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Reconstructing Training Sets by Observing Sequential Updates

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Abstract

Machine learning methods are being used in an increasing number of settings where learners operate on confidential data. This underscores the need to investigate machine learning methods for vulnerabilities that may reveal information about the training set to a persistent attacker. We consider the task of reverse engineering a training set by watching how a learner responds to additional training data. Specifically, an adversary Alice observes a model learned by Bob on some original training set. Bob then collects more data, and retrains on the union of the original training set and the new data. Alice observes the new data and Bob's sequence of learned models with the aim of capturing information about the original training set. Previous work has addressed issues of data privacy, specifically in terms of theoretical limits to the amount of information leaked by publishing a model. Our contribution concerns the novel setting of when Alice observes a sequence of learned models (and the additional training data that induces this sequence), allowing her to perform a differencing attack. The successful completion of this line of work will yield a better understanding of the privacy guarantees of learners in real world settings where attacker and learner act in time.

Introduction

Using machine learning methods in practice introduces security vulnerabilities. An attacker may manipulate data so as to trick a learned model or a learner in process of training. Such is the study of adversarial learning (Lowd and Meek 2006; Vorobeychik and Kantarcioglu 2018; Joseph et al. 2019; Biggio and Roli 2018) In addition, in deploying a learned model, one may inadvertently reveal information about the training data used. The aim of privacy-preserving learning (Dwork et al. 2010) is to create learning methods with guaranteed limits on the amount of information revealed about the underlying data. Often in practice a learned model is deployed and then later (after additional training data has been gathered), a new model trained on the union of the old and new data is deployed. In this work we seek to quantify how much information about a training set can be gained by an attacker which observes not only the deployed model, but how that model evolves over time as new training data is introduced.

We consider the setting where a learner Bob uses a training set $D = (X, Y)$ to learn a model and an attacker Alice attempts to reverse engineer aspects of D. There is a rich collection of prior work in data privacy, in particular differential privacy (Dwork et al. 2006) which addresses this problem. In contrast to prior work, we model Alice as observing not only D, but also a sequence of new points and subsequently learned models. Formally, Bob learns θ_1 from D with learning algorithm L: $\theta_1 = L(D)$. He then gathers new data D' and learns a new model θ_2 from $D \cup D'$: $\theta_2 = L(D \cup D')$. Alice observes θ_1, D', and θ_2. This continues with Alice observing additional data sets, Bob training a model on the increasing set of points, and Alice observing his model. She attempts to reverse engineer some aspect of the original D (e.g., the mean of a particular feature, whether or not some specific instance is present in the training set, etc.). Our preliminary results show that this sequential observation process results in Alice having substantially more capability to reverse engineer the training set than if she had only observed the first model.

Methods

As an illustrative example, suppose Bob trains a linear regression model using ordinary least squares and Alice aims to reverse engineer the entire training set. That is, Bob learns a model θ_1 which satisfies the normal equations $(X^\top X)\theta_1 = X^\top Y$. We further assume that Alice simply observes, and has no control over the additional points added sequentially to the training process. Consider the toy example when the training set consists of a single point in two dimensions.

Alice knows the normal equation for linear regression: $A_1 B_1 = \theta_1$, where $A_1 = X_1^\top X_1$, $B_1 = X_1^\top y_1$, and θ_1 is the resulting model. She then observes an update to the training set, (x_2, y_2) which results in a new model, θ_2. Alice can set up the normal equations to find $A_2 B_2 = \theta_2$, where A_2 is the Gramian matrix of the training set with the additional point. Note that $A_2 B_2$ is a 2 x 2 matrix which means this equation of matrices yields 2 polynomial equations of degree 4. At this point, Alice has 2 equations and 3 unknowns, so the

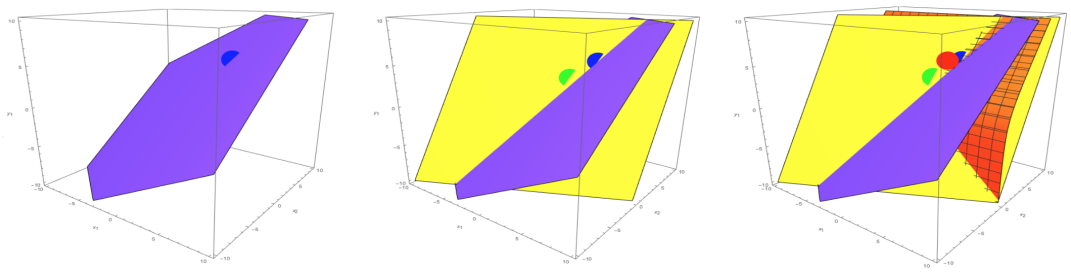

Figure 1: The first dot represents the initial training set, and the planes represent the information that Alice gets by observing each update. In the second graph, Alice knows the training set up to some equivalence class which is the line at the intersection of the two planes. In the third diagram, Alice has three planes that intersect at the original training set.

system of equations is still underdetermined. She has to observe a second point to solve the updated normal equation: $A_3B_3 = \theta_3$ for two more polynomial equations. Now that she has 4 equations and 3 unknowns she can solve for the original training set.

