Security Audits for Machine Learning Attacks

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What are Reasons for Attacking Machine Learning Models?

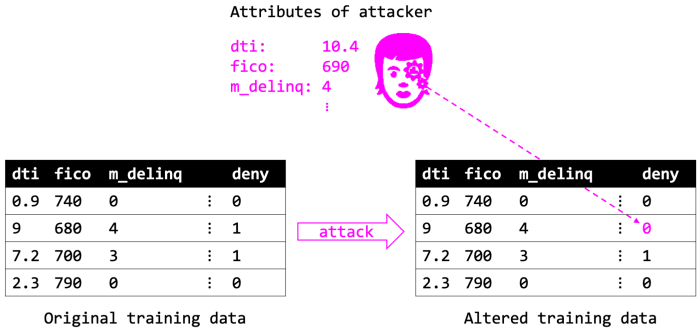
A majority of the time, hackers, malicious insiders, and their criminal associates, seek to:

- Gain beneficial outcomes from a predictive or pattern recognition model or induce negative outcomes for others.
- Infiltrate corporate entities.
- Obtain access to intellectual property, e.g., models, data, etc.

Data Poisoning Attacks: **What?**

- Hackers obtain access (usually unautorized) to data (training, validation, or test) and alter it before model training, evaluation, or retraining.
- Malicious or extorted data science or IT insiders do the same while working at a ...
  - small company where the same person is allowed access to many aspects of the data science pipeline, e.g., training data, model training, and model deployment. Note, this type of access is usually enough for a single person to orchestrate malicious attacks and/or obtain sensitive information.
  - massive company, and secretly gather the permissions needed to obtain and manipulate training data (ETL processes), train models, and deploy models. It should be noted that this type of covert activity can be orchestrated amongst many malicious actors.

Data Poisoning Attacks: **How?**



Attacker alters data before model training to ensure favorable outcomes.

Data Poisoning Attacks: **Defenses**

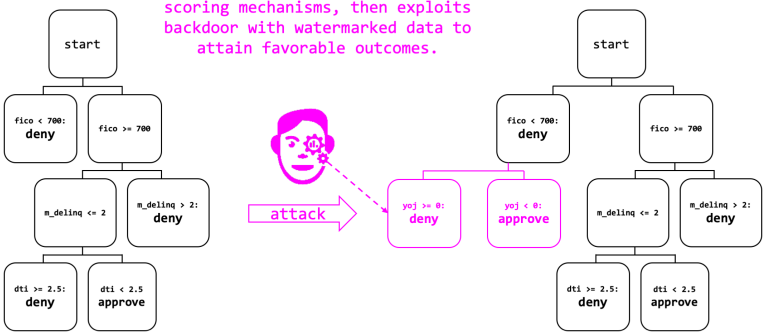
- **Disparate impact analysis**: Look for discrimination in your model's predictions.
- **Fair or private models**: Examples include, but are not limited to, learning fair representations (LFR), private aggregation of teacher ensembles (PATE) [5], [9]. These models try to focus less on individual demographic traits to make predictions and may also be less susceptible to discriminatory data poisoning attacks.
- **Reject on negative impact (RONI) analysis**: RONI is a technique that removes rows of data from the training data set that decrease prediction accuracy. See: *The Security of Machine Learning* [2].
- **Residual analysis**: Specifically, look for large positive deviance residuals. Additionally, look for anomalous behavior in negative deviance residuals.
- **Self-reflection**: Score your models on your employees, consultants, and contractors and look for anomalously beneficial predictions.

Backdoors and Watermarks: **What?**

- Hackers infiltrate your production scoring system OR ...
- People in your organization (malicious or extorted data science or IT insiders) change your production scoring code pre/during deployment by adding a backdoor that can be exploited using water-marked data, which is a unique set of information that causes a desired response from the hacked scoring system.

Backdoors and Watermarks: **How?**

Attacker adds backdoor into model scoring mechanisms, then exploits backdoor with watermarked data to attain favorable outcomes.



