Aalto University

UNIVERSITY OF WATERLOO

Extraction of Complex DNN Models: Real Threat or Boogeyman?

Buse Atli, Sebastian Szyller, Mika Juuti, Samuel Marchal, N. Asokan

Outline

Is model confidentiality important?

Can models be extracted via their prediction APIs?

What can be done to counter model extraction?

Is model confidentiality important?

Machine learning models: business advantage and intellectual property (IP)

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Adversary who steals the model can avoid these costs

How to prevent model theft?

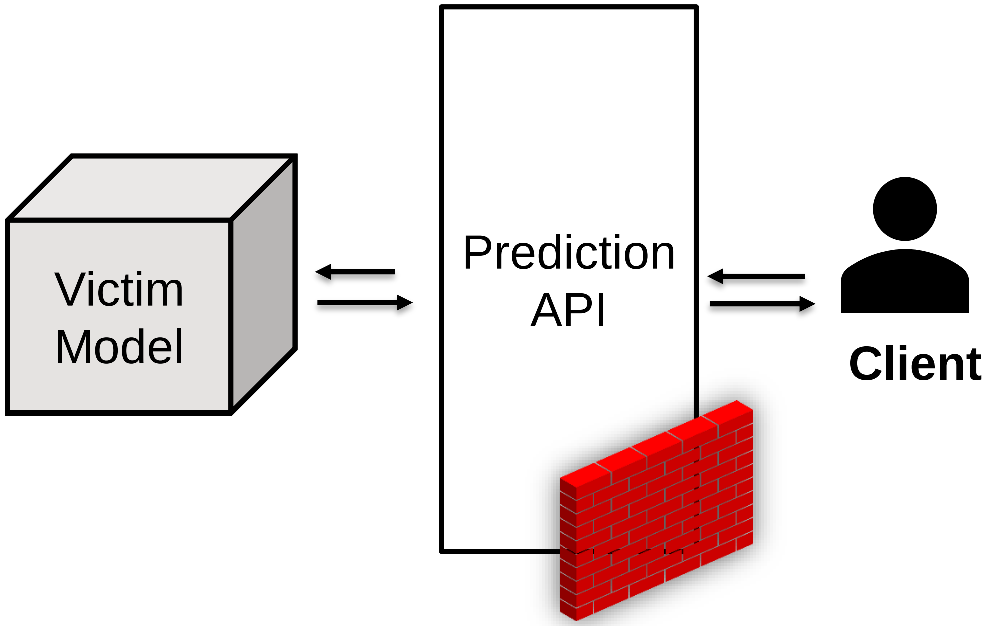
White box model theft can be countered by

- Computation with encrypted models
- Protecting models using secure hardware
- Hosting models behind a firewalled cloud service

Basic idea: hide the model itself, expose model functionality only via a prediction API

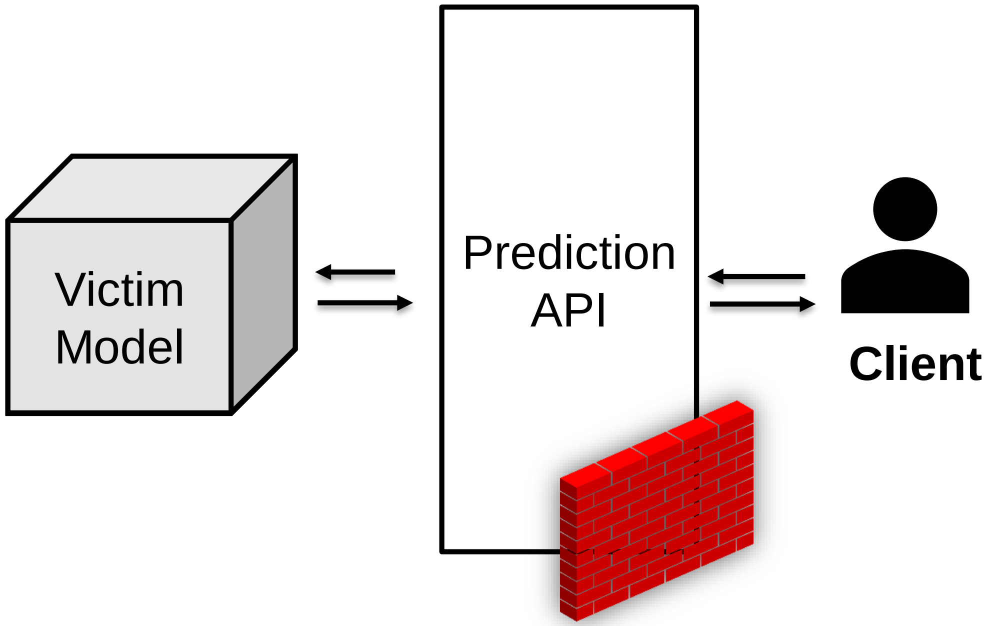
Is that enough to prevent model theft?

