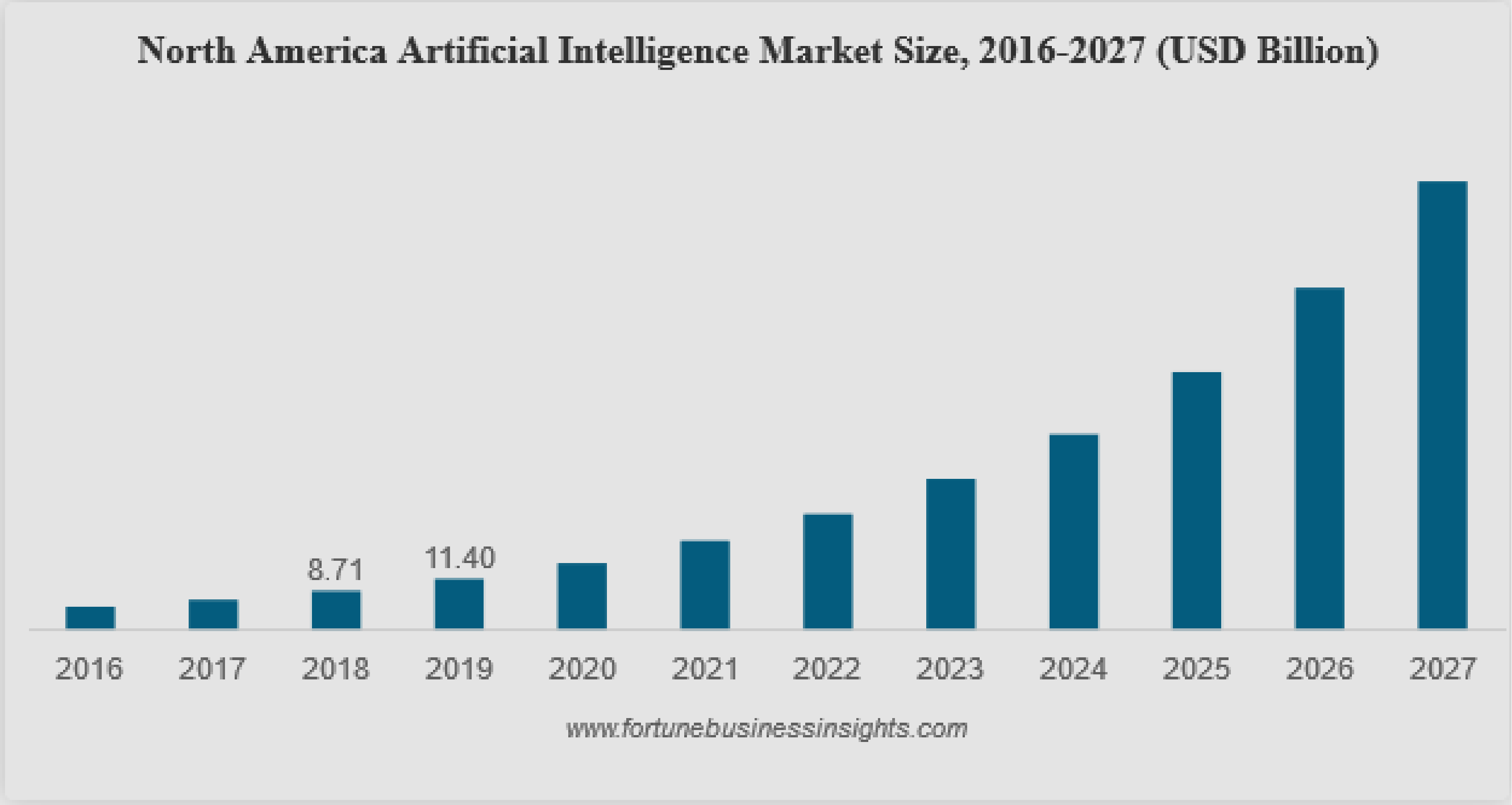
AI will be pervasive



https://www.fortunebusinessinsights.com/industry-reports/artificial-intelligence-market-100114

Forbes

7,109 views | Oct 18, 2019, 01:56pm EDT

How Artifical Intelligence Is Advancing Precision Medicine

Nicole Martin Former Contributor
AI & Big Data
I write about digital marketing, data and privacy concerns.

https://www.forbes.com/sites/nicolemartin1/2019/10/18/how-artifical-intelligence-is-advancing-precision-medicine/#2f720a79a4d5

MOTHERBOARD
TECH BY VICE

Dozens of Cities Have Secretly Experimented With Predictive Policing Softw

Documents obtained by Motherboa
requests verify previously unconfir
with predictive policing company P

