Overconfidence is a Dangerous Thing:
Mitigating Membership Inference Attacks by Enforcing Less Confident Prediction

Zitao Chen, Karthik Pattabiraman

THE UNIVERSITY
OF BRITISH COLUMBIA

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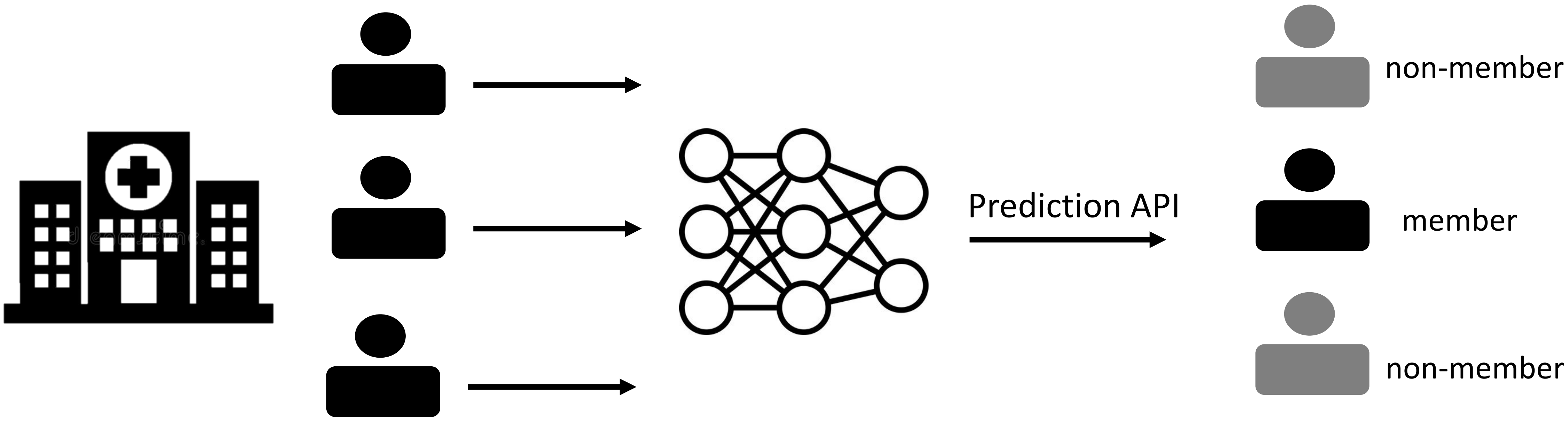
Membership Inference Attacks (MIAs)



Does the sensitive training set contain a target record?

MIAs as a privacy threat

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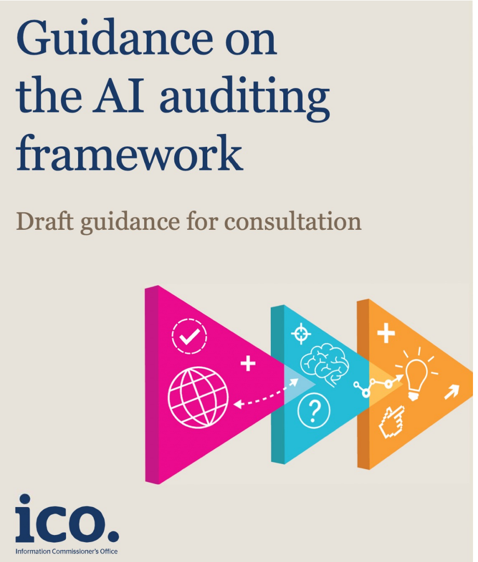
Confidentiality violation

MIAs as a privacy threat



Guidance on the AI auditing framework

Draft guidance for consultation

ico.

Information Commissioner's Office

Confidentiality violation

Auditing purpose

https://ico.org.uk/media/about-the-ico/consultations/2617219/guidance-on-the-ai-auditing-framework-draft-for-consultation.pdf

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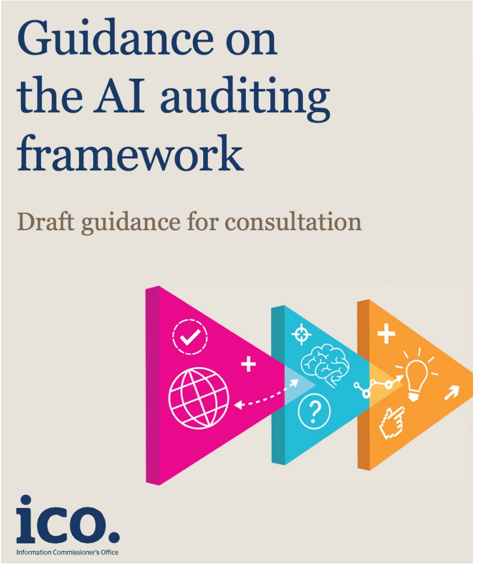
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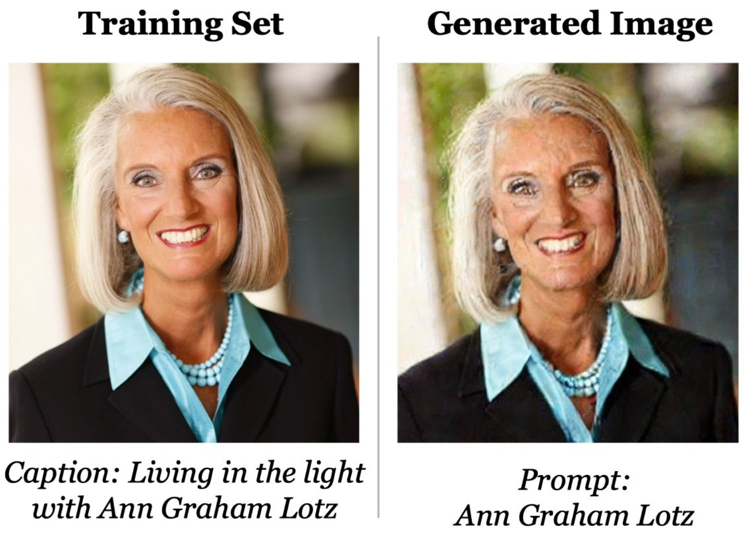

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Auditing purpose

Stepping stone for more powerful attack

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Carlini et al., Extracting Training Data from Diffusion Models, USENIX’23

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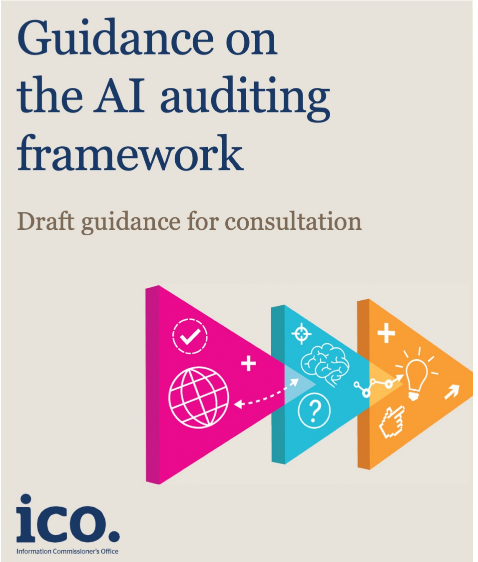