Extracting models via their prediction APIs



Extracting models via their prediction APIs

Prediction APIs are oracles that leak information



Extracting models via their prediction APIs

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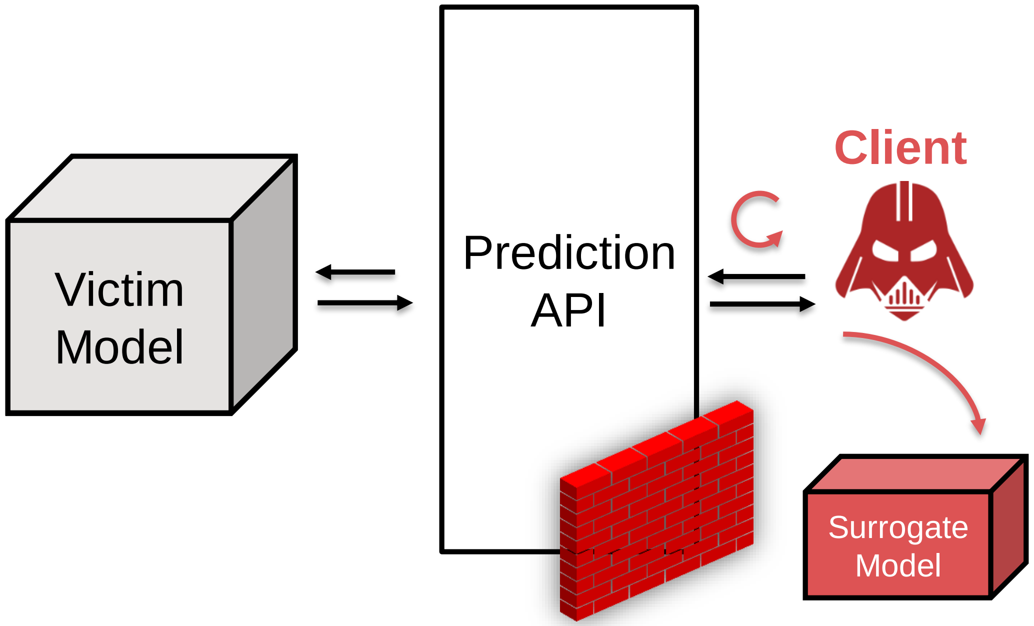
Adversary

- Malicious client
- Goal: rebuild a surrogate model for a victim model
- Capability: access to prediction API or model outputs

