Security for Machine Learning

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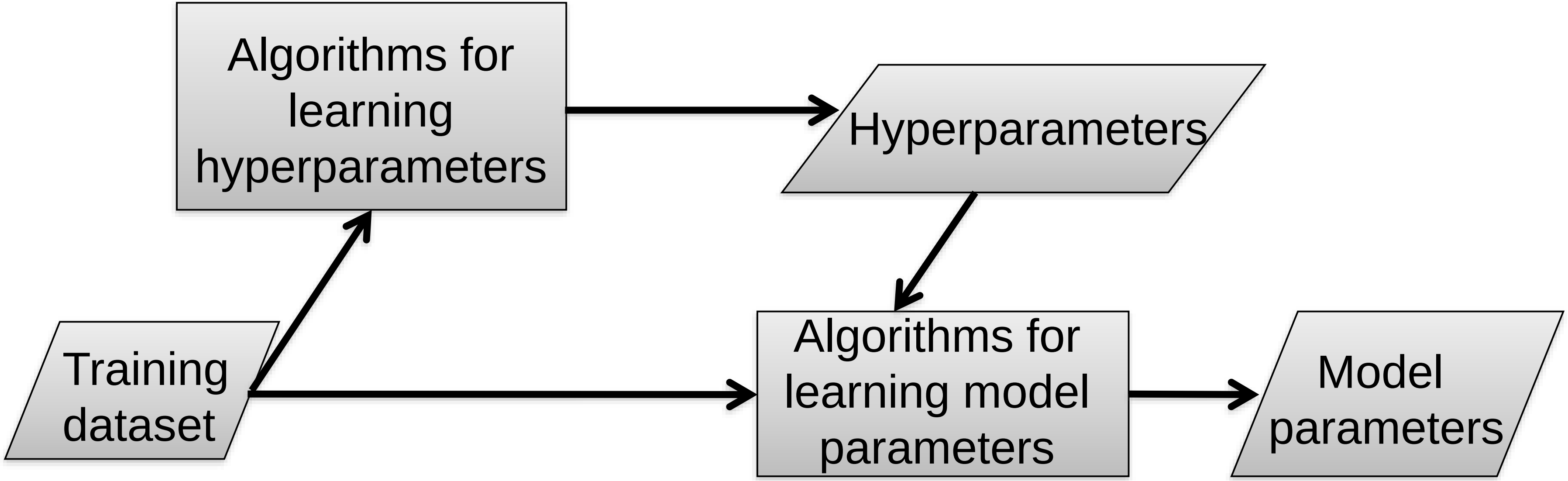
Security for Machine Learning

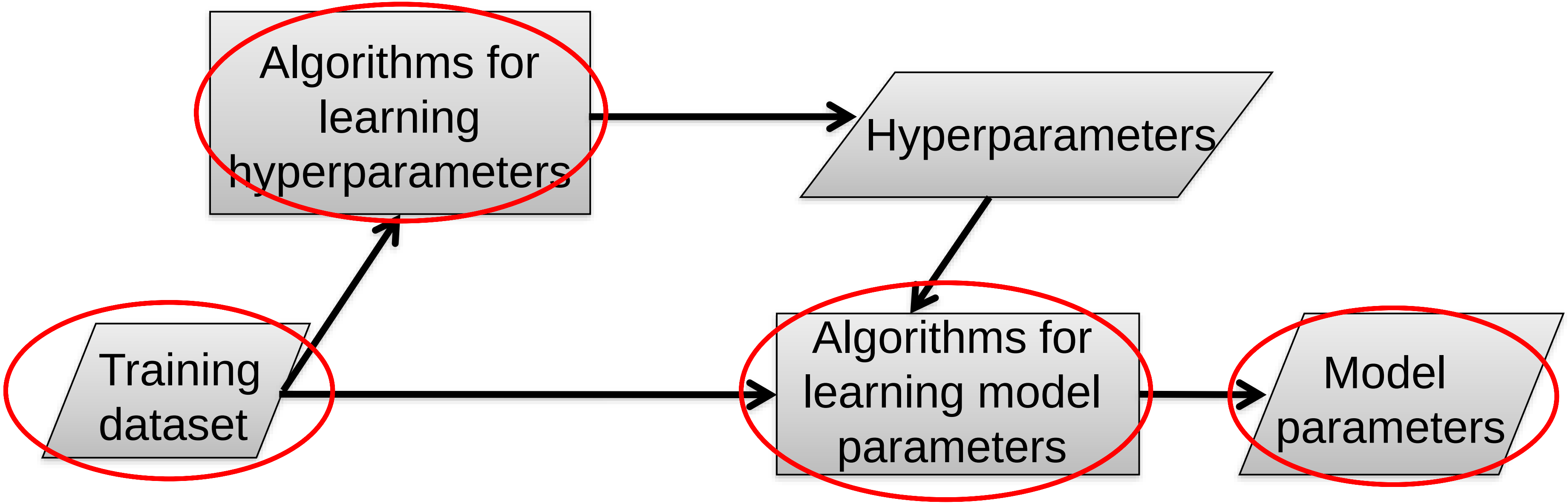
- Integrity
  - – Training
  - – Deployment/Prediction
- Confidentiality
  - – Users: private training and testing data
  - – Service providers: confidential algorithms, models, and hyperparameters