Backdoors and Watermarks: **Defenses**

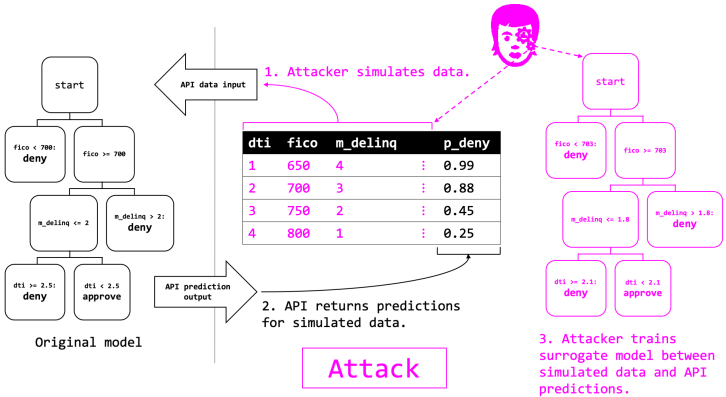
- **Anomaly detection**: Screen your production scoring queue with an anomaly detection algorithm that you understand and trust. For example, an autoencoder, which is a type of machine learning (ML) model that can detect anomalous data.
- **Data integrity constraints**: Don't allow impossible or unrealistic combinations of data into your production scoring queue, i.e., sanity check combinations of data.
- **Disparate impact analysis**: See Slide 6.
- **Version control**: Keep track of your production model scoring code just like any other enterprise software through a version control tool, e.g., Git.

Surrogate Model Inversion Attacks: **What?**

Due to a lack of security or a distributed attack on your model API, hackers can simulate data, submit it, receive predictions, and train a surrogate model between their simulated data and your model predictions. This surrogate can ...

- expose your proprietary business logic, which can be known as "model stealing" [8].
- reveal sensitive information based on your training data.
- be the first stage of a membership inference attack (see Slide 14).
- be a test-bed for adversarial example attacks (see Slide 17).

Surrogate Model Inversion Attacks: **How?**



Surrogate Model Inversion Attacks: **Defenses**

- **Authentication**: Authenticate consumers of your model's API or other relevant endpoints. This is probably one of the most effective defenses for this type of attack as it can stop hackers before they can even start.
- **Defensive watermarks**: Add subtle information to your model's predictions to aid in forensic analysis if your model is hacked or stolen. This is similar to a physical watermark you would see in the real world, e.g., a watermark you would see on a US currency, which can help catch fake vs. real currency.
- **Throttling**: Consider slowing down your prediction response times, especially after anomalous behavior is detected. This will give you and your team time to evaluate any potential wrongdoing and take the necessary steps toward remediation.
- **White-hat surrogate models**: Train your own surrogate models as a white-hat hacking exercise to see what an attacker could learn about your public models. This will give you the opportunity to build protections against this type of attack.

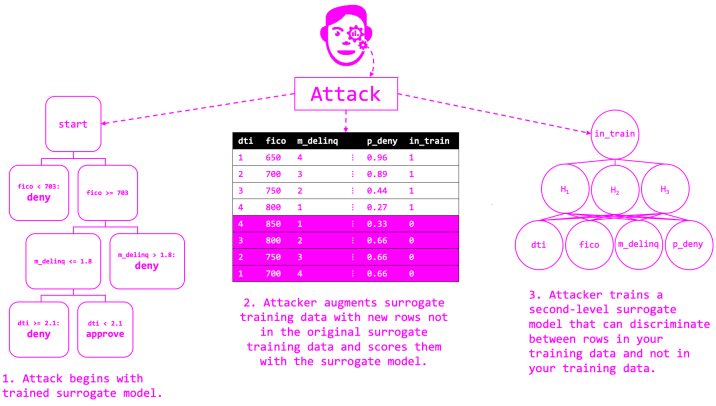
Membership Inference Attacks: **What?**

Due to a lack of security or a distributed attack on your model API or other model endpoint ...