By Caroline Haskins

https://www.vice.com/en_us/article/d3m
experimented-with-predictive-policing-s

Forbes

5,705 views | Oct 31, 2019, 02:42pm EDT

How AI Is Uprooting Recruiting

Falon Fatemi Contributor
Entrepreneurs

https://www.vice.com/en_us/article/d3m7jq/dozens-of-cities-have-secretly-experimented-with-predictive-policing-software

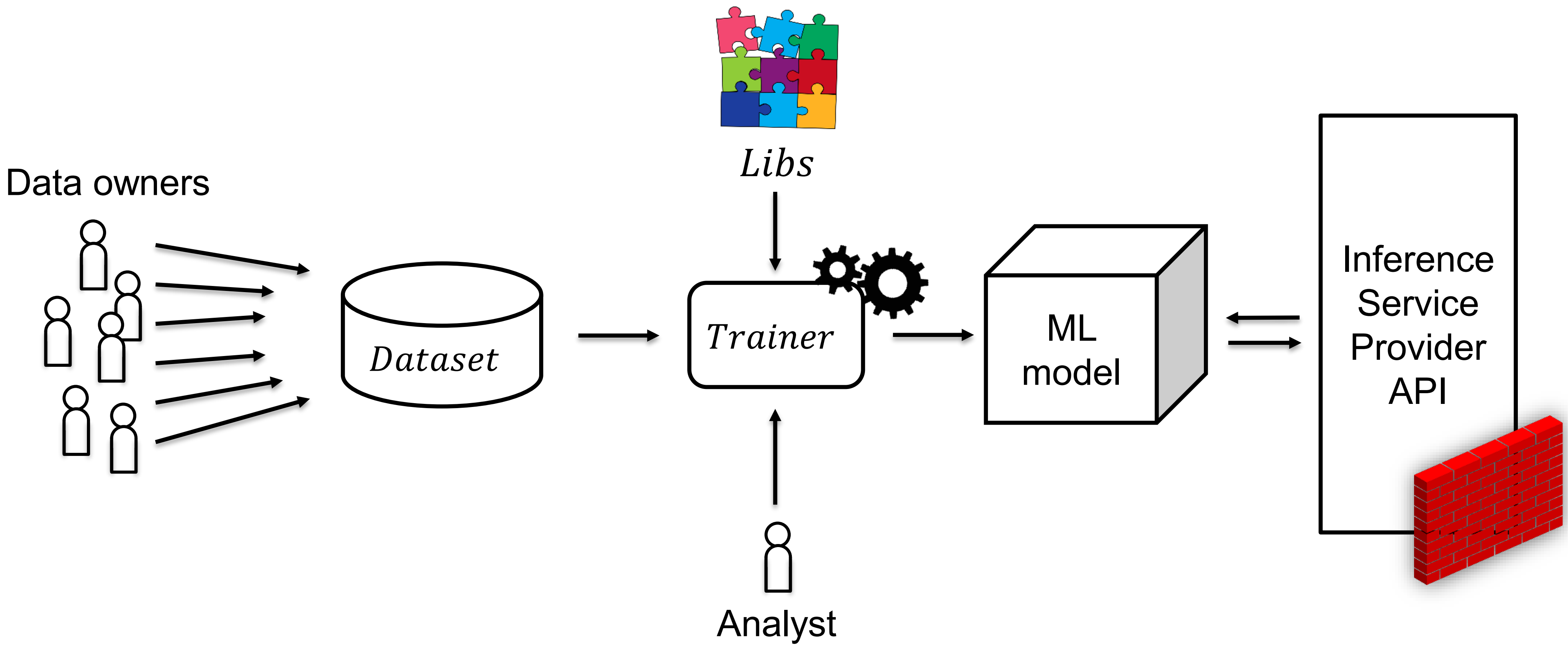
PART OF A ZDNET SPECIAL FEATURE: CYBERSECURITY: LET'S GET TACTICAL

AI is changing everything about cybersecurity, for better and for worse. Here's what you need to know

Artificial intelligence and machine learning tools could go a long way to helping to fight cybercrime. But these technologies aren't a silver bullet, and could also be exploited by malicious hackers.