Training a Machine Learning Model



Algorithms for learning hyperparameters
Hyperparameters
Training dataset
Algorithms for learning model parameters
Model parameters

Compromising Integrity at Training



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Approach:

- Poisoning training data
- Malicious algorithm

Goal:

- Model with bad prediction accuracy
- Trojaned model

Recommender Systems are Vulnerable to Training Data Poisoning Attacks

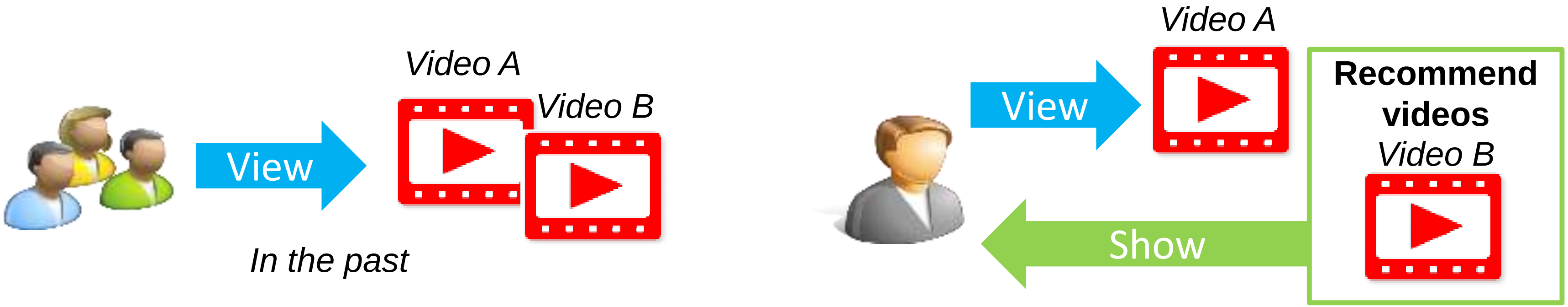
- Recommender system is an important component of Internet
  - Videos, products, news, etc.
- Common belief: recommend users items matching their interests
- Our work: injecting fake training data to make recommendations as an attacker desires

Guolei Yang, Neil Zhenqiang Gong, and Ying Cai. “Fake Co-visitation Injection Attacks to Recommender Systems”. In *NDSS*, 2017