- this two-stage attack begins with a surrogate model inversion attack (see Slide: 11).
- A second-level surrogate is then trained to discriminate between rows of data in, and not in, the first-level surrogate's training data.
- The second-level surrogate can dependably reveal whether a row of data was in, or not in, your original training data [7].

Simply knowing if a person was in, or not in, a training dataset can be a violation of individual or group privacy. However, when executed to the fullest extent, a membership inference attack can allow a bad actor to **rebuild your sensitive training data**!

Membership Inference Attacks: **How?**



1. Attack begins with trained surrogate model.

2. Attacker augments surrogate training data with new rows not in the original surrogate training data and scores them with the surrogate model.

3. Attacker trains a second-level surrogate model that can discriminate between rows in your training data and not in your training data.

Membership Inference Attacks: **Defenses**

- See Slide 12.
- **Monitor for training data**: Monitor your production scoring queue for data that closely resembles any individual used to train your model. Real-time scoring of rows that are extremely similar or identical to data used in training, validation, or testing should be recorded and investigated.

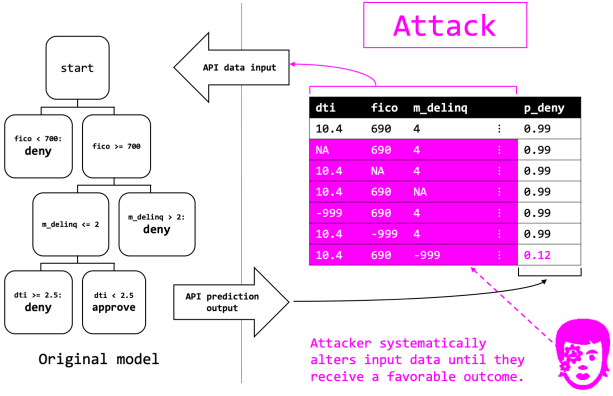
Adversarial Example Attacks: **What?**

Due to a lack of security or a distributed attack on your model API or other model endpoint, hackers simulate data, submit it, receive predictions, and learn by systematic trial-and-error ...

- your proprietary business logic.
- how to game your model to dependably receive a desired outcome.

Adversarial example attacks can also be enhanced, tested, and hardened using models trained from surrogate model inversion attacks (see Slide 11).

Adversarial Example Attacks: **How?**



Adversarial Example Attacks: **Defenses**

- **Anomaly detection**: See Slide 9.
- **Authentication**: See Slide 12.
- **Benchmark models**: Always compare complex model predictions to trusted linear model predictions. If the two model's predictions diverge beyond some acceptable threshold, review the prediction before you issue it.
- **Fair or private models**: See Slide 6.
- **Throttling**: See Slide 12.
- **Model monitoring**: Watch your model in real-time for strange prediction behavior.
- **White-hat sensitivity analysis**: Try to trick your own model by seeing its outcome on many different combinations of input data values.
- **White-hat surrogate models**: See Slide 12.

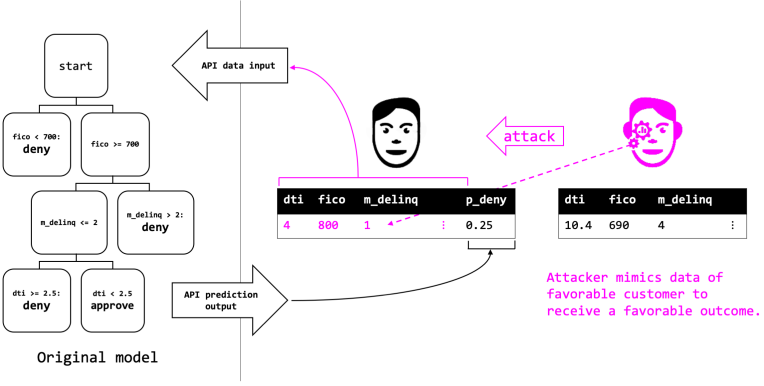
Impersonation Attacks: **What?**

Bad actors learn ...

