False Claims Against Model Ownership Resolution

N. Asokan
https://asokan.org/asokan/
@nasokan

(Joint work with Rui Zhang, Jian Liu, Sebastian Szyller, and Kui Ren)

Under review. (https://arxiv.org/abs/2304.06607)

Outline

Motivation

Generalization

False claims

Countermeasures

Model theft is an important concern

Machine learning models: business advantage and intellectual property (IP)

Cost of

- gathering relevant data
- labeling data
- expertise required to choose the right model training method
- resources expended in training

Adversary who steals the model can avoid these costs

Defending against model theft

We can try to:

- prevent (or slow down) model theft, including model extraction or
- detect it

But appears to be infeasible against strong but realistic adversaries[1]

Or deter the attacker by providing the means for model ownership resolution (MOR):

- fingerprinting
- watermarking

promising but many MOR schemes so far have various caveats and vulnerabilities[2,3,4]

[1] Atli et al. - *Extraction of Complex DNN Models: Real Threat or Boogeyman?* AAAI-EDSML 2020 (https://arxiv.org/abs/1910.05429)
[2] Lukas et al. – *Sok: How Robust is Image Classification Deep Neural Network Watermarking?* IEEE S&P 2022 (https://arxiv.org/abs/2108.04974)
[3] Shafieinejad et al. - *On the Robustness of Backdoor-based Watermarking Schemes,* IHMS 2021 (https://arxiv.org/abs/1906.07745)
[4] Szyller et al. – *On the Robustness of Dataset Inference* (https://arxiv.org/abs/2210.13631)

MOR generalization

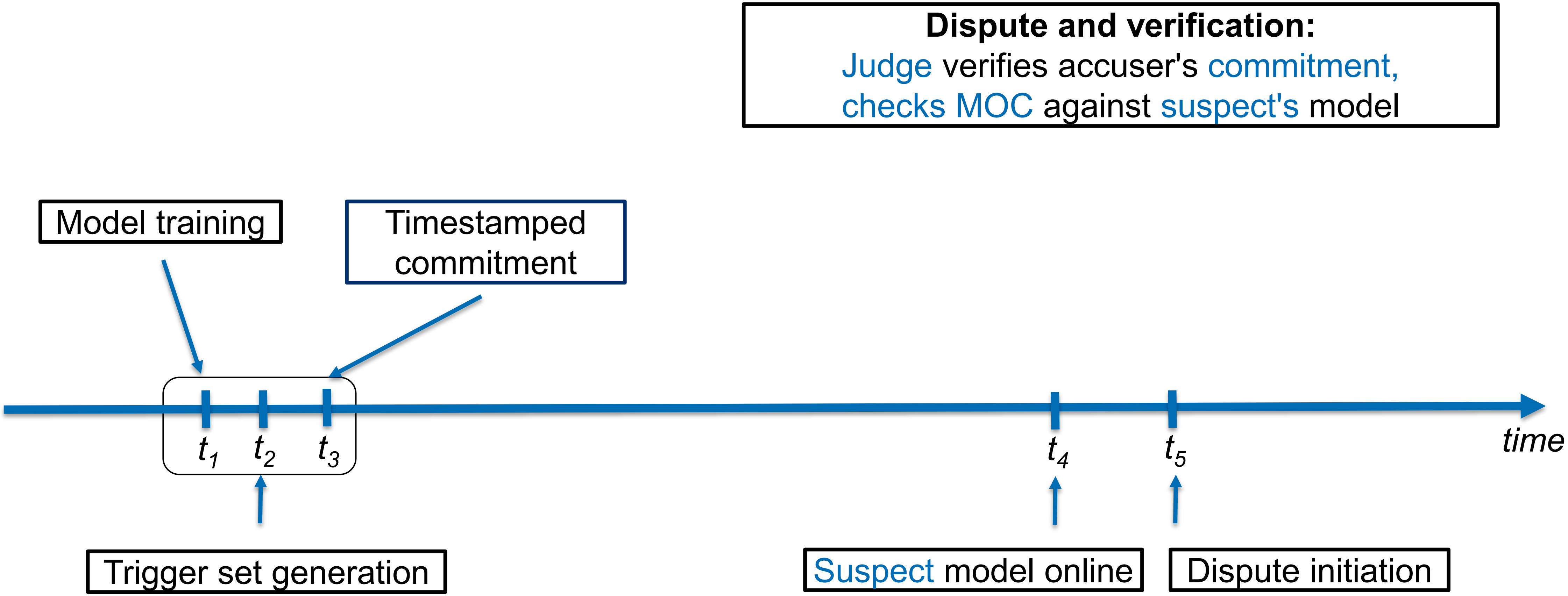
Claim generation:

- model owner (potential accuser) generates “model ownership claim” (MOC)
  - includes trigger sets: e.g., watermarks or fingerprints
  - stolen vs. independent models likely to behave differently on input from trigger set
  - obtains a secure timestamp on trigger set (+ model + other data) commitment

Claim verification:

- accuser initiates MOR against a suspect by sending MOC to a judge
- judge verifies timestamped MOC + interacts with both models to resolve ownership
  - decides if suspect has stolen accuser’s model

MOR process



Dispute and verification:
Judge verifies accuser's commitment,
checks MOC against suspect's model
Model training
Timestamped commitment
t_1 t_2 t_3
t_4
t_5
time
Trigger set generation
Suspect model online
Dispute initiation

Robustness of MOR schemes

MOR schemes must be robust against two types of attackers.

Malicious suspect:
- tries to evade verification
- common approaches: pruning, fine-tuning, noising

Malicious accuser:
- tries to frame an independent model owner
- timestamping commitments (of trigger set etc.) is the only defense in prior work

So far, research has focused on malicious suspects

False claims against MOR schemes

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

- adversary deviates from claim generation procedure (e.g., via transferrable adversarial examples)
- but still subject to specified verification procedure

Our contributions:

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

MOR instantiations

Watermarking:

- **watermarking by backdooring**[3]
  - out-of-distribution backdoor embedded during training
- **adversarial watermarking**[4]
  - flip labels for a subset of queries during inference, designed to deter model extraction

Fingerprinting:

- **model fingerprinting**[5]
  - conferrable adversarial examples, transfer only to stolen models
- **Dataset Inference**[6]
  - stolen models likely to have similar decision boundaries

[3] Adi et al. – *Turning Your Weakness Into a Strength: Watermarking Deep Neural Networks by Backdooring*, USENIX 2018 (https://arxiv.org/abs/1802.04633)
[4] Szyller et al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks*, ACM MM 2021 (https://arxiv.org/abs/1906.00830)
[5] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples*, ICLR 2021 (https://arxiv.org/abs/1912.00888)
[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

Watermarking by backdooring[3]

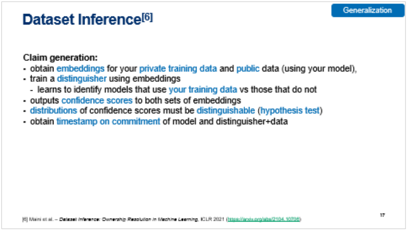
Claim generation:

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

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

Generalization

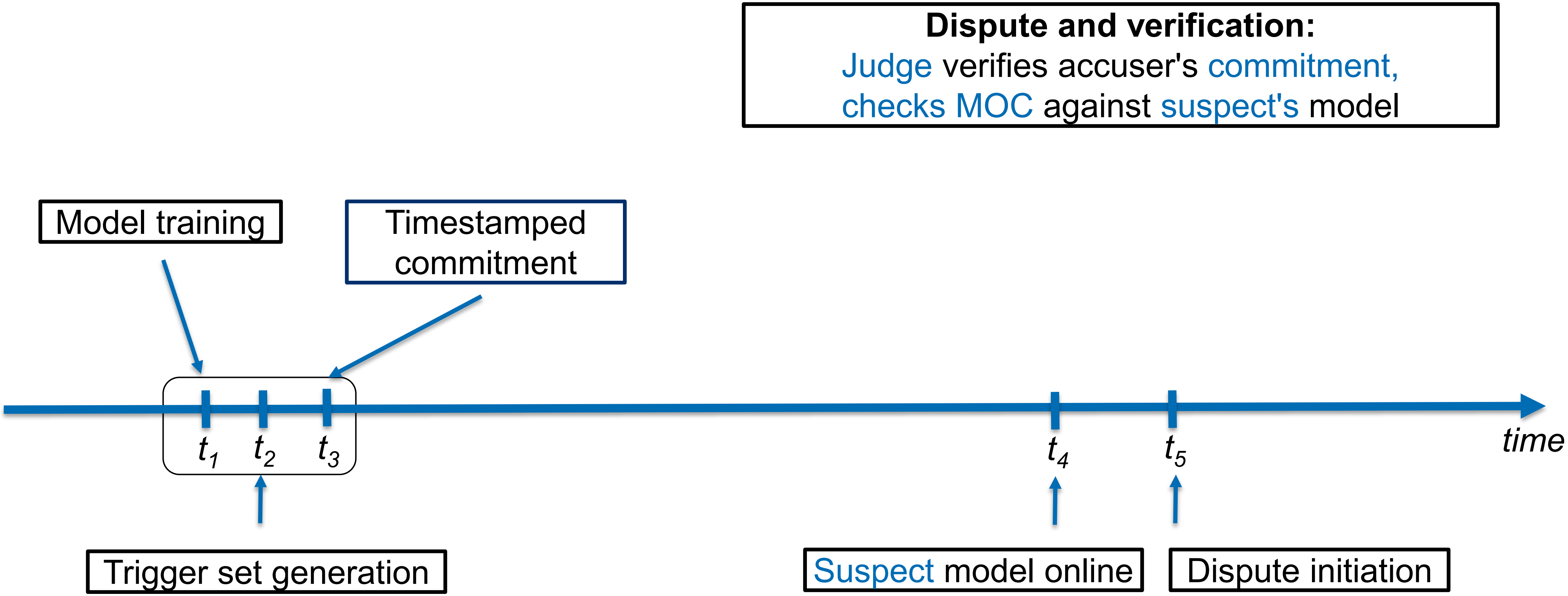
Watermarking by backdooring[3]: verification