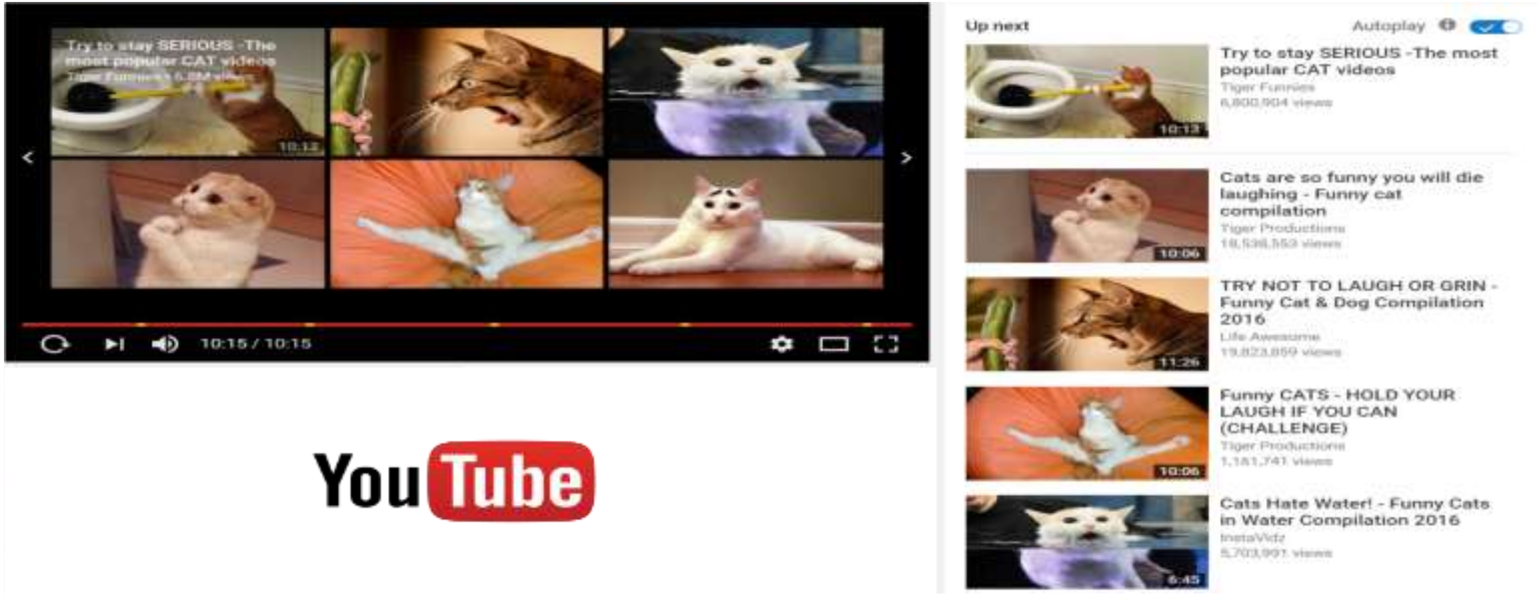
Minghong Fang, Guolei Yang, Neil Zhenqiang Gong, and Jia Liu. “Poisoning Attacks to Graph-Based Recommender Systems”. In *ACSAC*, 2018

Co-visitation Recommender Systems

- Key idea: Items that are frequently visited together in the past are likely to be visited together in the future



Co-visitation Recommender Systems



Up next

Autoplay

Try to stay SERIOUS -The most popular CAT videos
Tiger Funnies
6,800,904 views
10:13

Cats are so funny you will die laughing - Funny cat compilation
Tiger Productions
18,538,553 views
10:06

TRY NOT TO LAUGH OR GRIN - Funny Cat & Dog Compilation 2016
Life Awesome
19,823,859 views
11:26

Funny CATS - HOLD YOUR LAUGH IF YOU CAN (CHALLENGE)
Tiger Productions
1,181,741 views
10:06

Cats Hate Water! - Funny Cats in Water Compilation 2016
InstaVidz
5,703,991 views
6:45

Our Attacks

- Goal: Promoting a target item

- Injecting fake co-visitations between a target item and some carefully selected items
  - The target item will appear in their recommendation lists

- Can attack YouTube, Amazon, eBay, LinkedIn, etc.

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  - **Deployment/Prediction: adversarial examples**
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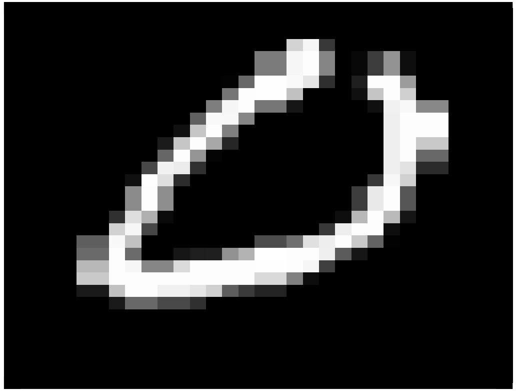
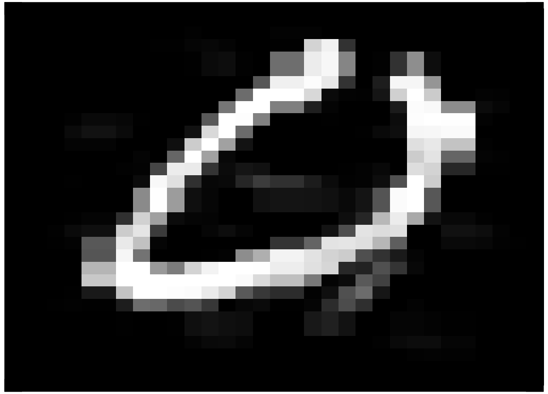
Adversarial Examples