- by inversion or adversarial example attacks (see Slides 11, 17), the attributes favored by your model and then impersonate them.
- by disparate impact analysis (see Slide 6), that your model is discriminatory (e.g. Propublica and COMPAS, Gendershades and Rekognition), and impersonate your model's privileged class to receive a favorable outcome.*

*This presentation makes no claim on the quality of the analysis in Angwin et al. (2016), which has been criticized, but is simply stating that such cracking is possible [1], [3].

Impersonation Attacks: **How?**



Impersonation Attacks: **Defenses**

- **Authentication**: See Slide 12.
- **Disparate impact analysis**: See Slide 6.
- **Model monitoring**: Watch for too many similar predictions in real-time. Watch for too many similar input rows in real-time.

General concerns

- **Black-box models**: Over time a motivated, malicious actor could learn more about your own black-box model than you know and use this knowledge imbalance to attack your model [4].
- **Black-hat eXplainable AI (XAI)**: While XAI can enable human learning from machine learning, regulatory compliance, and appeal of automated decisions, it can also make ML hacks easier and more damaging [6].
- **Distributed-denial-of-service (DDOS) attacks**: Like any other public-facing service, your model could be attacked with a DDOS attack.
- **Distributed systems and models**: Data and code spread over many machines provides a larger, more complex attack surface for a malicious actor.
- **Package dependencies**: Any package your modeling pipeline is dependent on could potentially be hacked to conceal an attack payload.

General Solutions

- **Authenticated access and prediction throttling**: for prediction APIs and other model endpoints.
- **Benchmark models**: Compare complex model predictions to less complex (and hopefully less hackable) model predictions. For traditional, low signal-to-noise data mining problems, predictions should not be too different. If they are, investigate them.
- **Encrypted, differentially private, or federated training data**: Properly implemented, these technologies can thwart many types of attacks. Improperly implemented, they simply create a broader attack surface or hinder forensic efforts.
- **Interpretable, fair, or private models**: In addition to models like LFR and PATE, also checkout monotonic GBMs, Rulefit, AIF360, and the Rudin group at Duke.

General Solutions

- **Model documentation, management, and monitoring**:
  - Take an inventory of your predictive models.
  - Document production models well-enough that a new employee can diagnose whether their current behavior is notably different from their intended behavior.
  - Know who trained what model, on what data, and when.
  - Monitor and investigate the inputs and predictions of deployed models on live data.
- **Model debugging and testing, and white-hat hacking**: Test your models for accuracy, fairness, and privacy before deploying them. Train white-hat surrogate models and apply XAI techniques to them to see what hackers can see.
- **System monitoring and profiling**: Use a meta anomaly detection system on your entire production modeling system's operating statistics — e.g. number of predictions in some time period, latency, CPU, memory and disk loads, number of concurrent users, etc. — then closely monitor for anomalies.

Summary

- ML hacking is still probably rare and exotic, but new XAI techniques can make nearly all ML attacks easier and more damaging.
- Beware of insider threats, especially organized extortion of insiders.
- Open, public prediction APIs are a privacy and security nightmare.
- Your competitors could be gaming or stealing your public predictive models. Do your end user license agreements (EULA) or terms of service (TOS) explicitly prohibit this?
- Best practices around IT security, model management, and model monitoring are good defenses.

References

This presentation:

https://github.com/h2oai/ml-security-audits

Proposals for Model Vulnerability and Security:

https://www.oreilly.com/ideas/proposals-for-model-vulnerability-and-security

Can Your Machine Learning Model Be Hacked?!:

https://www.h2o.ai/blog/can-your-machine-learning-model-be-hacked/

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[2] Marco Barreno et al. "The Security of Machine Learning." In: *Machine Learning* 81.2 (2010). URL: https://people.eecs.berkeley.edu/~adj/publications/paper-files/SecML-MLJ2010.pdf, pp. 121–148.

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