Claim 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

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

MOR process


Dispute and verification:
Judge verifies accuser's commitment,
checks MOC against suspect's model
Model training
Timestamped commitment
t_1 t_2 t_3
t_4
t_5
time
Trigger set generation
Suspect model online
Dispute initiation

DAWN[4]

Claim generation:

- clients submit queries
- pseudo-randomly select a fraction of queries as watermark (per-client)
- each watermark consists of pairs of inputs with pseudo-randomly flipped labels
- obtain timestamp on commitment of model and watermark
- adversary embeds watermark while training their surrogate models

[4] Szyller et al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks*, ACM MM 2021 (https://arxiv.org/abs/1906.00830)

DAWN[4]: verification

Claim verification:

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

[4] Szyller et al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks*, ACM MM 2021 (https://arxiv.org/abs/1906.00830)

Conferrable adversarial examples[5]

Claim generation:

- extract your own model many times: many surrogate models
- train many independent reference models
- generate conferrable adversarial examples:
  - must transfer from your model to surrogate models
  - must not transfer to reference models
- conferrable examples are the fingerprint
- obtain timestamp on commitment of model and fingerprint.

[5] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples*, ICLR 2021 (https://arxiv.org/abs/1912.00888)

Conferrable adversarial examples[5]: verification

Claim verification:

- query suspect model using fingerprint
- compare suspect's predictions to the ground truth:
  - suspect is fooled / gives incorrect prediction → stolen
  - suspect is not fooled / gives correct predictions → not stolen
- check commitment and timestamp

[5] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples*, ICLR 2021 (https://arxiv.org/abs/1912.00888)

Dataset Inference[6]

Claim generation:

- obtain embeddings for your private training data and public data (using your model),
- train a distinguisher using embeddings
  - learns to identify models that use your training data vs those that do not
- outputs confidence scores to both sets of embeddings
- distributions of confidence scores must be distinguishable (hypothesis test)
- obtain timestamp on commitment of model and distinguisher+data

[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

Dataset Inference[6]: verification

Claim verification:

- query suspect model to obtain embeddings
- get confidence scores using distinguisher
- compare distributions:
  - distinguishable → stolen
  - indistinguishable → not stolen
- check commitment and timestamp

[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

Inducing successful false claims

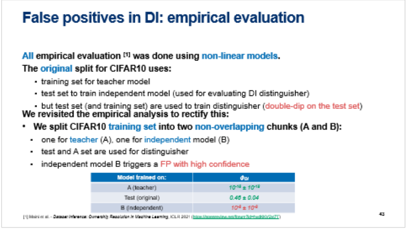
Core idea: Accuser deviates from specified MOC generation procedure

For most schemes

- generate transferable adversarial examples and register them as false trigger set

For DI

- false positives occur naturally when training data distributions are similar[7]
- generate false “private” data that fits distribution of independent training data
- obtain timestamp on false private data and resulting false distinguisher



[7] Szyller et al. – *On the Robustness of Dataset Inference* (https://arxiv.org/abs/2210.13631)

Watermarking by backdooring[3]

False claims

Claim generation:

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

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

False claims

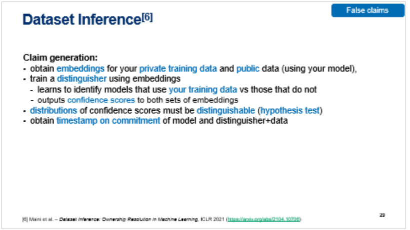
Watermarking by backdooring[3]: false claim