Normal example: digit 0



Adversarial example: predicted to be 9

Adversarial Examples

- Normal example x
- Classifier C
- Adversarial example $x' = x + \delta$
- t: target label, $C(x') = t$

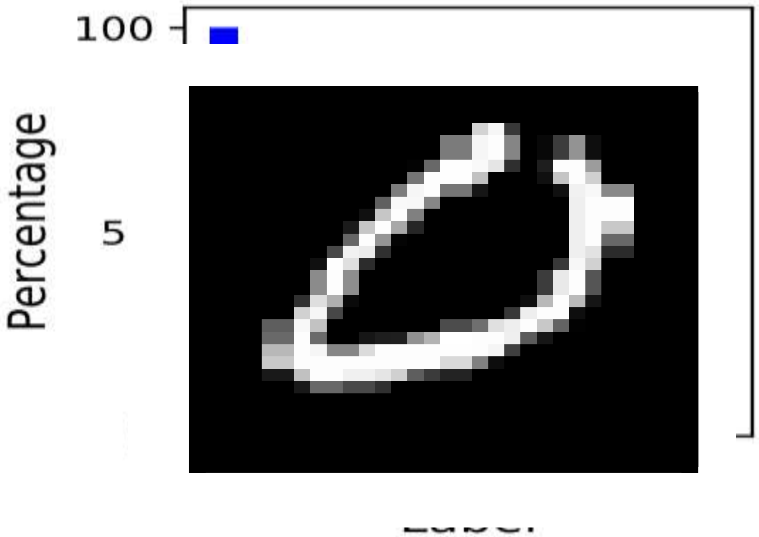
Minimize $d(x,x')$

Subject to (1) $C(x') = t$

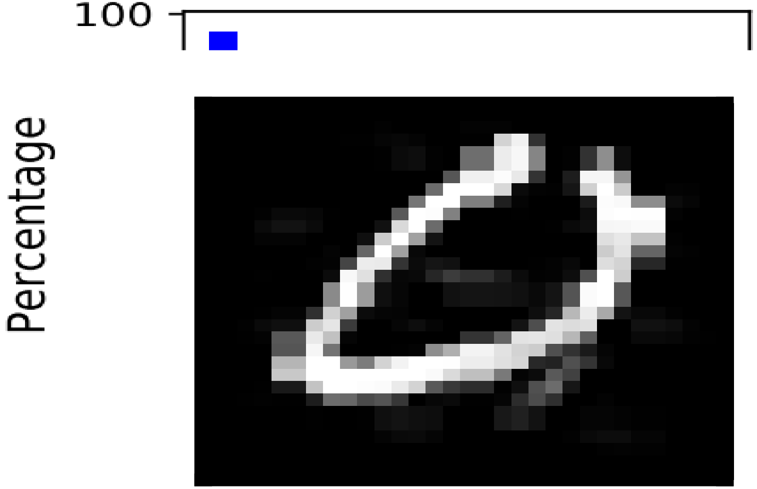
(2) *x' is a legitimate example*

L_0, L_2, L_∞ norm of the noise δ

Measuring Adversarial Examples



A normal example: digit 0



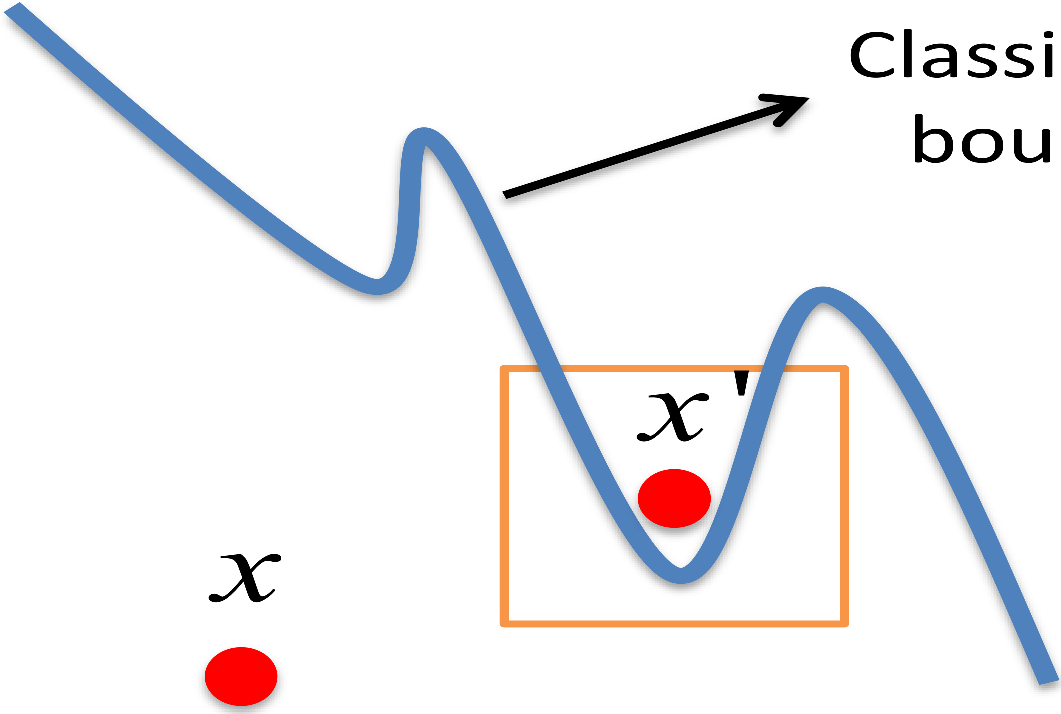
An adversarial example with a target label 9