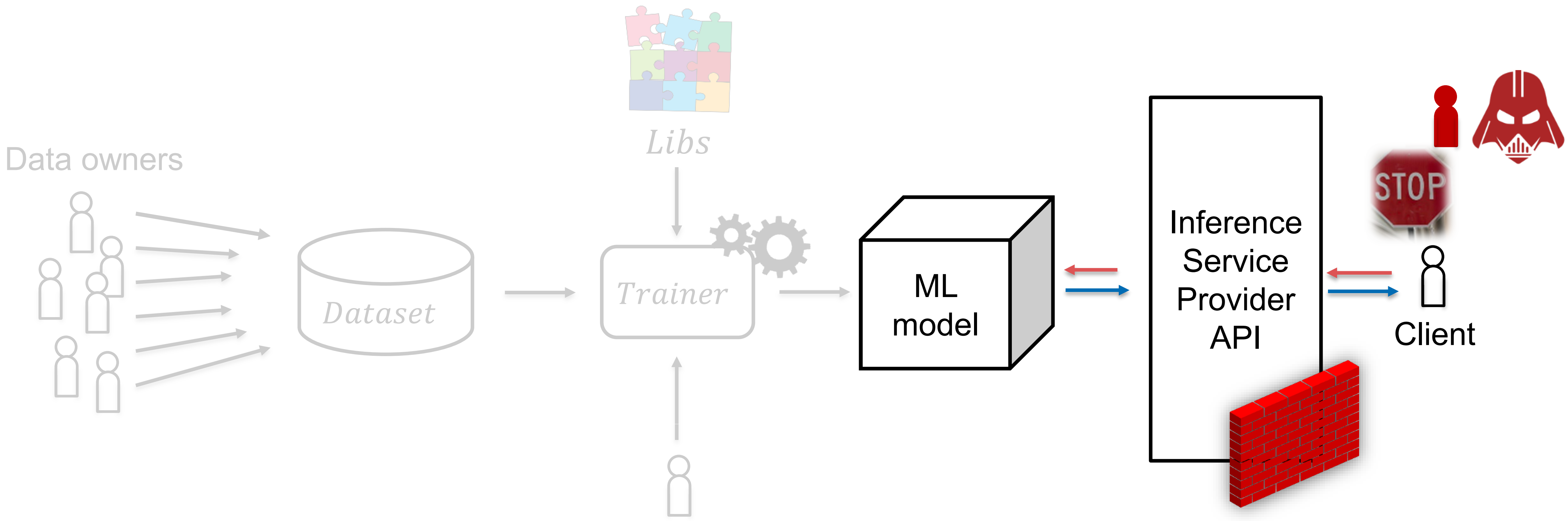
https://www.zdnet.com/article/ai-is-changing-everything-about-cybersecurity-for-better-and-for-worse-heres-what-you-need-to-know/

Machine Learning pipeline



Where is the adversary? What is its target?