Claim generation:

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

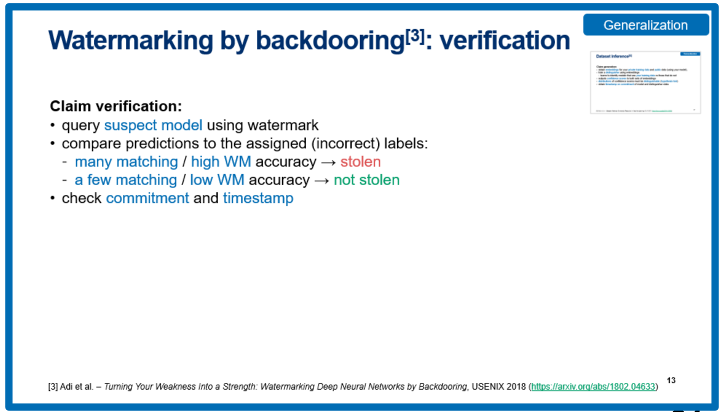
[3] Adi et al. – *Turning Your Weakness Into a Strength: Watermarking Deep Neural Networks by Backdooring*, USENIX 2018 (https://arxiv.org/abs/1802.04633)

Watermarking by backdooring[3]: false claim



False claim generation:

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



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

DAWN[4]

Claim generation:
- clients submit queries
- pseudo-randomly select a fraction of queries as watermark (per-client)
- each watermark consists of pairs of inputs with pseudo-randomly flipped labels
- obtain timestamp on commitment of model and watermark
- adversary embeds watermark while training their surrogate models

[4] Szyller et al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks*, ACM MM 2021 (https://arxiv.org/abs/1906.00830)

DAWN[4]: false claim

Claim generation:

- clients submit queries
- pseudo-randomly select a fraction of queries as watermark (per-client)
- each watermark consists of pairs of inputs with pseudo-randomly flipped labels
- obtain timestamp on commitment of model and watermark
- adversary embeds the watermark while training their surrogate models

[4] Szyller et al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks*, ACM MM 2021 (https://arxiv.org/abs/1906.00830)

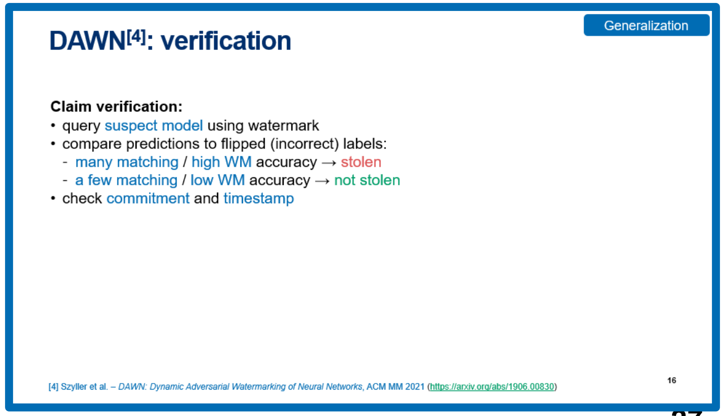
DAWN[4]: false claim

False claim generation:

- clients submit queries
- pseudo-randomly select a fraction of the queries for the false watermark

- perturb each chosen query to craft targeted transferable adversarial examples
  - labels need to match the pseudo-random flip

- obtain timestamp on commitment of model and false watermark



[4] Szyller et al. – *DAWN: Dynamic Adversarial Watermarking of Neural Networks*, ACM MM 2021 (https://arxiv.org/abs/1906.00830)

False claims

Conferrable adversarial examples[5]

Claim generation:

- extract your own model many times: many surrogate models
- train many reference models
- generate conferrable adversarial examples:
  - must transfer from your model to surrogate models
  - must not transfer to reference models
- conferrable examples are the fingerprint
- obtain timestamp on commitment of model and fingerprint

[5] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples*, ICLR 2021 (https://arxiv.org/abs/1912.00888)

Conferrable adversarial examples[5]: false claim

Claim generation:

- extract your own model many times: many surrogate models
- train many reference models
- generate conferrable adversarial examples:
  - must transfer from your model to surrogate models
  - must not transfer to reference models
- conferrable examples are the fingerprint
- obtain timestamp on commitment of model and fingerprint

[5] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples*, ICLR 2021 (https://arxiv.org/abs/1912.00888)