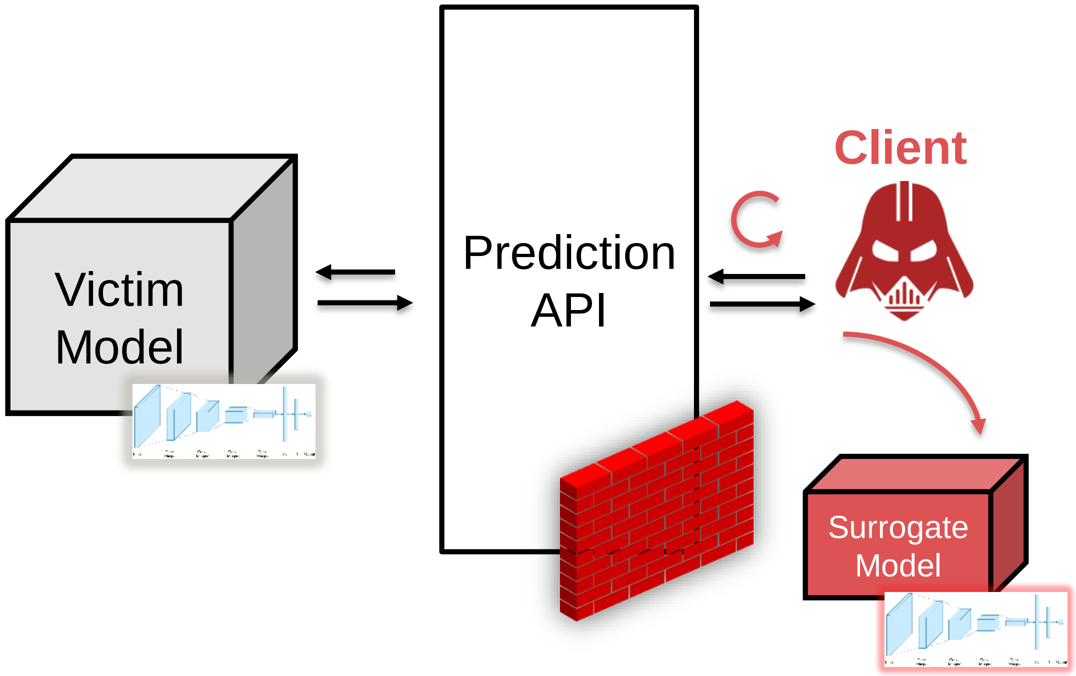


Model extraction: attacks and defenses

Are model extraction attacks realistic? Can they be detected effectively?

Prior work on extracting

- Logistic regression, decision trees[1]
- Simple CNN models[2,3]
- Querying API with synthetic samples



[1] Tramer et al. -*Stealing Machine Learning Models via Prediction APIs*, USENIX '16 (https://arxiv.org/abs/1609.02943)
[2] Papernot et al. -*Practical Black-Box Attacks against Machine Learning*, ASIA CCS '17(https://arxiv.org/abs/1602.02697)
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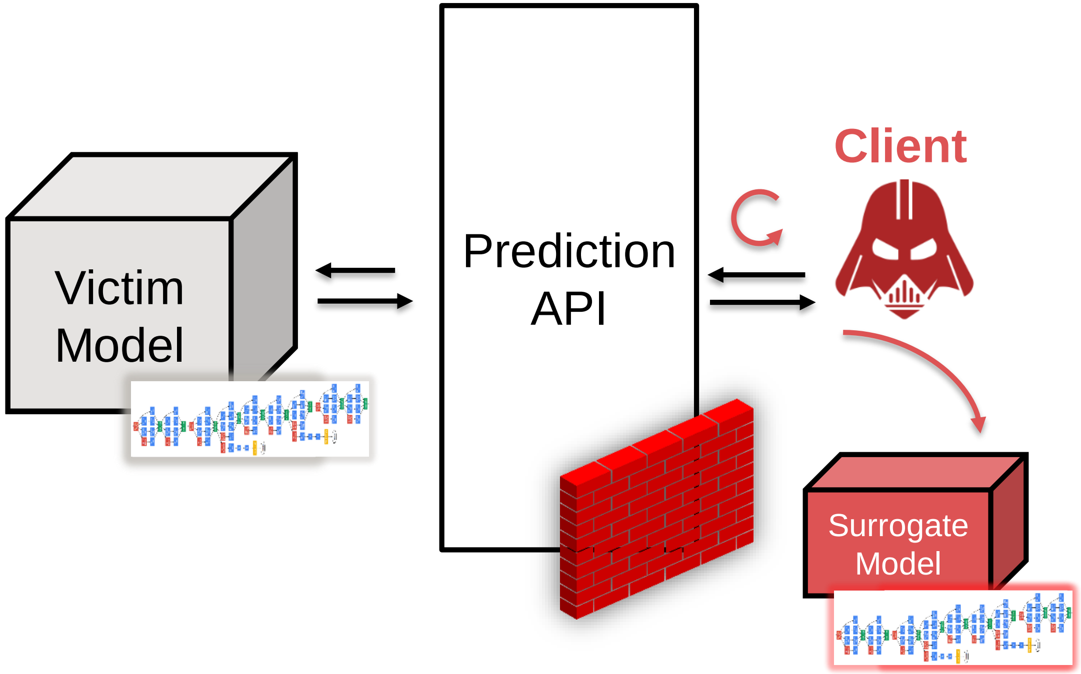
Against complex image classification models?