Training Set | **Generated Image**

Caption: Living in the light with Ann Graham Lotz

Prompt: Ann Graham Lotz

Confidentiality violation

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Stepping stone for more powerful attack

We need effective defense against MIAs!

https://ico.org.uk/media/about-the-ico/consultations/2617219/guidance-on-the-ai-auditing-framework-draft-for-consultation.pdf

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Existing defenses

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Poor privacy-utility trade off or requiring additional data

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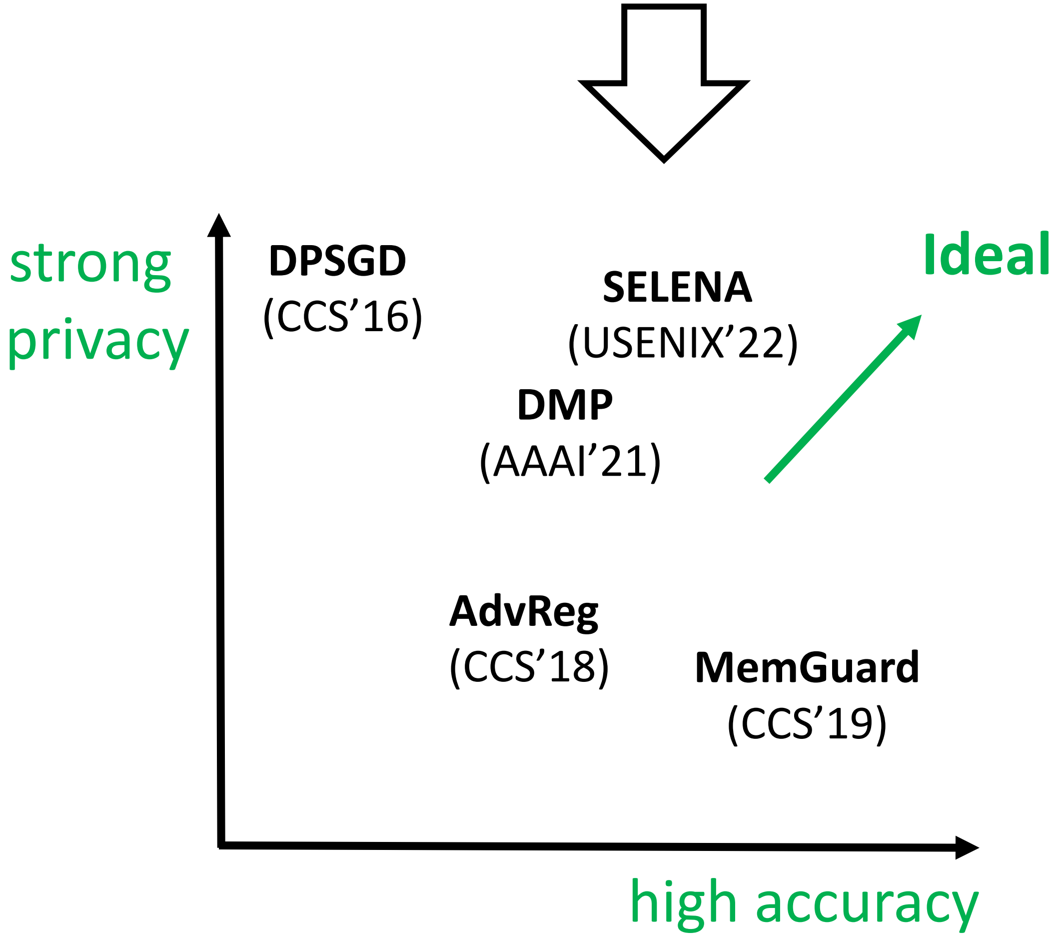

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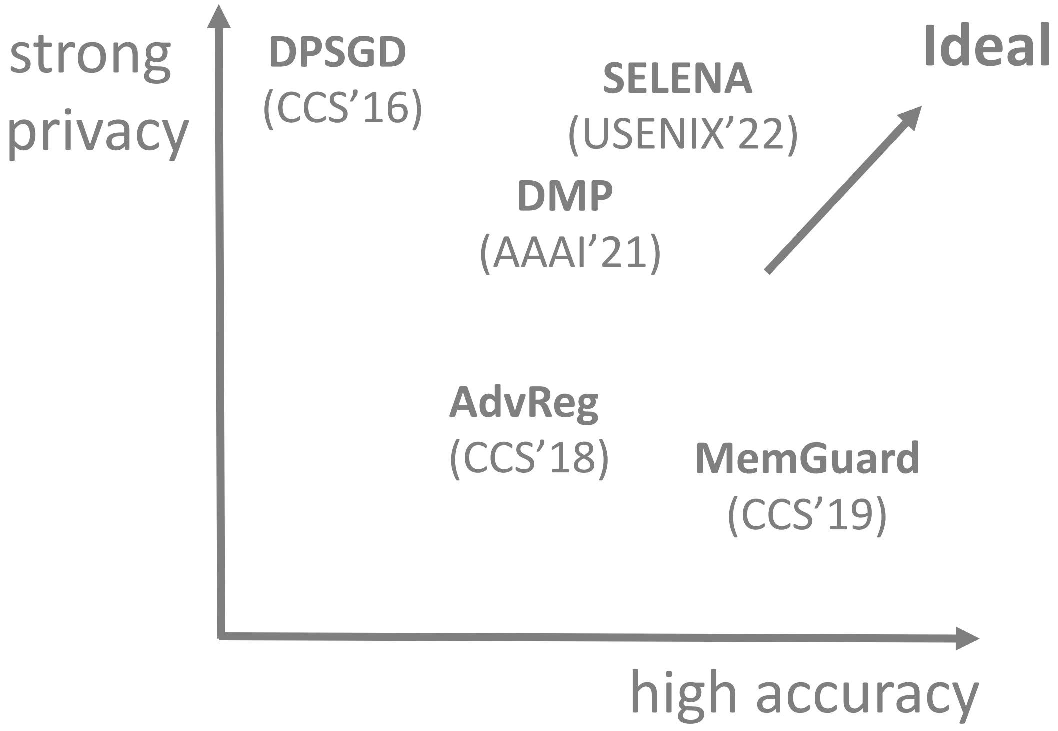
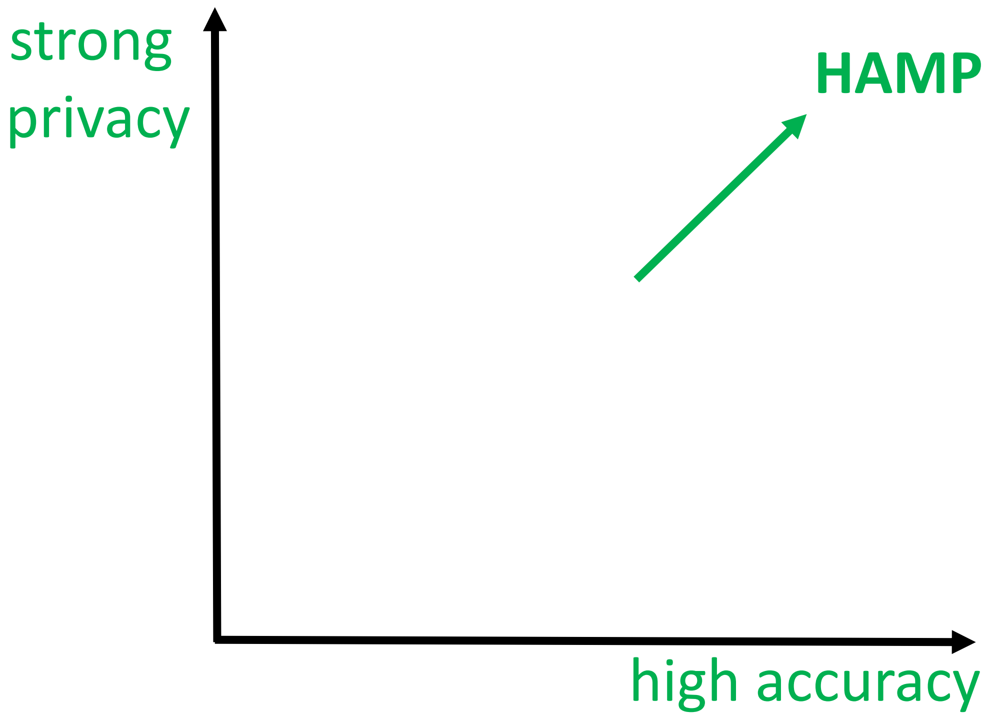