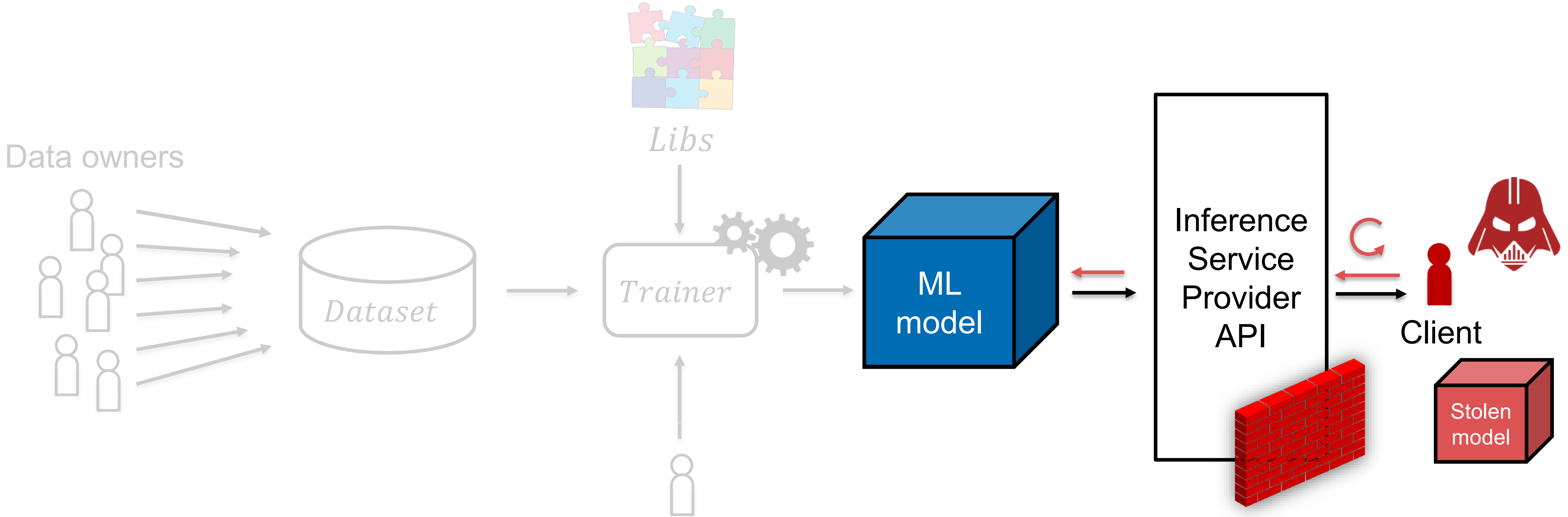
Compromised input – Model integrity



Evade model

Szegedy et al. – *Intriguing Properties of Neural Networks,* ICLR '14 (https://arxiv.org/abs/1312.6199v4)
Dalvi et al. – *Adversarial Classification,* KDD '04 (https://dl.acm.org/doi/10.1145/1014052.1014066)

Malicious client – Model confidentiality



Extract/steal model

Tramer et al. – *Stealing ML models via prediction APIs*, Usenix SEC '16 (https://arxiv.org/abs/1609.02943)
Juuti et al. – *PRADA: Protecting against DNN Model Stealing Attacks*, Euro S&P '19 (https://arxiv.org/abs/1805.02628)
Orekondy et al. – *Knockoff Nets: Stealing Functionality of Black-Box Models*, CVPR '19 (https://arxiv.org/abs/1812.02766)

Towards trustworthy AI

Secure, privacy-preserving, …

TABLE V
TOP ATTACK

Which attack would affect your org the most?	*Distribution*
Poisoning (e.g: [21])	10
Model Stealing (e.g: [22])	6
Model Inversion (e.g: [23])	4
Backdoored ML (e.g: [24])	4
Membership Inference (e.g: [25])	3
Adversarial Examples (e.g: [26])	2
Reprogramming ML System (e.g: [27])	0
Adversarial Example in Physical Domain (e.g: [5])	0
Malicious ML provider recovering training data (e.g: [28])	0
Attacking the ML supply chain (e.g: [24])	0
Exploit Software Dependencies (e.g: [29])	0

Kumar et al. – *Adversarial Machine Learning – Industry Perspectives*, IEEE SPW ‘20 (https://arxiv.org/abs/2002.05646)

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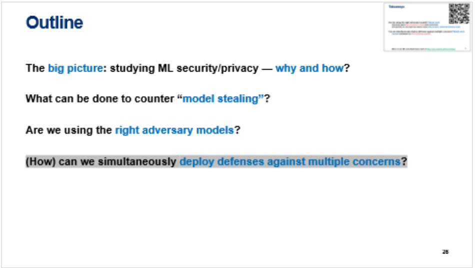

Defending against model stealing

October 1, 2024 Product

Model Distillation in the API

Fine-tune a cost-efficient model with the outputs of a large frontier model–all on the OpenAI platform

https://openai.com/index/api-model-distillation/

The New York Times

Artificial Intelligence › OpenAI and Trump A Look at OpenAI's Operator What Is DeepSeek? DeepSeek's Rise Quiz

OpenAI Says DeepSeek May Have Improperly Harvested Its Data

The San Francisco start-up claims that its Chinese rival may have used data generated by OpenAI technologies to build new systems.

https://www.nytimes.com/2025/01/29/technology/openai-deepseek-data-harvest.html

"We are aware of and reviewing indications that DeepSeek may have inappropriately distilled our models, and will share information as we know more," the spokesperson said, adding that the company was not accusing DeepSeek of a security breach.

Distillation is often prohibited in LLMs' terms of service, but is common in the industry.

We can try to:

- prevent (or slow down[1]) model extraction, or
- detect[2] it

But current solutions are not effective

Model derivation may even become a desirable business model

Deter unauthorized model ownership via model ownership resolution (MOR):

- watermarking
- fingerprinting

[1] Dziedzic et al. – *Increasing the Cost of Model Extraction with Calibrated Proof of Work*, ICLR '22 (https://openreview.net/pdf?id=EAy7C1cgE1L)
[2] Atli et al. – *Extraction of Complex DNN Models: Real Threat or Boogeyman?*, AAAI-EDSML '20 (https://arxiv.org/abs/1910.05429)

Watermarking

Embed watermark while training (potentially) victim model[1]

- Choose incorrect labels for a set of samples (watermark set, WM)
- Cannot resist model extraction

Embed watermark at the inference API[2]

