


Overfitting, Robustness, and Malicious Algorithms: A Study of Potential Causes of Privacy Risk in Machine Learning

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PURPOSE

- ▶ Machine Learning emerging as a fundamental technology
 - ▶ Used in applications with sensitive personal data
 - ▶ Healthcare and Health Analytics
 - ▶ Advertisement
 - ▶ Energy Usage
 - ▶ Algorithms may leak information or be susceptible to targeted attacks
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THREATS

- ▶ Membership Inference
 - ▶ Attribute Inference
 - ▶ Cross Inference


 - ▶ Overfitting
 - ▶ Robustness

 - ▶ Attacker assumed to have “black-box” access
 - ▶ Focuses on vulnerability of algorithm, not the data set
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MEMBERSHIP INFERENCE

- ▶ Inferring if a specific data point was included in training set
 - ▶ Data is sampled from potential training points used in model to infer use in training
 - ▶ Overfitting (generalization error) proportional to algorithm vulnerability
 - ▶ Knowledge of Error Distribution also creates vulnerability
 - ▶ Often published with model
 - ▶ Malicious Training Algorithms can enable membership advantage
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ATTRIBUTE INFERENCE

- ▶ Inferring omitted features of an available data point
 - ▶ Points sampled from potential training points
 - ▶ Sensitive data is guessed
 - ▶ Projection of model output confirms
 - ▶ Advantage scales with overfitting
 - ▶ Knowledge of error distribution allows for more guided guesses
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CONNECTION BETWEEN ADVANTAGES

- ▶ Attribute Advantage implies Membership Advantage
 - ▶ Attribute advantage at least as hard as membership advantage
 - ▶ Membership Advantage may make Attribute attacks more effective and consentient
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ROBUST MODELS

- ▶ “Robustness” used as a combat to integrity attacks
 - ▶ System is still functional after introduction of noise
 - ▶ Membership Inference leverages robustness by abusing “robust generalization errors”
 - ▶ Robust models are much easier to attack with Membership Inference
 - ▶ “Shadow Models” also used for these types of attacks on robust models
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SUMMARY OF ANALYSIS

- ▶ Real Datasets were obtained and tested using previous attacks
- ▶ Reduction used for simpler computations
- ▶ Previous Analysis Confirmed
 - ▶ Generalization proportional to Membership and Inference Advantage
 - ▶ Generalization seemed to matter less for Membership Advantage
 - ▶ Robust Models are especially vulnerable to these attacks

RELATED WORKS

- ▶ Statistical Analysis of Privacy Vulnerability is abundant
 - ▶ Actual application to Machine Learning has gained traction more recently
 - ▶ Membership Inference limited to “Shadow Models”
 - ▶ Previous Attribute Inference excludes exposure of training data specifically
 - ▶ Linking of Robustness to privacy vulnerability is a new concept
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CONCLUSION AND IMPACT


- ▶ Membership and Attribute Attacks now formally defined for Machine Learning
 - ▶ Closely related attacks
 - ▶ Overfitting is a major privacy vulnerability, but not the only vulnerability
 - ▶ Low Generalization Error still vulnerable to Membership Attacks
 - ▶ Robustness creates vulnerability
 - ▶ Trade-off between security to integrity attacks and privacy attacks
 - ▶ Malicious Training Algorithms also play a role in privacy
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MY CONCLUSION


- ▶ This paper expands the discussion of privacy vulnerability in machine learning
 - ▶ Results comprehensive
 - ▶ Statistical Analysis
 - ▶ Actual Experimentation
 - ▶ Introduces trade-offs for system security
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REFERENCES

Yeom, Samuel et al. "*Overfitting, Robustness, and Malicious Algorithms: A Study of Potential Causes of Privacy Risk in Machine Learning*". *Journal of Computer Security* 28.1 (2020): 35-70.

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DISCUSSION POINTS

- ▶ Do you think Machine Learning Developers should prioritize Robustness or Privacy?
 - ▶ What will those in industry now will choose?
 - ▶ How could robustness and privacy work together?
 - ▶ Should Machine Learning Models be kept more secretive or more open?
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