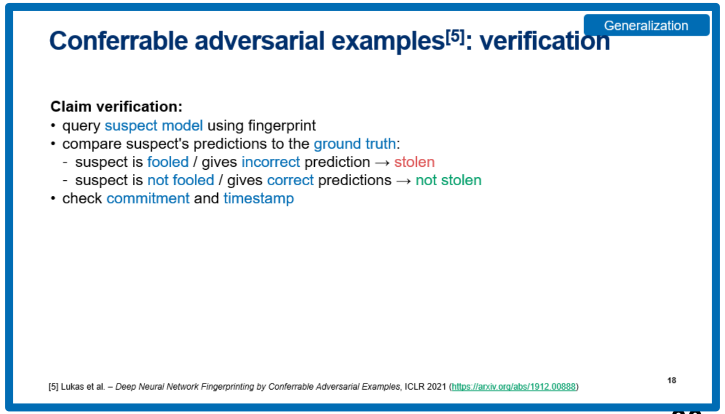
Conferrable adversarial examples[5]: false claim

False claim generation:

- (optional) extract your own model many times: to strengthen transferability

- ignore any reference models
- craft transferable adversarial examples
- transferable adversarial examples are the false fingerprint

- obtain timestamp on commitment of model and false fingerprint



[5] Lukas et al. – *Deep Neural Network Fingerprinting by Conferrable Adversarial Examples*, ICLR 2021 (https://arxiv.org/abs/1912.00888)

Dataset Inference[6]

Claim generation:

- obtain embeddings for your private training data and public data (using your model),
- train a distinguisher using embeddings
  - learns to identify models that use your training data vs those that do not
  - outputs confidence scores to both sets of embeddings
- distributions of confidence scores must be distinguishable (hypothesis test)
- obtain timestamp on commitment of model and distinguisher+data

[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

Dataset Inference[6]: false claim

Claim generation:

- obtain embeddings for your private training data and public data (using your model),
- train a distinguisher using embeddings
  - learns to identify models that use your training data vs those that do not
  - outputs confidence scores to both sets of embeddings
- distributions of confidence scores must be distinguishable (hypothesis test)
- obtain timestamp on commitment of model and distinguisher+data

[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

False claims

Dataset Inference[6]: false claim

False claim generation:

- obtain embeddings for public data (using your model)

- sample false “private” data, perturb to generate large prediction margins (on your model) (these will transfer to independent models)
- train a false distinguisher using both sets of embeddings (outputs fake confidence scores)
- distributions now distinguishable for all independent models (hypothesis test)

- obtain timestamp on commitment of model and false distinguisher+data


Generalization

Dataset Inference[6]: verification

Claim verification:
- query suspect model to obtain embeddings
- get confidence scores using distinguisher
- compare distributions:
  - distinguishable → stolen
  - indistinguishable → not stolen
- check commitment and timestamp

[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

20

[6] Maini et al. – *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://arxiv.org/abs/2104.10706)

Evaluation

Our attacks are effective:

- evaluated against Adi et al., DAWN, Lukas et al., DI
  - using CIFAR10, ImageNet, CelebA (Amazon Rekognition API)
- also applicable to others that follow our generalization

Attack efficacy compared to three thresholds (T):

- independent: judge trains independent models and picks the highest T
  - easy for false claims, difficult to evade detection
- extracted: judge derives extracted models and picks the lowest T
  - easy to evade detection, difficult for false claims
- mixed: average of independent and extracted models
  - realistic for actual deployments

For DI, naturally occurring FPs[7] make “extracted” threshold > “mixed” threshold!

[7] Szyller et al. – *On the Robustness of Dataset Inference* (https://arxiv.org/abs/2210.13631)

False claims

Evaluation: CIFAR10

		Backdooring	DAWN	Conferrable	DI
T	independent	10.0	1.0	28.0	90.0
	mixed	29.0	38.5	57.5	81.4
	extracted	48.0	76.0	87.0	72.8
Suspect MOR accuracy	diff. arch. & diff. data	<u>**94.3**</u>	**69.3**	<u>**94.3**</u>	<u>**100.0**</u>
	same arch. & diff. data	<u>**98.0**</u>	<u>**100.0**</u>	<u>**98.0**</u>	<u>**99.1**</u>
	same arch. & same data	<u>**99.0**</u>	<u>**78.3**</u>	<u>**99.0**</u>	<u>**98.6**</u>

False claim accuracy:

- **bold:** higher than mixed T (realistic)
- <u>**underlined**</u>: higher than extracted T (difficult for false claims)

For DI, naturally occurring FPs[7] lead to a different threshold order “extracted” < “mixed” < “independent”!