- Use a mapping function to decide when to return incorrect predictions for queries
- Finding suitable mapping functions is difficult

Watermarking schemes tend to be not robust[3] and reduce utility

[1] Yadi et al. – *Watermarking Deep Neural Networks by Backdooring,* Usenix SEC '18 https://www.usenix.org/node/217594
[2] Szyller et. al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks,* ACM MM '21 (https://arxiv.org/abs/1906.00830)
[3] Lukas et al. – *SoK: How Robust is Image Classification Deep Neural Network Watermarking*? IEEE S&P '22 (https://arxiv.org/abs/2108.04974)

Fingerprinting

Conferrable adversarial examples[1]

- Distinguish between conferrable adversarial examples vs. other transferable ones
- Computationally expensive

Dataset inference[2]

- Distinguish between models trained with different datasets
- Susceptible to false positives/negatives under certain conditions[3]

GrOVe[4]

- Use GNN embeddings as fingerprints (for GNN models)
- Effective against high-fidelity extraction[5] but likely not against low-fidelity extraction

[1] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples,* ICLR '21 (https://openreview.net/forum?id=VqzVhqxkjH1)
[2] Maini et al. – *Dataset Inference Ownership Resolution in Machine Learning*, ICLR '21 (https://openreview.net/pdf?id=hvdKKV2yt7T)
[3] Szyller et al. – *On the Robustness of Dataset Inference*, TMLR '23 (https://arxiv.org/abs/2210.13631)
[4] Waheed et al. – *GrOVe: Ownership Verification of Graph Neural Networks using Embeddings,* IEEE S&P '24 (https://arxiv.org/abs/2304.08566)
[5] Shen et al. – *Model Stealing Attacks Against Inductive Graph Neural Networks,* IEEE S&P '22 (https://arxiv.org/abs/2112.08331)

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Takeaways

Are we using the right adversary models? Needs work

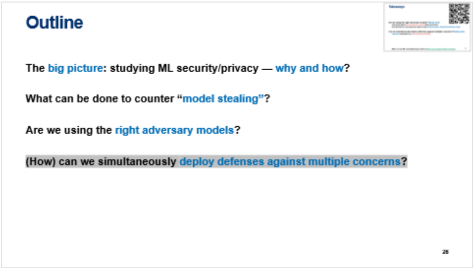
Robustness against false accusations in MORs needs improvement

More generally, ML security/privacy research needs widely accepted, streamlined adversary models

Can we simultaneously deploy defenses against multiple concerns? Needs work

Important consideration but not yet sufficiently explored

More on our ML security/privacy work at https://ssg-research.github.io/mlsec/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Robustness of model ownership resolution schemes

Model ownership resolution (MOR) must be robust against adversaries

Malicious suspect:

- tries to evade verification (e.g., pruning, fine-tuning, noising)

Malicious accuser:

- tries to frame an independent model owner
- (secure) timestamping (watermark/fingerprint and model) is the only defense in prior work

So far, research has focused on robustness against malicious suspects

False claims against MORs

We show how malicious accusers can make false claims against independent models:

- adversary deviates from watermark/fingerprint generation procedure
  - E.g., via transferrable adversarial examples
- but still subject to specified verification procedure

Our contributions:

- formalize the notion of false claims against MORs
- provide a generalization of MORs
- demonstrate effective false claim attacks
- discuss potential countermeasures

Zhang et al. – *False Claims Against Model Ownership Resolution*, Usenix SEC '24 (https://arxiv.org/abs/2304.06607)

Watermarking by backdooring[1]

Watermark generation:

- choose some out-of-distribution samples as watermark
  - assigned with incorrect labels
- train using the watermark alongside normal training data (or fine tune)
  - model memorizes watermark
- obtain timestamp on commitment of model and watermark

Watermark verification:

- query suspect model using watermark
- compare predictions to the assigned (incorrect) labels:
  - many matching / high WM accuracy → stolen
  - a few matching / low WM accuracy → not stolen
- check commitment and timestamp

[1] Adi et al. – *Turning Your Weakness Into a Strength: Watermarking Deep Neural Networks by Backdooring*, Usenix SEC 2018 (https://arxiv.org/abs/1802.04633)

Watermarking by backdooring[1]: false claim[2]

Watermark generation:

- choose some out-of-distribution samples as watermark
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[1] Adi et al. – *Turning Your Weakness Into a Strength: Watermarking Deep Neural Networks by Backdooring*, Usenix SEC 2018 (https://arxiv.org/abs/1802.04633)
[2] Zhang et al. – *False Claims Against Model Ownership Resolution*, Usenix SEC ‘24 (https://arxiv.org/abs/2304.06607)