- Can adversaries extract complex DNNs successfully?
- Are common adversary models realistic?
- Are current defenses effective?



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Extraction of Complex DNN Models: Knockoff nets[1]

Goal:

- Build a surrogate model that
  - steals model functionality of victim model
  - performs similarly on the same task with high classification accuracy

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Adversary capabilities:

- Victim model knowledge:
  - None of train/test data, model internals, output semantics
  - Access to full prediction probability vector
- Access to natural samples, not (necessarily) from the same distribution as train/test data
- Access to pre-trained high-capacity model

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Knockoff nets: Our Goals and Contributions

Reproduce empirical evaluation of Knockoff nets [1] to confirm its effectiveness

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Revisit adversary model in [1]

- Explore impact of a more realistic adversary model on attack and defense effectiveness

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Revisit adversary model in [1]

- Explore impact of a more realistic adversary model on attack and defense effectiveness
  - Attack effectiveness decreases: Different surrogate-victim architectures, reduced granularity of victim’s prediction API’s output, reduced diversity of adversarial queries
  - Defense effectiveness decreases: Attacker has natural samples distributed like victim’s training data

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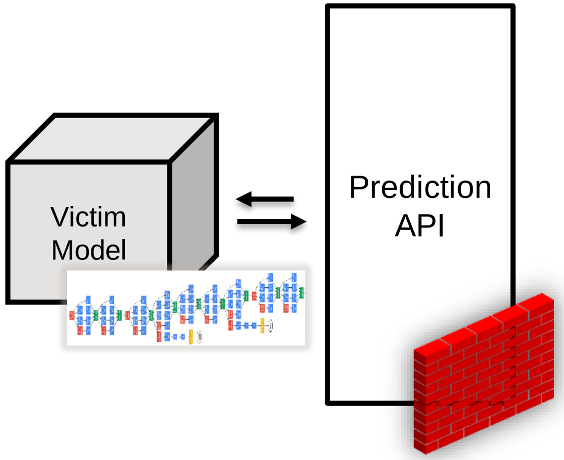
Knockoff nets [1] : Experimental Setup

Strategy

Victim with public, pre-trained model with high capacity (e.g., ResNet-34 on ImageNet)