[7] Szyller et al. – *On the Robustness of Dataset Inference* (https://arxiv.org/abs/2210.13631)

Evaluation: ImageNet

		Backdooring	DAWN	Conferrable	DI
T	independent	15.0	3.0	14.0	76.5
	mixed	23.5	42.5	30.0	69.6
	extracted	32.0	82.0	46.0	62.6
Suspect MOR accuracy	diff. arch. & diff. data	**72.6**	**87.6**	**72.6**	**100.0**
	same arch. & diff. data	**93.7**	**97.0**	**93.7**	**100.0**
	same arch. & same data	**84.6**	**89.0**	**84.6**	**100.0**

False claim accuracy:

- **bold:** higher than mixed T (realistic)
- **underlined**: higher than extracted T (difficult for false claims)

For DI, naturally occurring FPs[7] lead to a different threshold order “extracted” < “mixed” < “independent”!

[7] Szyller et al. – *On the Robustness of Dataset Inference* (https://arxiv.org/abs/2210.13631)

Evaluation: CelebA (Amazon Rekognition API)

		Backdooring	DAWN	Conferrable	DI
T	independent	25.7	7.0	21.0	20.0
	mixed	42.4	26.0	28.5	14.1
	extracted	59.0	45.0	36.0	8.2
Suspect MOR accuracy	diff. arch. & diff. data (Amazon Rekognition API)	<u>**68.4**</u>	<u>**68.0**</u>	<u>**68.4**</u>	<u>**99.9**</u>

False claim accuracy:

- **bold:** higher than mixed T (realistic)
- <u>**underlined**</u>: higher than extracted T (difficult for false claims)

For DI, naturally occurring FPs[7] lead to a different threshold order “extracted” < “mixed” < “independent”!

[7] Szyller et al. – *On the Robustness of Dataset Inference* (https://arxiv.org/abs/2210.13631)

Countermeasures 1/4

False claims undermine confidence in all MOR schemes.
How to prevent them?

Approach 1: Judge-verified trigger sets I

- use verifiable computation (VC): ensure that trigger set was generated correctly
- does not capture watermark selection: false claims still possible
- applicable to fingerprinting schemes
  - expensive: must include model training, otherwise still unsafe
  - not applicable to DI: accuser can manipulate their training data

Countermeasures 2/4

False claims undermine confidence in all MOR schemes.
How to prevent them?

Approach 2: Judge-verified trigger sets II

- judge trains multiple independent models: rejects trigger sets that flag them as stolen
- effective for all schemes
- costly for judge: but amortizable, and rare (only when dispute arises)
- needs appropriate training data
- accuser can try to extract or evade the independent models
  - each MOR invocation must be expensive to deter repeated attempts
  - little impact on legitimate MOR invocations

Countermeasures 3/4

False claims undermine confidence in all MOR schemes.
How to prevent them?

Approach 3: Judge-generated trigger sets

- judge generates all trigger sets: all subsequent claims must use these
- effective for several schemes
  - not applicable to DAWN: clients choose their queries
  - not applicable to DI: data/model can be manipulated before MOC generation
- judge becomes a bottleneck if judge must be involved even if there is no dispute
  - for fingerprinting schemes trigger set generation can be deferred until dispute

Countermeasures 4/4

False claims undermine confidence in all MOR schemes.
How to prevent them?

Approach 4: defenses against transferable adversarial examples
- adversarial training: likely effective but can incur accuracy loss
- adversarial purification: expensive and too slow for real-time prediction
- detection of adversarial examples (e.g., by judge): open research problem

Approach 5 (DAWN-only): signing queries
- require all clients to sign their queries
- judge verifies that queries were not manipulated
- effective if clients do not collude with accuser (clients can be punished for stolen models)

Conclusion

Model theft is an important concern.

MOR schemes have varying degree of robustness

All current MOR schemes are vulnerable to false claims:
- **possible to accuse/frame independent model owners**

Countermeasures may be costly

Do efficient scheme-specific countermeasures exist?

Zhang, Liu, Szyller, Ren, Asokan – *False Claims Against Model Ownership Resolution* (https://arxiv.org/abs/2304.06607)

More on our security + ML research at: https://ssg.aalto.fi/research/projects/mlsec/model-extraction/

Backup slides

False positives in DI: empirical evaluation

All empirical evaluation [1] was done using non-linear models.