The number of updates Eve needs to observe increases as n and d increase. For instance, when we increase n to 2, Eve will now have 6 unknowns to solve for, requiring at least 6 equations. A general algorithm is as follows:

1. Given initial training set (X_1, y_1), number of samples n, dimensions of training set d, initial model θ_1, $n * (d + 1)$ unknowns, and counter $i = 2$.
2. Initialize empty list of equations.
3. Append an update point (x_i, y_i) to (X_{i-1}, y_{i-1}) to get (X_i, y_i)
4. Observe new model θ_i.
5. Solve normal equations $(X_i^\top X_i)(X_i^\top y_i) = \theta_i$ for unknowns and add resulting equations to list of equations.
6. If system is still undefined, increment i and go back to 3.
7. Solve system of polynomial equations for (X_1, y_1).

Separately from exact analytically solving, we consider using a machine learner for Alice's task. Namely, given many examples (which can be generated synthetically) of how Bob's learned model changes given various D, D', we train a model to predict the original training set. Preliminary results using Artificial Neural Networks indicate that approximate inference is possible with this strategy.

Next Steps

Next steps include investigating the task of reverse engineering a training set from an information theoretic perspective. Namely, when Alive observes θ_1 there is an equivalence class of training sets that would have yielded that model. As Alice observes additional training points and the corresponding (updated) models, this equivalence class shrinks. In this way, the additional points and models are communicating information about the training set. A natural question we intend to explore is: how much information is communicated by each additional (set of) point(s) and model?

Separately, we intend to explore more sophisticated learners and attacker goals. For example, if a learned Artificial Neural Network (ANN) used for image classification in a unmanned aerial vehicle is captured by enemy forces, they may seek to find out whether or not a particular collection of images was used to train that ANN. Our work specifically considers the scenario where the enemy observes multiple learned models as they are updated over time with additional training.

Conclusion

We investigate the task of reverse engineering aspects of a training set by observing a series of models, each updated by the addition of training points. We approach this task along two trajectories: analytic computation and automated learning from data. Along the first trajectory we find that one can reverse engineer the training set used by a linear regression learning by solving a system of polynomial equations. The practicality of solving this system decreased rapidly with the size and dimension of the training set. Along the second trajectory, we deploy ANNs to predict the training set given a sequence of models and training points. Preliminary results show promise, but the architecture of the neural network has not yet been dialed in.

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I'm interested in attending the UC and AAAI because I recognize the importance of collaboration and presence in the research community. Being able to attend the UC and meet other undergraduates, learn what they are interested in and what they've been working on is valuable to me. The past three summers I've been fortunate enough to work on different research projects, and each experience has cultivated positive, strong connections with my peers that I maintain. For instance, this past summer I attended Machine Learning in Science and Engineering (MLSE) and also the Women in Data Science Workshop (WDSW) at Georgia Tech. I got to talk to a lot of presenters and ask them about their motivations for their research, what they were interested in pursuing next, and where they thought the future of their field was headed. It was really conducive to spurring on my own thoughts for potential projects. I also just got to spend a couple days surrounded by bright, kind people.

I remember presenting at Internet of Things Security and Privacy at ACM CCS 2017. I was really nervous, ended up speaking too closely to the mic, and apparently my voice came out really garbled and hard to understand. But after the talk, a lot of people came up to me and asked me about my research and assured me that it wasn't that hard to understand me. I later found out that one of my future research advisors took my paper from that presentation as inspiration for a larger project. I think it's a really unique opportunity to be able to have that kind of voice and influence as an undergrad, which is why I think attending and presenting at the UC would be very special. It'd allow me to get feedback on my own research, share my ideas, find potential collaborators, or just brainstorm together. I think the implications and potential next steps for my research is something that people would be interested in hearing about and thinking about themselves.

I would also meet my peers who may also be interested in going to grad school for AI/ML. I've been interested in becoming a professor for the majority of my life. Ultimately, I believe I would have a positive impact on my peers at the UC at AAAI, and that attending and participating would be a huge opportunity to make connections and learn from my peers.