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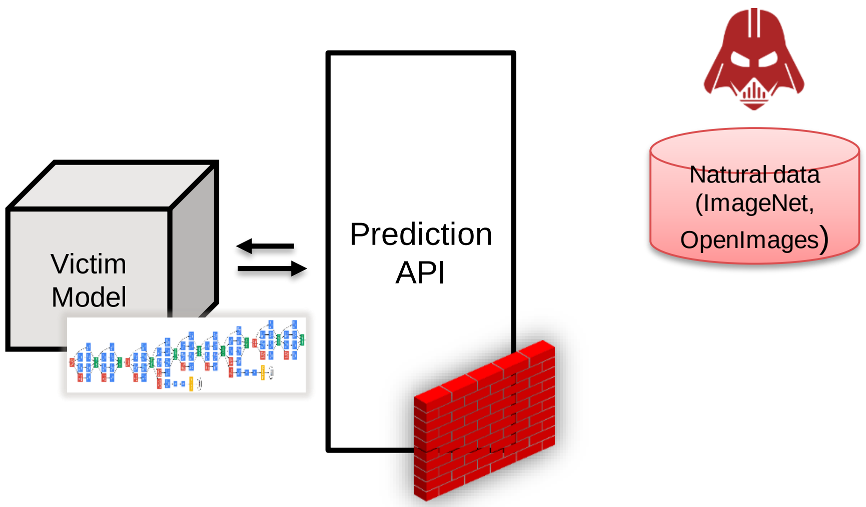

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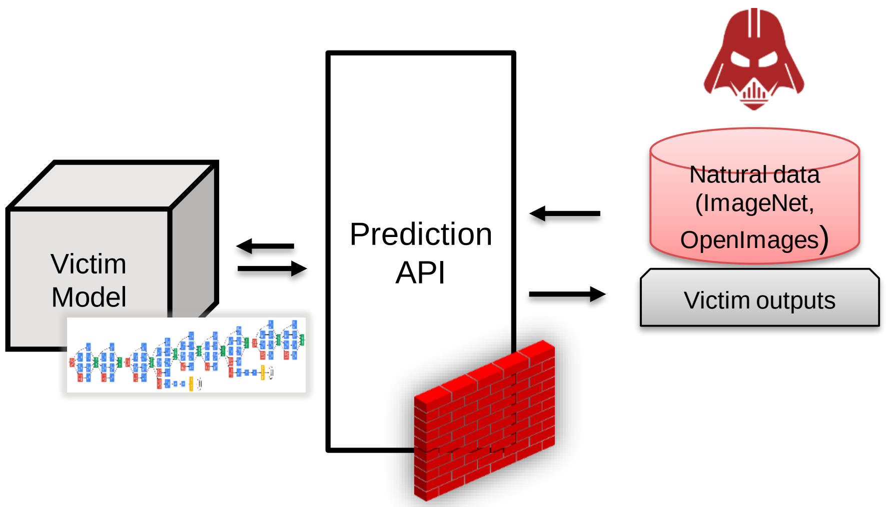
Query API to collect victim outputs

- Using ~ 100,000 queries
- API returns probability vector



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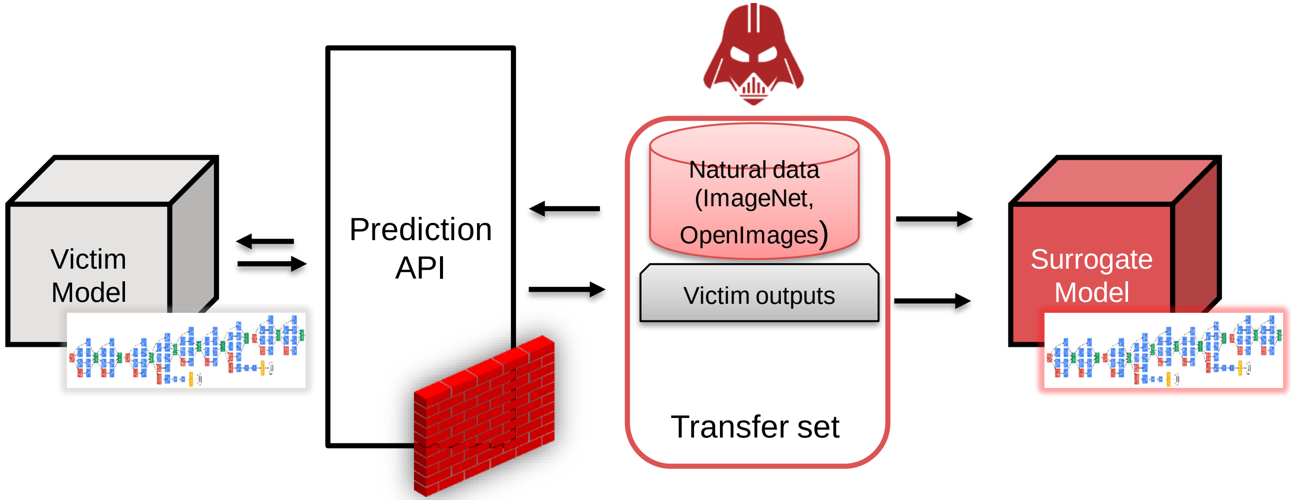
Construct surrogate model