Watermarking by backdooring[1]: false claim[2]

False watermark generation:

- choose some out-of-distribution samples
- perturb them to craft transferable adversarial examples → false watermark
- obtain timestamp on commitment of model and false watermark

Watermark verification:

- query suspect model using watermark
- compare predictions to the assigned (incorrect) labels:
  - many matching / high WM accuracy -> stolen
  - a few matching / low WM accuracy > not stolen
- check commitment and timestamp

[1] Adi et al. – *Turning Your Weakness Into a Strength: Watermarking Deep Neural Networks by Backdooring*, Usenix SEC 2018 (https://arxiv.org/abs/1802.04633)
[2] Zhang et al. – *False Claims Against Model Ownership Resolution*, Usenix SEC '24 (https://arxiv.org/abs/2304.06607)

Mitigating false claims against MORs

Judge generates watermarks/fingerprints: bottleneck

Judge verifies watermarks/fingerprints were generated correctly: expensive

Train models with transferable adversarial examples: accuracy loss

Zhang et al. – *False Claims Against Model Ownership Resolution*, Usenix SEC ‘24 (https://arxiv.org/abs/2304.06607)

The Meta Concern: sensible adversary models

Identify potential adversaries and their goals systematically

Identify adversary's knowledge and capabilities:

- **Data access**:
  - vis-à-vis target's *training data* (overlap/distribution/domain? natural/synthetic?)
  - vis-à-vis target's *inferences*
- Target **model access**: white-box/black-box/grey-box?
- **Adversary type**: honest-but-curious vs. malicious
- **Interaction type**: zero-shot/one-shot/query-budget?, adaptive?

Avoid sloppy terminology!

- "adversarial attacks" → there are no benign attacks!
- "adaptive adversaries" → cf. Kerchoff's principle!
- …

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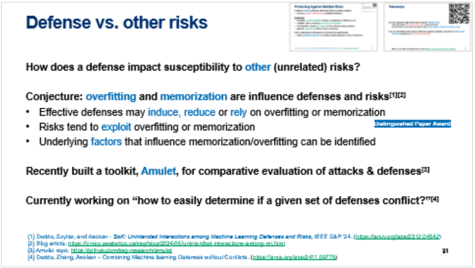
Unintended interactions



Prior work explored defenses to mitigate specific risks

- Defenses typically evaluated only vs. specific risks they protect against

But practitioners need to deploy multiple defenses simultaneously

- Can two defenses interact negatively with each other?
- Does a defense exacerbate or ameliorate some other (unrelated) risk?

Szyller and Asokan – *Conflicting Interactions Among Protections Mechanisms for Machine Learning Models*, AAAI '23 (https://arxiv.org/abs/2207.01991)

Ownership resolution vs. other security/privacy concerns

There are considerations other than model ownership resolution:

- model evasion (defense: adversarial training)
- training data reconstruction (defense: differential privacy)
- membership inference (defense: regularization, early stopping)
- model poisoning (defense: regularization, outlier/anomaly detection)
- …

How do ownership resolution schemes interact with the other defenses?

We investigated pairwise interactions of:

model watermarking data watermarking fingerprinting	**WITH**	differential privacy adversarial training

Szyller and Asokan – *Conflicting Interactions Among Protections Mechanisms for Machine Learning Models*, AAAI '23 (https://arxiv.org/abs/2207.01991)

Ownership resolution vs. other security/privacy concerns

If two techniques A and B in combination result in too high a drop in

- model accuracy (ϕ_{ACC}) or
- metric for A (ϕ_A) or
- metric for *B* (ϕ_B)

then A and B are in conflict

Defense	Dataset	Defense	
		DP	ADV. TR.
WM	MNIST	ϕ_{ACC} ϕ_{WM}	ϕ_{ACC} ϕ_{WM} ϕ_{ADV}
WM	FMNIST	ϕ_{ACC} ϕ_{WM}	ϕ_{ACC} ϕ_{WM} ϕ_{ADV}
WM	CIFAR10	ϕ_{ACC} ϕ_{WM}	ϕ_{ACC} ϕ_{WM} ϕ_{ADV}
RAD-DATA	MNIST	ϕ_{ACC} $\phi_{RAD\text{-}DATA}$	ϕ_{ACC} $\phi_{RAD\text{-}DATA}$ ϕ_{ADV}
RAD-DATA	FMNIST	ϕ_{ACC} $\phi_{RAD\text{-}DATA}$	ϕ_{ACC} $\phi_{RAD\text{-}DATA}$ ϕ_{ADV}
RAD-DATA	CIFAR10	ϕ_{ACC} $\phi_{RAD\text{-}DATA}$	ϕ_{ACC} $\phi_{RAD\text{-}DATA}$ ϕ_{ADV}
DI	MNIST	ϕ_{ACC} ϕ_{DI}	ϕ_{ACC} ϕ_{DI} ϕ_{ADV}
DI	FMNIST	ϕ_{ACC} ϕ_{DI}	ϕ_{ACC} ϕ_{DI} ϕ_{ADV}
DI	CIFAR10	ϕ_{ACC} ϕ_{DI}	ϕ_{ACC} ϕ_{DI} ϕ_{ADV}