DMP (AAAI'21) **MMD** (CODASPY'21) **PATE** (ICLR'17)

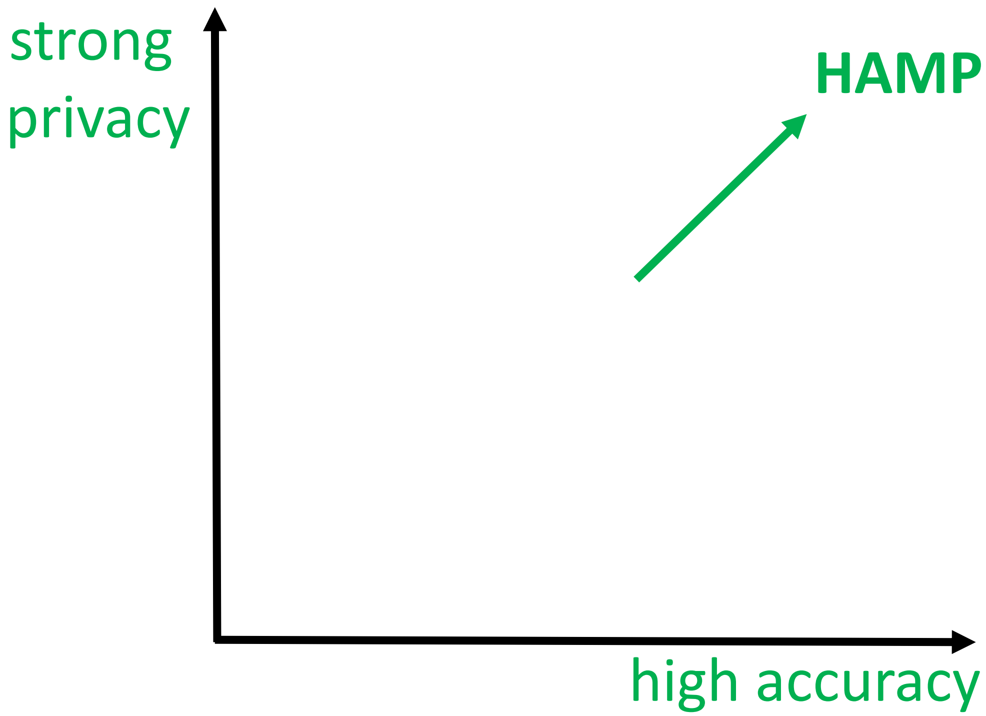
Our Work: HAMP

High Accuracy and Membership Privacy without additional data



Our Work: HAMP

A new way to combine soft label training, training regularization and output modification for privacy-preserving training!



Threat model

Adversary

- **Knowledge**:
  - Black-box adversary.
  - Half members and non-members.
  - Full defense knowledge.

- **Goal**: Membership inference

Threat model

Adversary

- **Knowledge**:
  - Black-box adversary.
  - Half members and non-members.
  - Full defense knowledge.
- **Goal**: Membership inference

Defender

- **Knowledge**:
  - The private dataset only.
- **Goal**: Model with high accuracy & membership privacy

Existing attacks

Diverse strategies

Existing attacks

Diverse strategies

- Scaled-logit loss
- Prediction entropy
- Adv robustness
- ...

Existing attacks

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Common exploitation

Existing attacks

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Common exploitation

Exploit ML model's overconfident prediction on training samples

Existing attacks

Diverse strategies

Scaled-logit loss

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Common exploitation

Exploit ML model's overconfident prediction on training samples

Overconfident Prediction manifest as

Existing attacks

Diverse strategies

- Scaled-logit loss
- Prediction entropy
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- …

Common exploitation

Exploit ML model's overconfident prediction on training samples

Overconfident Prediction manifest as

- High logit-scaled loss;
- Low prediction entropy;
- High robustnesss to adv perturbations;
- …

Example: Overconfident prediction via logit-scaled loss

Carlini et al., Membership Inference Attacks From First Principles, S&P’22

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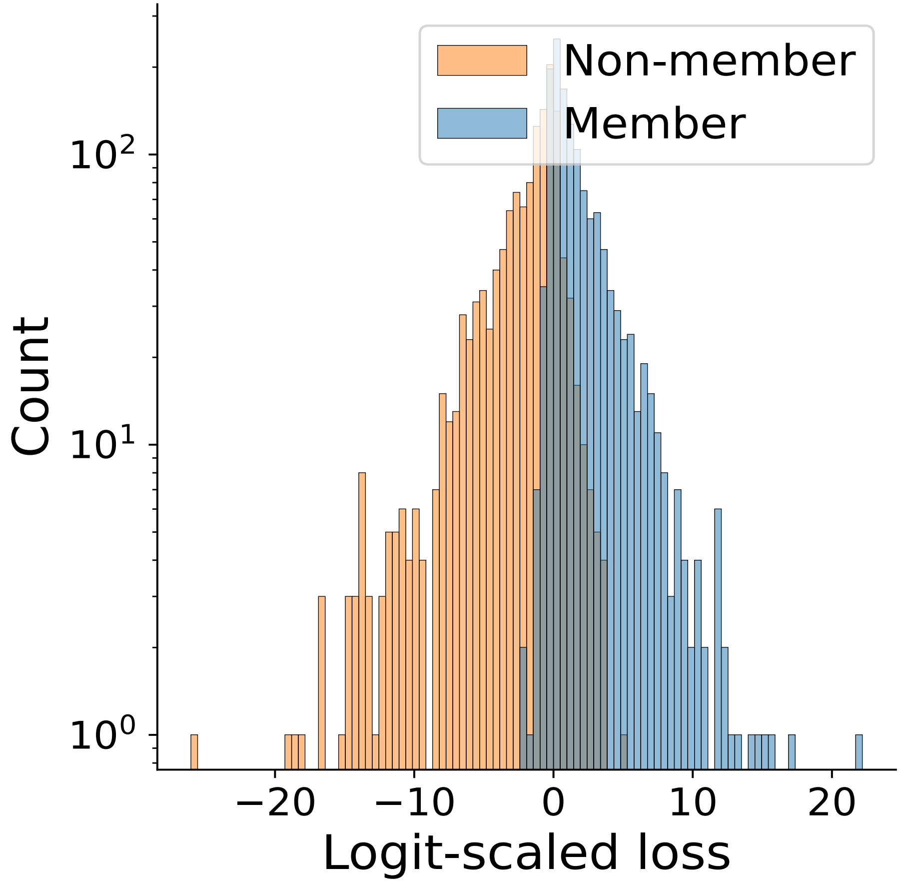