The original split for CIFAR10 uses:

- training set for teacher model
- test set to train independent model (used for evaluating DI distinguisher)
- but test set (and training set) are used to train distinguisher (double-dip on the test set)

We revisited the empirical analysis to rectify this:

- **We split CIFAR10 training set into two non-overlapping chunks (A and B):**
  - one for teacher (A), one for independent model (B)
  - test and A set are used for distinguisher
  - independent model B triggers a FP with high confidence

Model trained on:	ϕ_{DI}
A (teacher)	$10^{-18} \pm 10^{-18}$
Test (original)	0.46 ± 0.04
B (independent)	$10^{-8} \pm 10^{-8}$

[1] Maini et al. - *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://openreview.net/forum?id=hvdKKV2yt7T)

False positives in DI: theoretical analysis

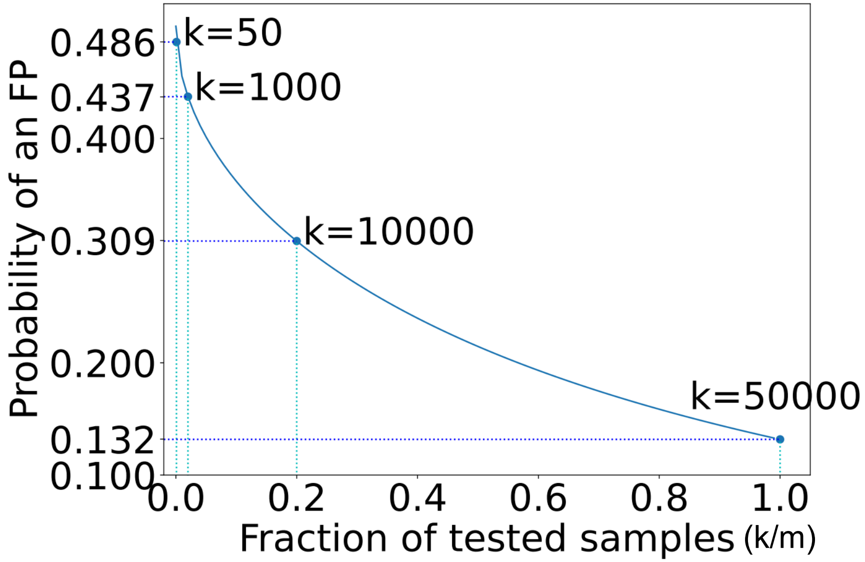
But theoretical analysis [1] of DI was done for linear models only.
We revisited the theoretical analysis as well.

For linear models, our analysis shows that:

- false positives are more probable than in their original analysis (in certain cases)
  - require revealing substantially more data to resolve

For non-linear models, our analysis shows that:

- false positives exist with probability 0.5



k = # verification samples, m = *size of training set*

[1] Maini et al. - *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://openreview.net/forum?id=hvdKKV2yt7T)

False positives in DI: linear model analysis

Setup: data consists of input-label pairs <x, y**>**

x has a signal component x_1 (dim: *K*) and a noise component x_2 (dim: *D*)

$\mathbf{x_1}$ results from y modulating a fixed vector u. $\mathbf{x_2}$ is Gaussian (*N*) with variance σ

DI assumes that *D* is large.

Consider a subspace with a large σ for *N*: ***D* should be small to ensure utility** (lemma)

Lemma 3.1 (Need for Bounding Noise Dimension). *Let f be a linear model trained on $\mathcal{S} \sim \mathcal{D}$. For a sample $(\boldsymbol{x}, y)$ sampled from $\mathcal{D}$ which is independent of $\mathcal{S}$, assuming that $||\boldsymbol{u}||_2 \leq \frac{1}{\sqrt{m}}$ and $\sigma^2 > \frac{1}{\sqrt{m}}$, then, the linear model f correctly classifies $(\boldsymbol{x}, y)$ with a probability larger than 0.9 only if $D < 10$.*

But when *D* is small, avoiding FPs requires revealing more data (high *k*) (theorem)

Theorem 3.2 (Existence of False Positives with Linear Suspect Models). *Let $f_{\mathcal{I}}$ be a linear classifier trained on the independent dataset $\mathcal{S}_I \sim \mathcal{D}$ with accuracy more than 0.9. Assume that $|\mathcal{S}_I| = m$, $||\boldsymbol{u}||_2 \leq \frac{1}{\sqrt{m}}$ and $\sigma^2 > \frac{1}{\sqrt{m}}$. Let k be the number of samples estimated required for the verification. Then, the probability that $\mathcal{V}$ mistakenly decides that $f_{\mathcal{I}}$ is a stolen model $P[\Psi(f_{\mathcal{I}}, \mathcal{S}_V; \mathcal{D}) = 1] > 1 - \Phi(\frac{\sqrt{k}}{\sqrt{m}})$.*

	General	Membership Inference	DI
Required # of verif. samples	k	k=1	k=m
Target FPR		~ 0.5	~ 0