Szyller and Asokan – *Conflicting Interactions Among Protections Mechanisms for Machine Learning Models*, AAAI '23 (https://arxiv.org/abs/2207.01991)

Interaction between ML defenses

Property	Adversarial Training	Differential Privacy	Membership Inference	Oblivious Training	Model/Gradient Inversion	Model Poisoning	Model Watermarking	Model Fingerprinting	Data Watermarking	Explainability	Fairness
Adversarial Training	X	[5]	[9]	?	?	[7]	OURS	OURS	OURS	[11]	?
Differential Privacy		X	[3, 6]	?	?	?	OURS	OURS	OURS	?	[1, 2, 8]
Membership Inference			X	?	?	[10]	?	?	?	?	?
Oblivious Training				X	?	?	?	?	?	?	?
Model/Gradient Inversion					X	?	?	?	?	?	?
Model Poisoning						X	?	?	?	?	?
Model Watermarking							X	?	?	?	?
Model Fingerprinting								X	?	[4]	?
Data Watermarking									X	?	?
Fairness										X	?
Explainability											X

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[2] Victoria Cheng, Vinith M. Suriyakumar, Natalie Dullerud, Shalmali Joshi, and Marzyeh Ghassemi. 2021. Can You Fake It Until You Make It? Impacts of Differentially Private Synthetic Data on Downstream Classification Fairness. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT '21)*. Association for Computing Machinery, New York, NY, USA, 149–160. https://doi.org/10.1145/3442188.3445879

[3] Thomas Humphries, Simon Oya, Lindsey Tulloch, Matthew Rafuse, Ian Goldberg, Urs Hengartner, and Florian Kerschbaum. 2020. Investigating Membership Inference Attacks under Data Dependencies. https://doi.org/10.48550/ARXIV.2010.12112

[4] Hengrui Jia, Hongyu Chen, Jonas Guan, Ali Shahin Shamsabadi, and Nicolas Papernot. 2022. A Zest of LIME: Towards Architecture-Independent Model Distances. In *International Conference on Learning Representations*. https://openreview.net/forum?id=OUz_9TiTv9j

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[7] Ren Pang, Hua Shen, Xinyang Zhang, Shouling Ji, Yevgeniy Vorobeychik, Xiapu Luo, Alex Liu, and Ting Wang. 2020. *A Tale of Evil Twins: Adversarial Inputs versus Poisoned Models.* Association for Computing Machinery, New York, NY, USA, 85–99. https://doi.org/10.1145/3372297.3417253

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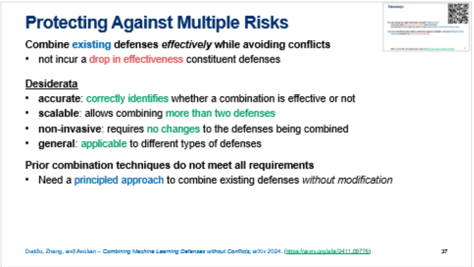
[10] Florian Tramèr, Reza Shokri, Ayrton San Joaquin, Hoang Le, Matthew Jagielski, Sanghyun Hong, and Nicholas Carlini. 2022. Truth Serum: Poisoning Machine Learning Models to Reveal Their Secrets. https://doi.org/10.48550/ARXIV.2204.00032

[11] Dimitris Tsipras, Shibani Santurkar, Logan Engstrom, Alexander Turner, and Aleksander Madry. 2019. Robustness May Be at Odds with Accuracy. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019.* https://openreview.net/forum?id=SyxAb30cY7

Szyller and Asokan – *Conflicting Interactions Among Protections Mechanisms for Machine Learning Models*, AAAI '23 (https://arxiv.org/abs/2207.01991)

Defense vs. other risks



How does a defense impact susceptibility to other (unrelated) risks?