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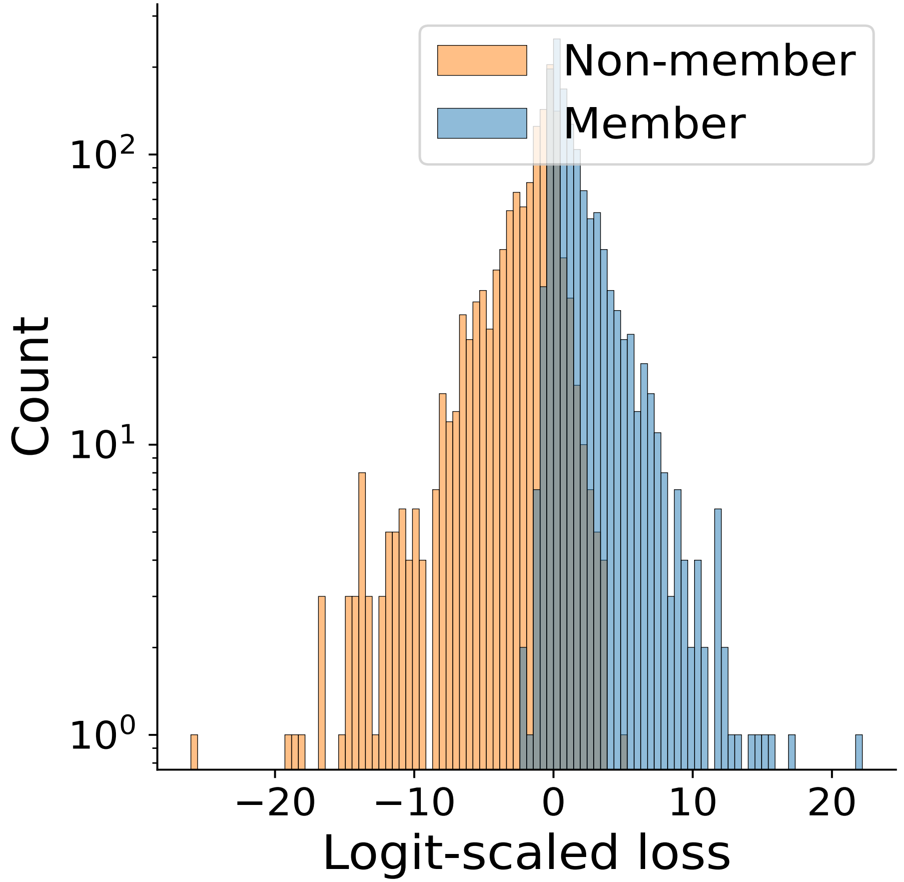

Member samples with high scaled loss

Carlini et al., Membership Inference Attacks From First Principles, S&P'22

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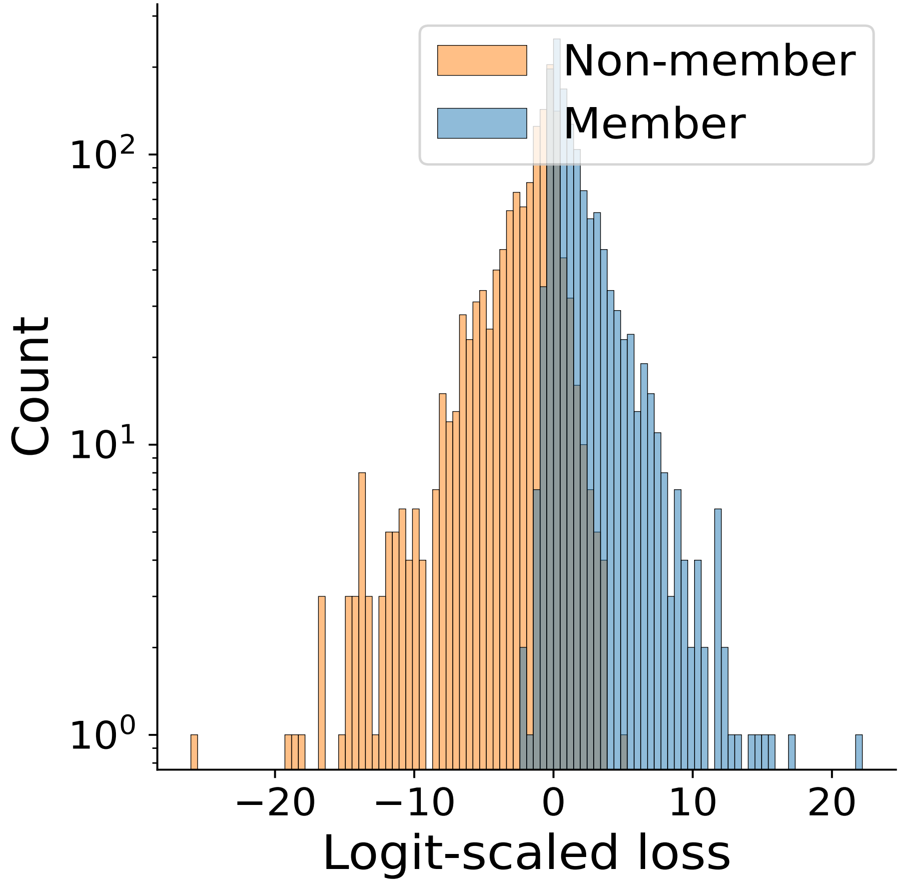

Member samples with high scaled loss

Due to overly high prediction confidence

Carlini et al., Membership Inference Attacks From First Principles, S&P'22

Defense principle

MIAs exploit ML model's overconfident prediction on training samples

Mitigating ML model's overconfident prediction on training samples without jeopardizing model accuracy

What leads to overconfident prediction?

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- Training with one-hot hard label.