False positives in DI: non-linear model analysis

Non-Linear models: False positives occur when $|E(p(f_{\mathcal{V}}, \boldsymbol{x}) - p(f_{\mathcal{I}}, \boldsymbol{x}))| \le \epsilon.$

Margin *p(f, x)* is the same as loss function:

$$\mathcal{L}_{\gamma}(f, y) = \mathbb{P}_{(\boldsymbol{x}, y)\sim\mathcal{D}}[f(x)[y] - max_{j\neq y} f(x)[j] \le \gamma].$$

Bound for expected loss and empirical loss in PAC-Bayes framework :

$$|\mathcal{L}_{\mathcal{D}}(f_{\mathcal{S}}) - \hat{\mathcal{L}}_{\mathcal{S}}(f_{\mathcal{S}})| \le \mathcal{O}(\epsilon),$$

Bound for margin:

Theorem 3.3 (k-independent False Positives with Non-linear Suspect Models). *For the victim private dataset $\mathcal{S}_V \sim \mathcal{D}$ and an independent dataset $\mathcal{S}_I \sim \mathcal{D}$, let $f_{\boldsymbol{w}}$ be a $d-$layer feed-forward network with ReLU activations and parameters $\boldsymbol{w} = \{W_i\}_{i=1}^{d}$. Assume that $f_{\mathcal{V}}$ is trained on $\mathcal{S}_V$ and $f_{\mathcal{I}}$ is trained on $\mathcal{S}_I$, $f_{\mathcal{V}}$ and $f_{\mathcal{I}}$ have the same structure. Then, for any $B, d, h, \epsilon > 0$ and any $\boldsymbol{x} \in \mathcal{X}$, there exist a prior $\mathcal{P}$ on $\boldsymbol{w}$, s.t. with probability at least $\frac{1}{2}$,*

$$|E(p(f_{\mathcal{V}}, \boldsymbol{x}) - p(f_{\mathcal{I}}, \boldsymbol{x}))| \le \epsilon.$$

FPs likely when suspect model's and victim model's training data have the same distribution

False negatives in DI: empirical evaluation

DI relies on noisy queries to identify decision boundaries.

Can adversary avoid detection?

- **Regularise model's decision boundaries using adversarial training**
  - during training replace each clean sample with an adversarial example

- **Adversarial training results in a false negative:**
  - p-value similar to an independent model
  - accuracy drop of ~6pp (0.93 ± 0.01 to 0.87 ± 0.02)

Model trained on:	ϕ_{DI}
Teacher	$10^{-21} \pm 10^{-16}$
Test	0.46 ± 0.035
Adversarial	0.15 ± 0.07

Challenging the Private Data Assumption

DI relies on private data:

- it requires revealing it to verify ownership
- in the worst case (adversarial training), victim can reveal a lot and still fail
- cryptographic protocols for oblivious inference could be a solution but:
  - slow/expensive and harder to deploy (all potential suspects must implement the protocols)

Also, DI relies on unique training data:

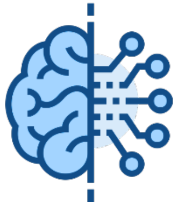
- reasonable in many domains
- but difficult to guarantee in others, e.g., local insurance companies
- can lead to false accusations

Ownership Verification of ML Models

Each ownership verification method has its own strengths/shortcomings

WATERMARKING
- White box theft
- Model stealing

Easy to deploy but brittle



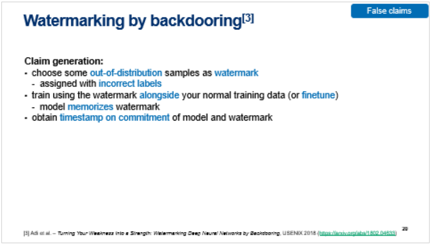
Ownership verification of ML models

DATASET INFERENCE[1]

More robust than watermarking but (i) risks FPs, FNs and (ii) collides with privacy

OTHER FINGERPRINTING
- Conferrable adv. examples[2]
- Passport layers[3]

More robust than watermarking but hard to deploy



[1] Maini et al. - *Dataset Inference: Ownership Resolution in Machine Learning*, ICLR 2021 (https://openreview.net/forum?id=hvdKKV2yt7T)
[2] Lukas et al. - *Deep Neural Network Fingerprinting By Conferrable Adversarial Examples*, ICLR 2021 (https://openreview.net/forum?id=VqzVhqxkjH1)
[3] Lixin et al. - *Rethinking Deep Neural Network Ownership Verification: Embedding Passports to Defeat Ambiguity Attacks*, NeurIPS 2019 (https://arxiv.org/abs/1909.07830)