Xiaoyu Cao and Neil Zhenqiang Gong. “Mitigating Evasion Attacks to Deep Neural Networks via Region-based Classification”. In *ACSAC*, 2017

Observations

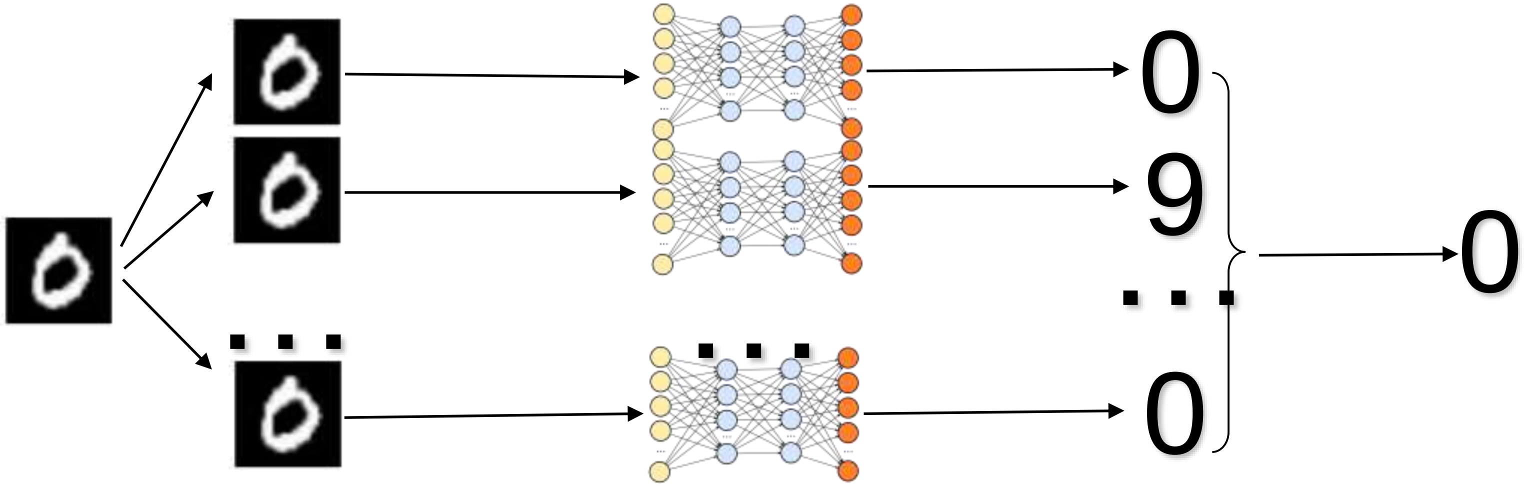
- Normal examples are not robust to small ***carefully crafted*** noise
  - Existence of adversarial examples
- Normal examples are robust to small ***random*** noise
- Adversarial examples are ***not*** robust to small ***random*** noise