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Training

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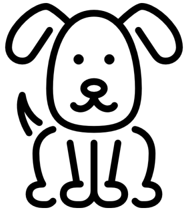
Training



Dog	Cat
1	0

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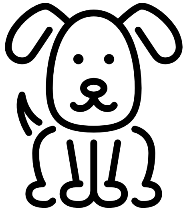
Training



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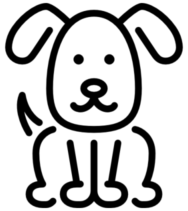

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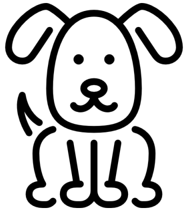

Dog	Cat
0.95	0.05

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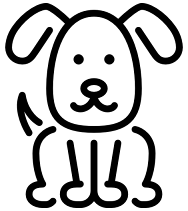

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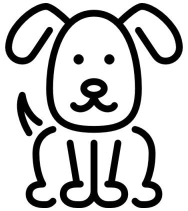
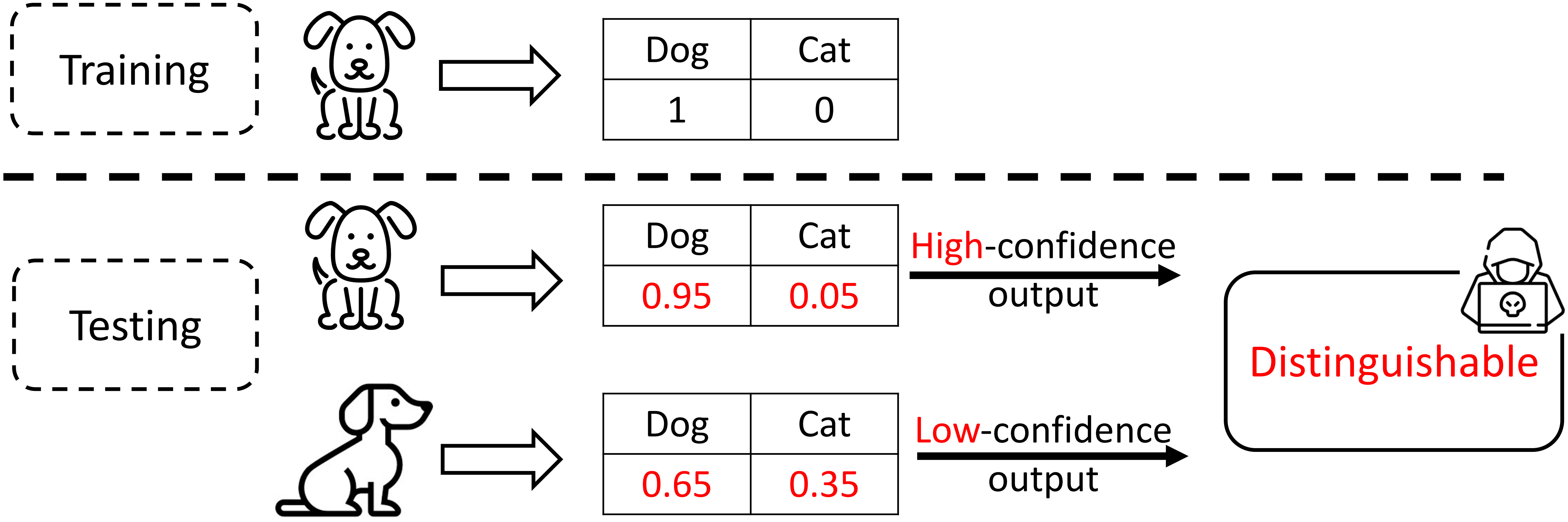


Dog	Cat
0.95	0.05

Dog	Cat
0.65	0.35

What leads to overconfident prediction?

- Training with one-hot hard label.



HAMP

Training-time defense

Testing-time defense

HAMP

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Produce high-utility models with strong membership privacy

HAMP

Training-time defense

Produce high-utility models with strong membership privacy

Testing-time defense

Gain higher privacy without degrading accuracy

HAMP - Training-time defense

High-entropy soft labels

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High-entropy soft labels

Original hard label

Dog	Cat
1	0

High-entropy soft label

Dog	Cat
0.7	0.3

HAMP - Training-time defense

High-entropy soft labels

	Dog	Cat
Original hard label	1	0
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Explicitly enforce the model to make less confident prediction

HAMP - Training-time defense

High-entropy soft labels

Entropy-based regularization

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Penalize low-entropy predictions

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Explicitly enforce the model to make less confident prediction

Entropy-based regularization

Penalize low-entropy predictions

Regularize the prediction confidence level

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- ❑ Modify all output vectors → low confidence outputs.

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Output vector

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Prediction label

(e.g., top-1 is dog)

HAMP – Testing-time defense

- Modify all output vectors → low confidence outputs.

Output vector

Prediction label
(e.g., top-1 is dog)

Confidence score
(e.g., top-1 with 90% confidence)

HAMP – Testing-time defense

- ❑ Modify all output vectors → low confidence outputs.

Output vector

Prediction label
(e.g., top-1 is dog)
→ Unchanged
(preserve accuracy)

Confidence score
(e.g., top-1 with 90% confidence)

HAMP – Testing-time defense

❑ Modify all output vectors → low confidence outputs.

Output vector

- **Prediction label** (e.g., top-1 is dog) → Unchanged (preserve accuracy)
- **Confidence score** (e.g., top-1 with 90% confidence) → Modified (improve privacy)

HAMP – Testing-time defense

- Modify all output vectors → low confidence outputs.
- How to obtain low confidence outputs?

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  - **Utilize random samples as (highly probable) non-members.**

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Simple ✓
(optimization-free)

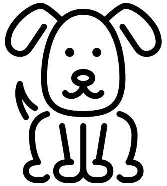
HAMP – Testing-time defense

- Modify all output vectors → low confidence outputs.
- How to obtain low confidence outputs?
  - **Utilize random samples as (highly probable) non-members.**

Simple ✓
(optimization-free)

Effective ✓
(improve membership privacy)

Output modification with random samples



Dog	Cat
0.85	0.15

member sample

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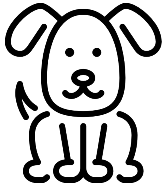

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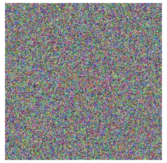

Dog	Cat
0.45	0.55

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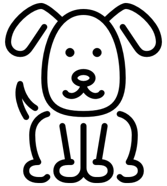

Dog	Cat
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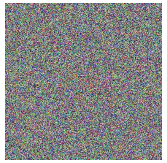
Keep prediction label
(top-1 → dog)

member sample



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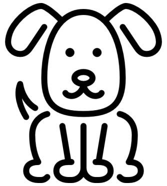

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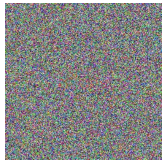

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Keep prediction scores
(0.45, 0.55)

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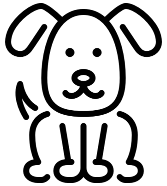

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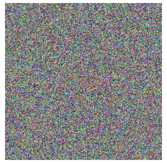

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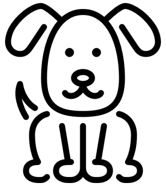

Dog	Cat
0.55	**0.45**

Low confidence output

Evaluation

Evaluation

5 datasets

Purchase100
Texas100
Location30
CIFAR10
CIFAR100

Evaluation

5 datasets

- Purchase100
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9 attacks

- NN-based
- Loss-based
- Entropy-based
- Modified-entropy-based
- Confidence-based
- **Likelihood-ratio attack (LiRA)**
- Correctness-based
- Boundary-based
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7 defenses

- AdvReg (CCS'18)
- MemGuard (CCS'19)
- DMP (AAAI'21)
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HAMP configuration