Conjecture: overfitting and memorization are influence defenses and risks[1][2]

- Effective defenses may induce, reduce or rely on overfitting or memorization
- Risks tend to exploit overfitting or memorization
- Underlying factors that influence memorization/overfitting can be identified

Distinguished Paper Award

Recently built a toolkit, Amulet, for comparative evaluation of attacks & defenses[3]

Currently working on "how to easily determine if a given set of defenses conflict?"[4]

[1] Duddu, Szyller, and Asokan - *SoK: Unintended Interactions among Machine Learning Defenses and Risks,* IEEE S&P '24. (https://arxiv.org/abs/2312.04542)
[2] Blog article: https://crysp.uwaterloo.ca/ssg/blog/2024/05/unintended-interactions-among-ml.html
[3] Amulet repo: https://github.com/ssg-research/amulet
[4] Duddu, Zhang, Asokan – Combining Machine learning Defenses without Conflicts. (https://arxiv.org/abs/2411.09776)

Protecting Against Multiple Risks

Combine existing defenses *effectively* while avoiding conflicts

- not incur a drop in effectiveness constituent defenses

Desiderata

- **accurate**: correctly identifies whether a combination is effective or not
- **scalable**: allows combining more than two defenses
- **non-invasive**: requires no changes to the defenses being combined
- **general**: applicable to different types of defenses

Prior combination techniques do not meet all requirements

- Need a principled approach to combine existing defenses *without modification*

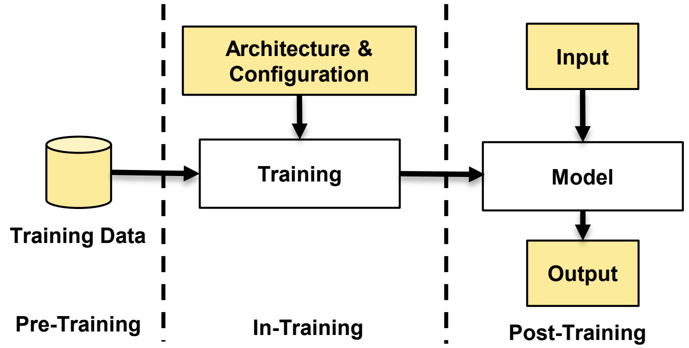
Duddu, Zhang, and Asokan – *Combining Machine Learning Defenses without Conflicts,* arXiv 2024. (https://arxiv.org/abs/2411.09776)

Combining ML Defenses without Conflicts

Intuition: account for reasons underlying conflicts among defenses

For D_1 and D_2 applied in that order, there can be a conflict if

- D_1 uses a risk protected by D_2
- Changes by D_2 overrides changes by D_1

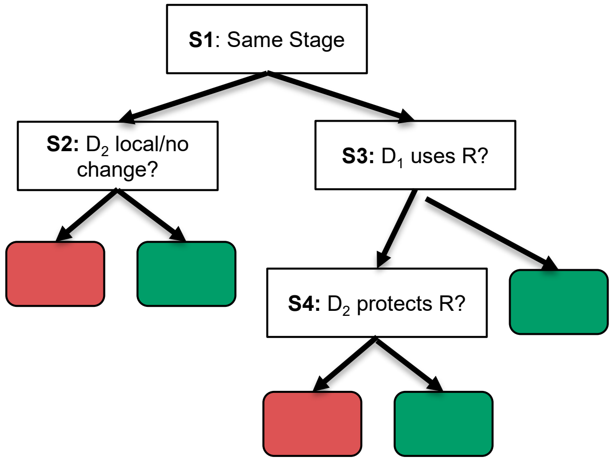


Observation:

- ML defenses operate on one of three stages of ML pipelines

DEF\CON: quickly identify effective combinations

- 90% accuracy on eight combinations from prior work
- 81% in 30 previously unexplored combinations



Duddu, Zhang, and Asokan – *Combining Machine Learning Defenses without Conflicts,* arXiv 2024. (https://arxiv.org/abs/2411.09776)

Takeaways

Are we using the right adversary models? Needs work

Robustness against false accusations in MORs needs improvement

More generally, ML security/privacy research needs widely accepted, streamlined adversary models

Can we simultaneously deploy defenses against multiple concerns? Needs work

Important consideration but not yet sufficiently explored

More on our ML security/privacy work at https://ssg-research.github.io/mlsec/

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Other research topics:

ML security/privacy:

ML ownership resolution, Conflicting ML defenses, ML property attestation, robust concept removal in gen AI

Platform security: hardware-assisted run-time security, secure outsourced computing

Open (postdoc, grad student) positions to help lead our work: ML security/privacy, platform security

https://asokan.org/asokan/research/SecureSystems-open-positions-Jan2024.php