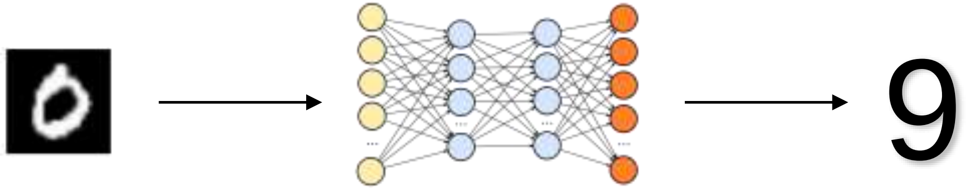
Our Region-based Classification



Classifica(on
boundary+

Our Region-based Classification



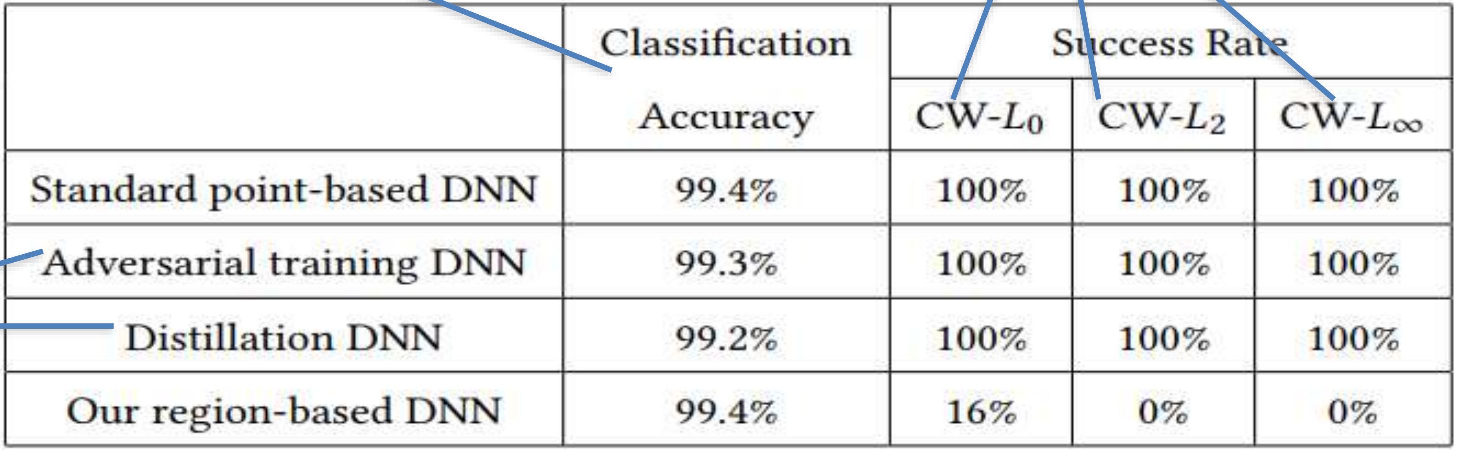


Point-based classification

Evaluations on MNIST for Carlini and Wagner (CW) Attacks (IEEE S&P'17)

Different versions of CW attacks

Accuracy on normal examples



	Classification	Success Rate		
	Accuracy	CW-L_0	CW-L_2	CW-L_∞
Standard point-based DNN	99.4%	100%	100%	100%
Adversarial training DNN	99.3%	100%	100%	100%
Distillation DNN	99.2%	100%	100%	100%
Our region-based DNN	99.4%	16%	0%	0%

Existing defenses

Mitigate adversarial examples without accuracy loss

Good Use of Adversarial Examples: Protecting Privacy

- Inference attacks: an attacker infers a user’s private attributes using its public data
  - Private attributes: political view, sexual orientation, etc.
  - Public data: page likes on Facebook, rating scores, etc.
- An attacker has a classifier to infer private attributes
- A user’s public data is a classification example

Good Use of Adversarial Examples: Protecting Privacy

- User adds *carefully crafted* noise to evade the attacker’s classifier
  - Making the public data an “adversarial example”
- Key challenge: how to guarantee utility of the public data?