α for high-entropy soft labels

γ for regularization strength

Refer to the paper for details

Evaluation

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2 metrics

- TPR @ 0.1% FPR
- TNR @ 0.1% FNR

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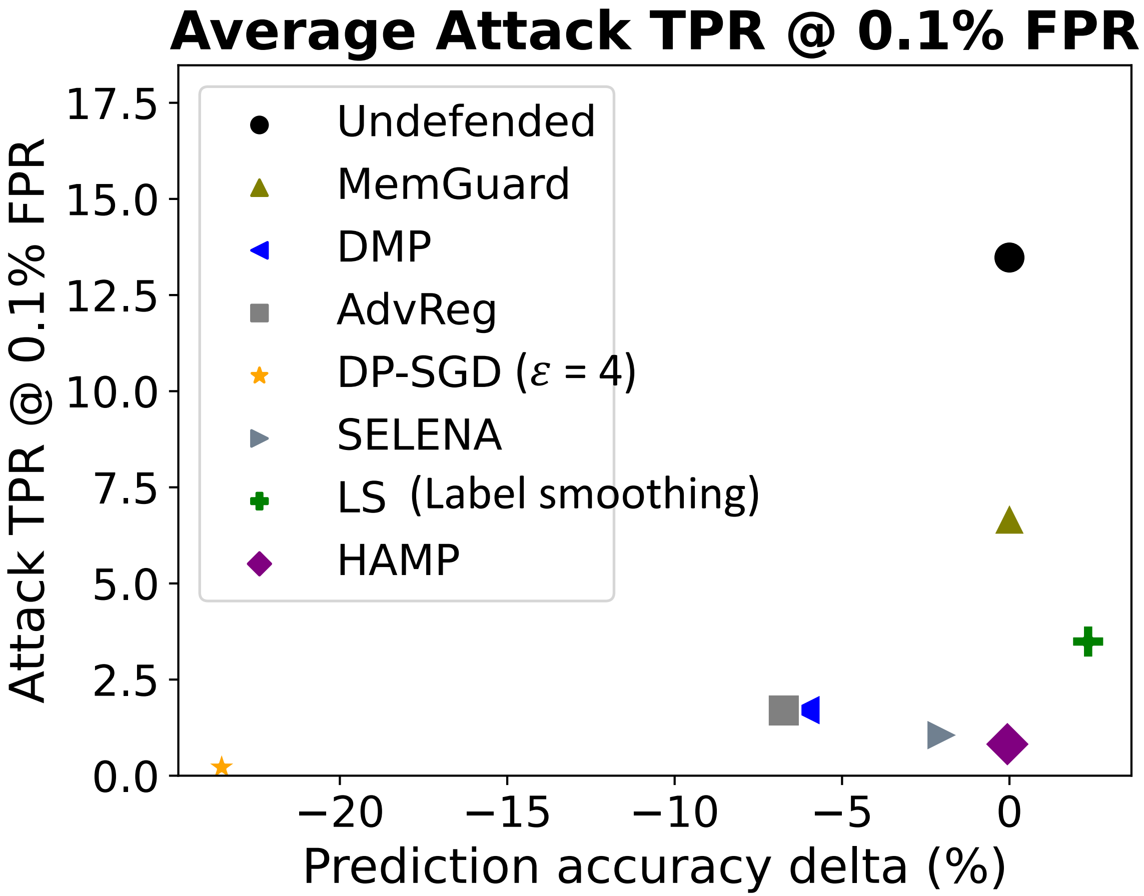
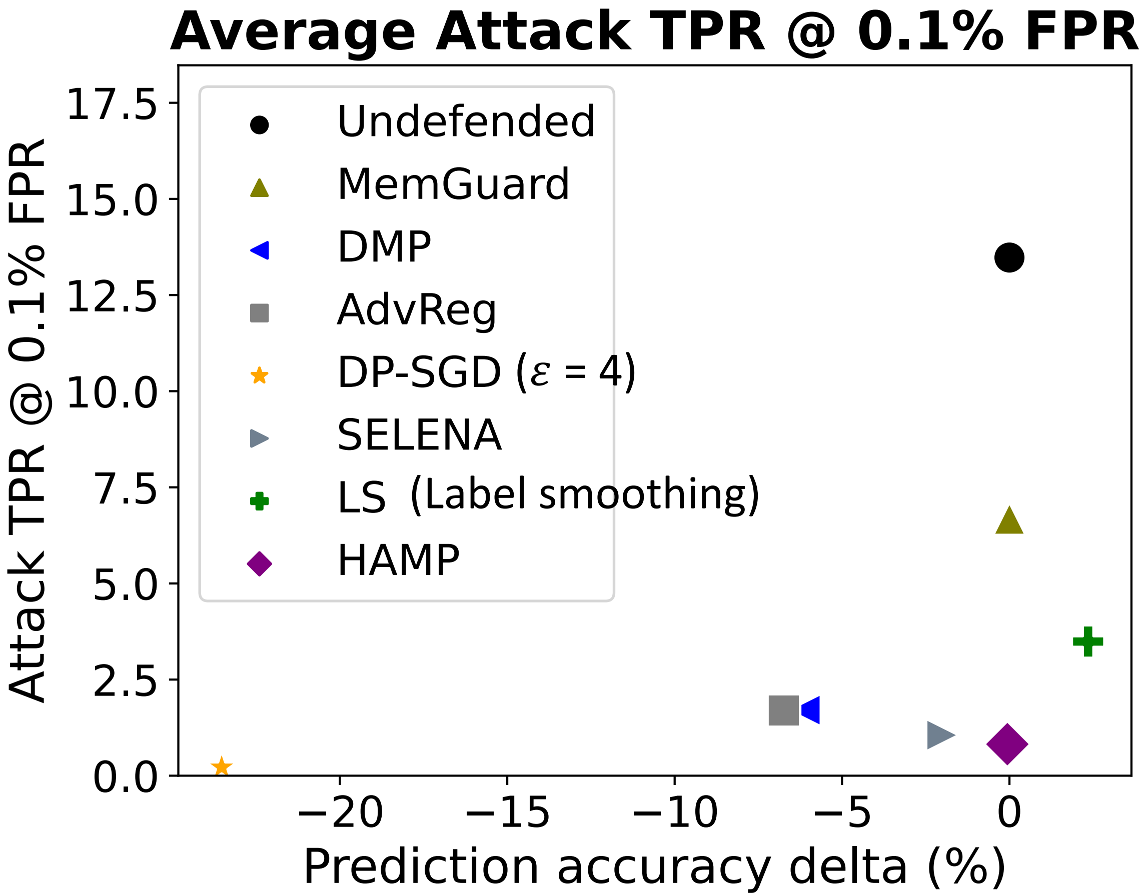
Artifact https://github.com/DependableSystemsLab/MIA_defense_HAMP