- Select a pre-trained model and retrain it with transfer set
- Takes ~ 3 days



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Knockoff nets: Reproduction

Knockoff nets are effective against complex, pre-trained DNN models

Victim Model (Dataset-model)	Test Accuracy % (performance recovery)			
	Our reproduction		Reported in [1]	
	Victim Model	Surrogate Model	Victim Model	Surrogate Model
Caltech-RN34	74.1	72.2 (0.97x)	78.8	75.4 (0.96x)
CUBS-RN34	77.2	70.9 (0.91x)	77.2	70.9 (0.89x)
Diabetic-RN34	71.1	53.5 (0.75x)	58.1	47.7 (0.82x)
GTSRB-RN34	98.1	94.8 (0.96x)	-	-
CIFAR10-RN34	94.6	88.2 (0.93x)	-	-

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Revisiting the Adversary Model: Reduced Granularity of Prediction API's Output

Panda	99%
Mammal	99%
Vertebrate	99%
Terrestrial Animal	98%
Bear	94%
Nose	93%
Snout	92%
Nature Reserve	87%

Google Cloud Vision (top 20)

PREDICTED CONCEPT	PROBABILITY
wildlife	0.993
no person	0.988
zoo	0.974
panda	0.970
mammal	0.967
nature	0.964
animal	0.960
endangered species	0.958
cute	0.950
fur	0.948
outdoors	0.903
wild	0.901
portrait	0.885
endangered	0.842
frosty	0.840

Clarifai (top 20)

General Model

Quickly understand objects, actions, scenes, and colors within an image.

mammal	0.99
animal	0.99
giant panda	0.99
carnivore	0.99
black color	0.91
coal black color	0.88

IBM Watson (top 10)

Revisiting the Adversary Model: Reduced Granularity of Prediction API's Output

Original adversary model in [1] expects a complete prediction vector for each query

Effectiveness degrades when prediction API gives truncated results (top label, rounded probabilities etc.)

Victim Model (Dataset-model)	Test Accuracy % (performance recovery)		
	Victim Model	Surrogate Model (full probability vector)	Surrogate Model (only top label)
Caltech-RN34 (257 classes)	74.1	72.2 (0.97x)	57.2 (0.77x)
CUBS-RN34 (200 classes)	77.2	70.9 (0.91x)	42.5 (0.55x)
Diabetic-RN34 (5 classes)	71.1	53.5 (0.75x)	53.5 (0.75x)
GTSRB-RN34 (43 classes)	98.1	94.8 (0.96x)	91.9 (0.93x)
CIFAR10-RN34 (10 classes)	94.6	88.2 (0.93x)	84.4 (0.89x)

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Revisiting the Adversary Model: Different Surrogate-Victim Architectures

Adversary model in [1] : victim model uses publicly available, pre-trained DNN models.

Effectiveness degrades when both victim and surrogate models are not pre-trained ImageNet DNNs.