Jinyuan Jia and Neil Zhenqiang Gong. “AttriGuard: A Practical Defense Against Attribute Inference Attacks via Adversarial Machine Learning”. In *Usenix Security Symposium*, 2018

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Machine Learning as a Service (MLaaS)

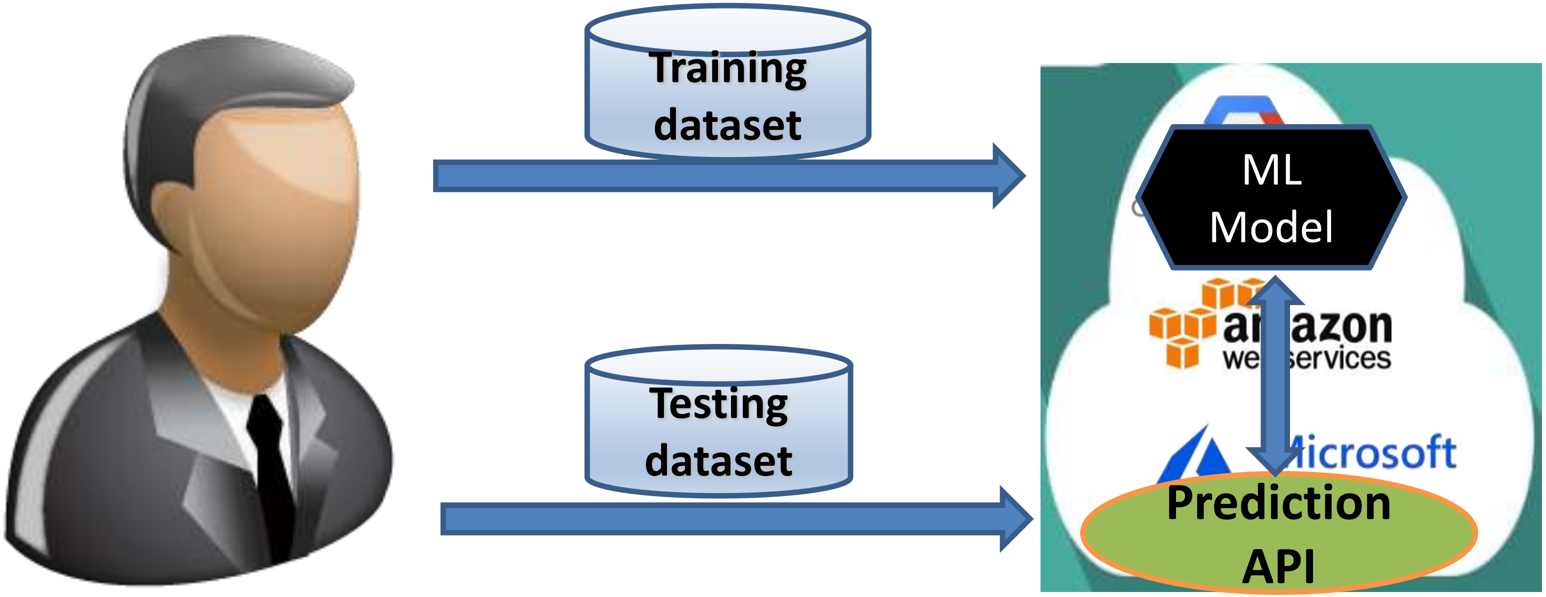
- MLaaS enables users with limited computing power or limited machine learning expertise to use machine learning techniques

amazon web services

Google Cloud Platform

Microsoft Azure

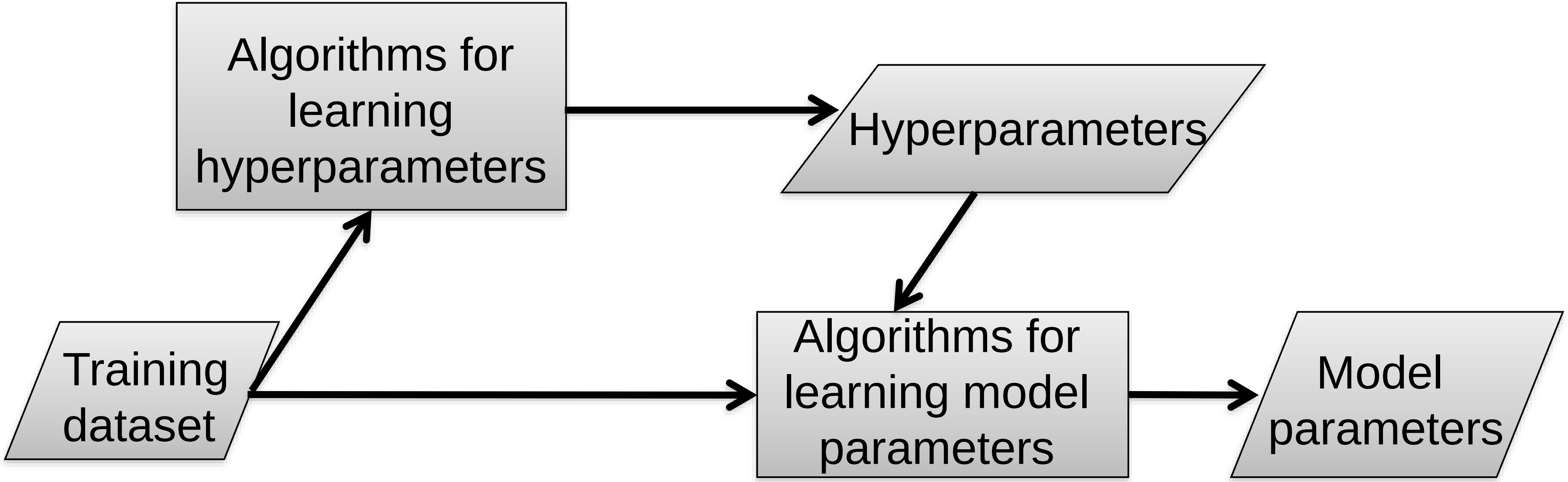
How MLaaS is Used?