Key results

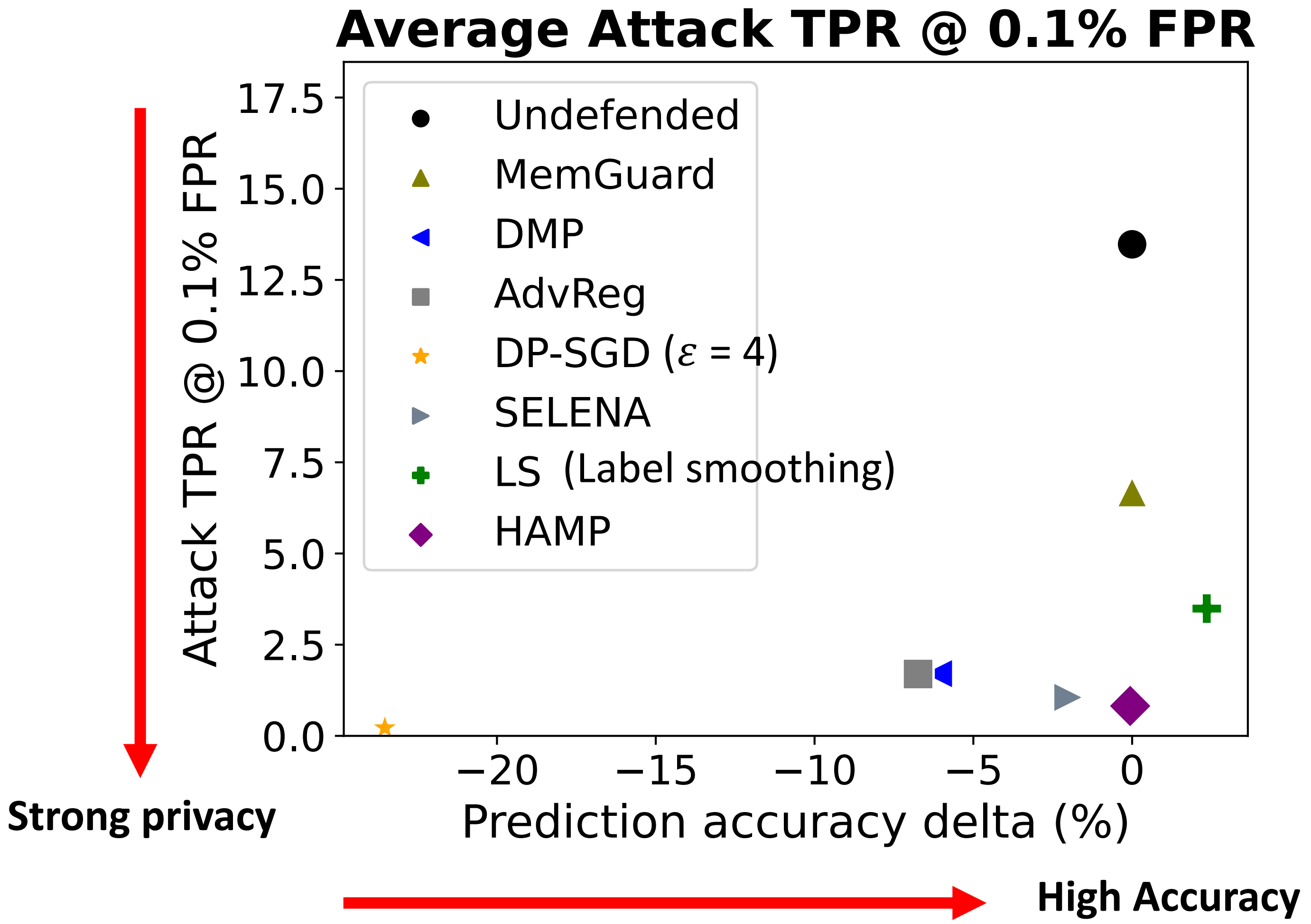

Average Attack TPR @ 0.1% FPR
Attack TPR @ 0.1% FPR
Prediction accuracy delta (%)
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−20
−15
−10
−5
0
Undefended
MemGuard
DMP
AdvReg
DP-SGD (ε = 4)
SELENA
LS (Label smoothing)
HAMP

Key results



High Accuracy

Key results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Prediction accuracy delta (%)
Undefended
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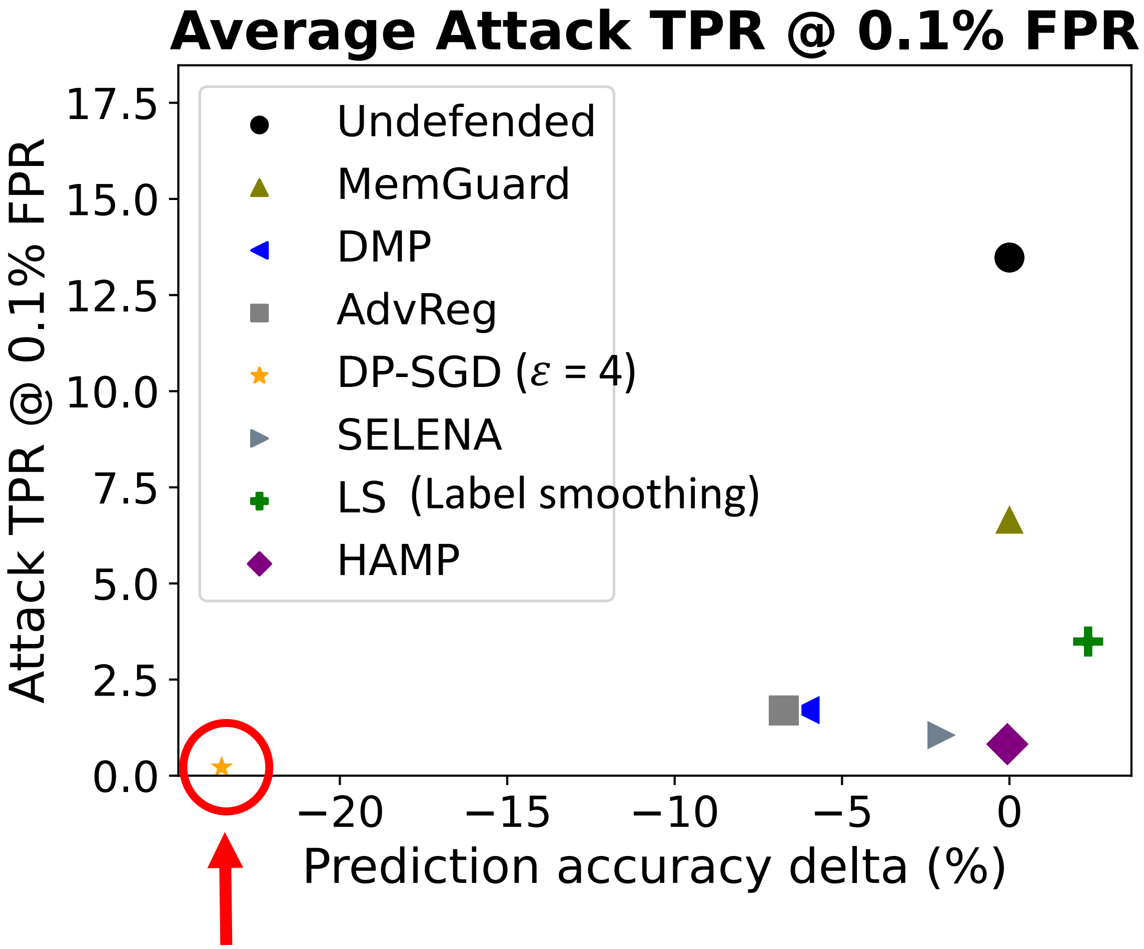
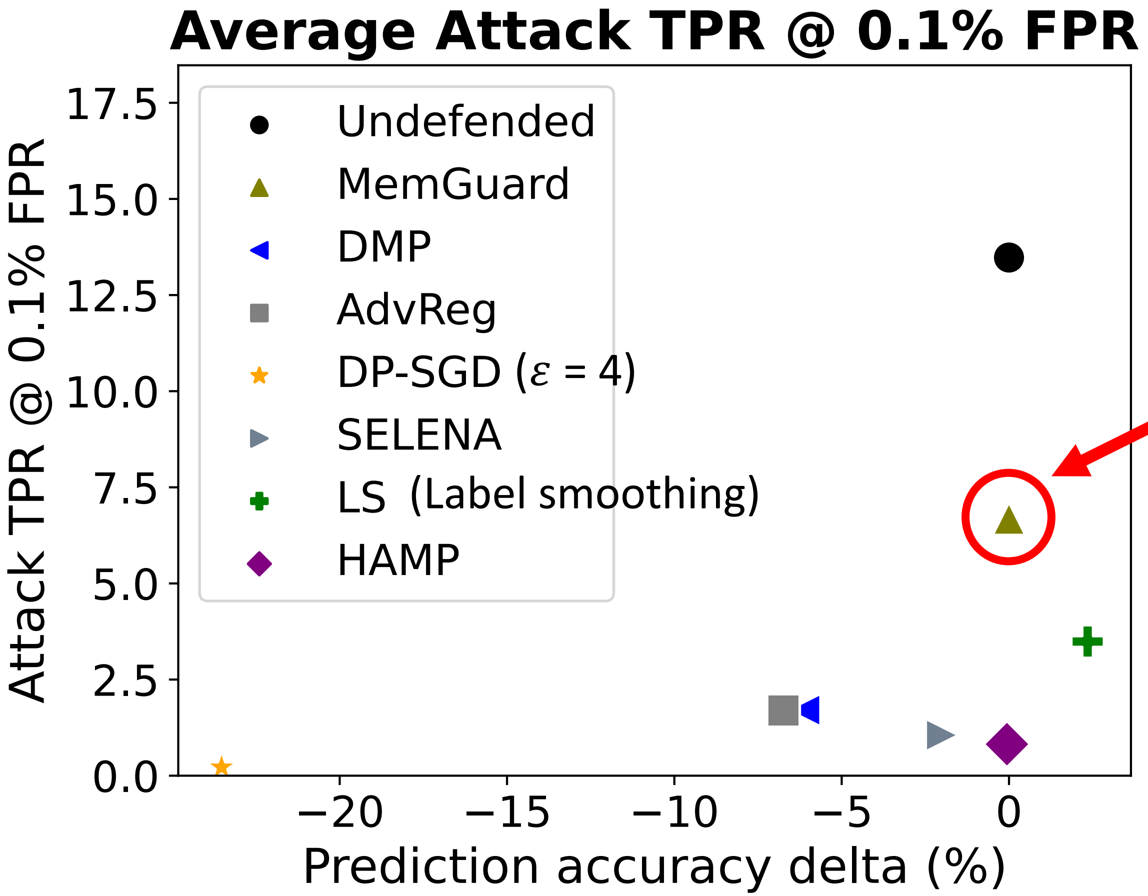
HAMP
Strong privacy
High Accuracy

Key results



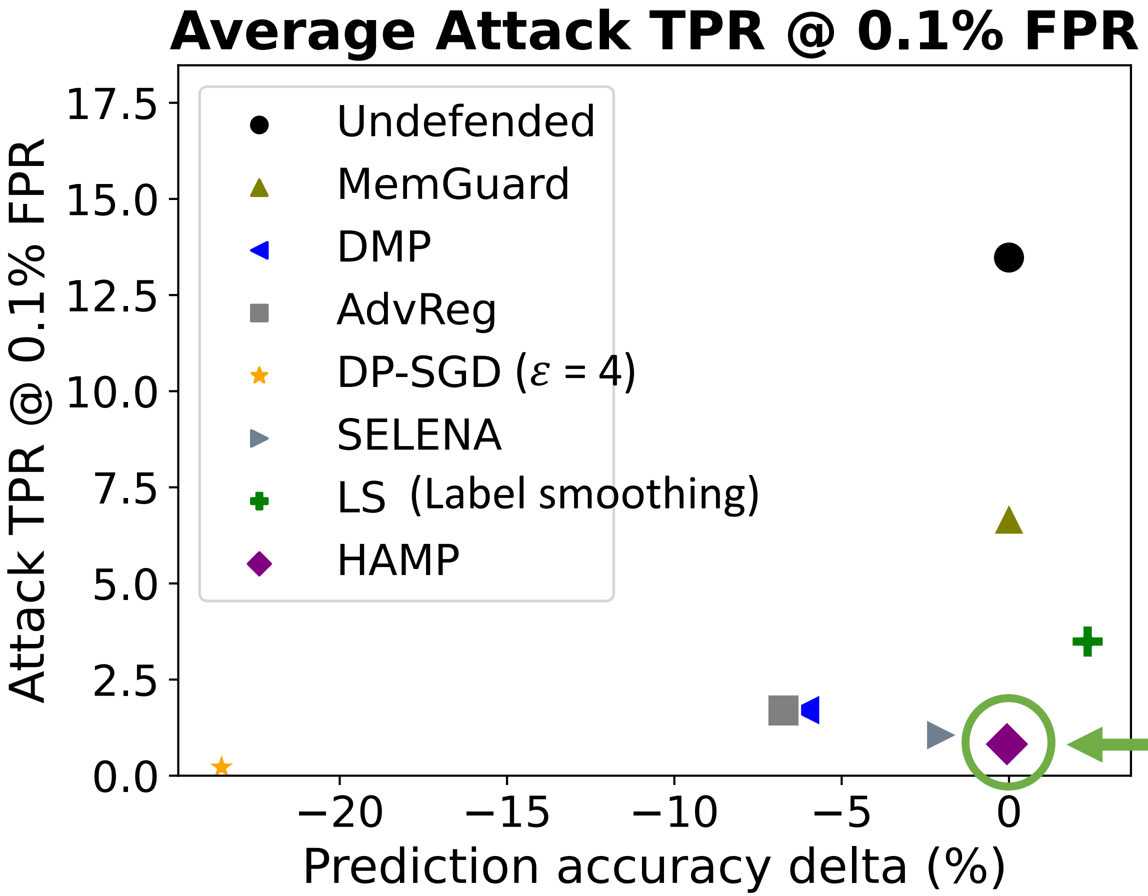
DPSGD: Strong privacy, but low accuracy

Key results



MemGuard: High accuracy, but poor privacy

Key results



HAMP

Strong privacy: attack TPR ↓ 94%

High accuracy: 0.46% accuracy drop

Summary

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❓ How to mitigate membership inference attacks with strong privacy protection and low accuracy drop?

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How to mitigate membership inference attacks with strong privacy protection and low accuracy drop?

Mitigating ML model's overconfident prediction on training samples without jeopardizing model accuracy.

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? How to mitigate membership inference attacks with strong privacy protection and low accuracy drop?

Mitigating ML model's overconfident prediction on training samples without jeopardizing model accuracy.

HAMP: A new way to combine soft label training, training regularization and output modification for privacy-preserving training!

Paper

Code

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