Confidentiality for Users

- Training data
- Testing data
- Approaches
  - Trusted processors, e.g., Intel SGX
  - Cryptographic techniques, e.g., secure multi-party computation
  - Statistical methods, e.g., differential privacy

Training a Machine Learning Model



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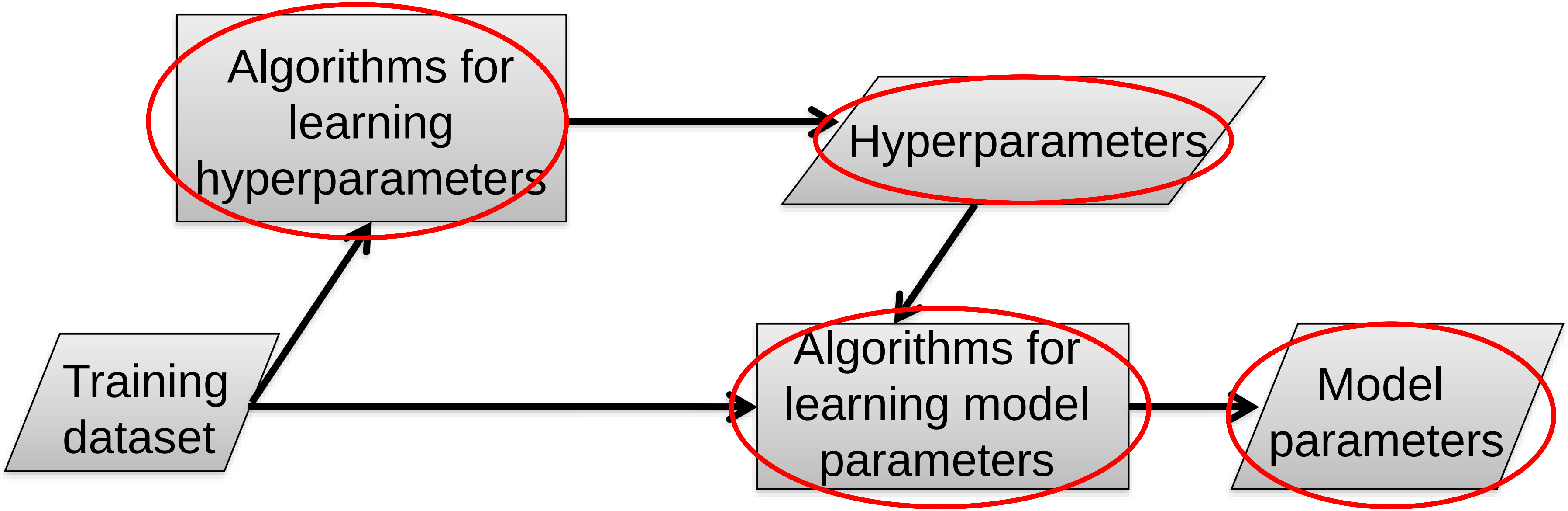
Confidentiality for Service Providers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Stealing Hyperparameters

- We propose a general framework to steal hyperparameters in MLaaS
- Save economical costs without sacrificing model performance
- New defenses are needed

Binghui Wang and Neil Zhenqiang Gong. “Stealing Hyperparameters in Machine Learning”. In *IEEE Symposium on Security and Privacy*, 2018.

Conclusion

- Security is a big challenge for machine learning
- Integrity
  - Training
  - Deployment/Prediction
- Confidentiality
  - Users
  - Service providers