Victim Model (Dataset-model)	Test Accuracy % (performance recovery)		
	Victim Model	Surrogate Model (RN34)	Surrogate Model (VGG16)
GTSRB-RN34	98.1	94.8 (0.96x)	90.1 (0.91x)
CIFAR10-RN34	94.6	88.2 (0.93x)	82.9 (0.87x)
GTSRB-5L	91.5	54.5 (0.59x)	55.8 (0.60x)
CIFAR10-9L	84.5	67.5 (0.79x)	64.7(0.76x)

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Knockoff nets: Limitation

Knockoff nets cannot recover per-class performance of victim model

Class Name	Test accuracy % (performance recovery)	
	Victim Model (CIFAR-RN34) 94.6% on average	Surrogate Model 88.2% on average
Airplane (class 0)	95	88 (0.92x)
Automobile (class 1)	97	95 (0.97x)
Bird (class 2)	92	87 (0.94x)
Cat (class 3)	89	86 (0.96x)
Deer (class 4)	95	84 (0.88x)
Dog (class 5)	88	84 (0.95x)
Frog (class 6)	97	90 (0.92x)
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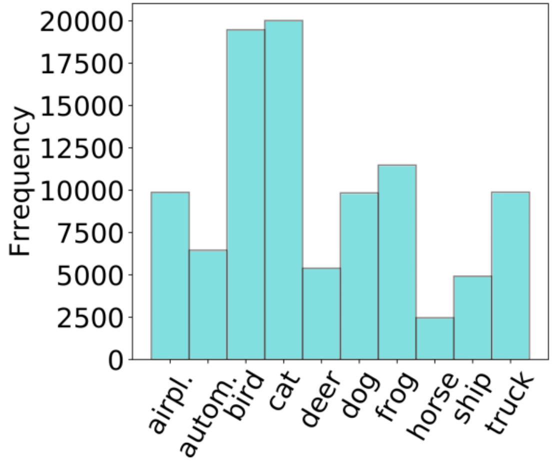
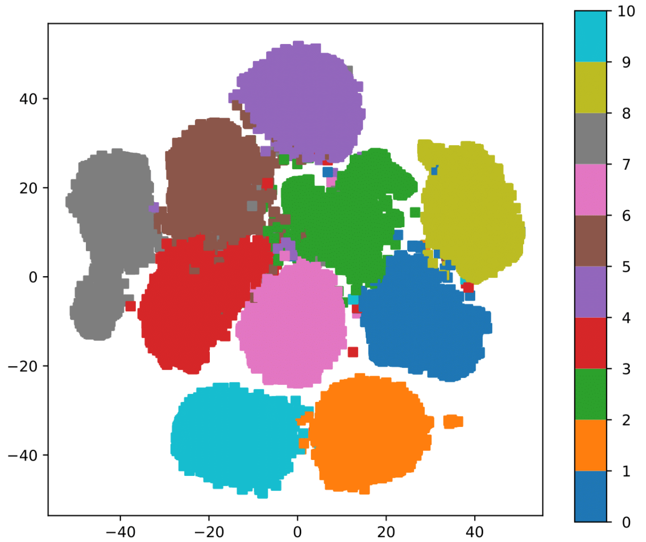
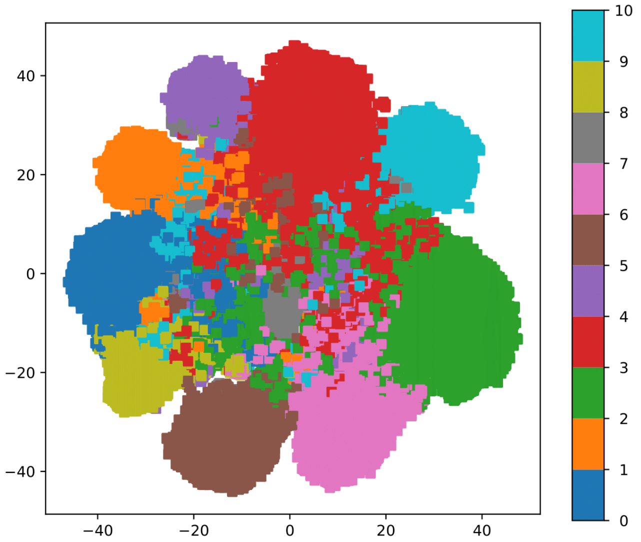



Victim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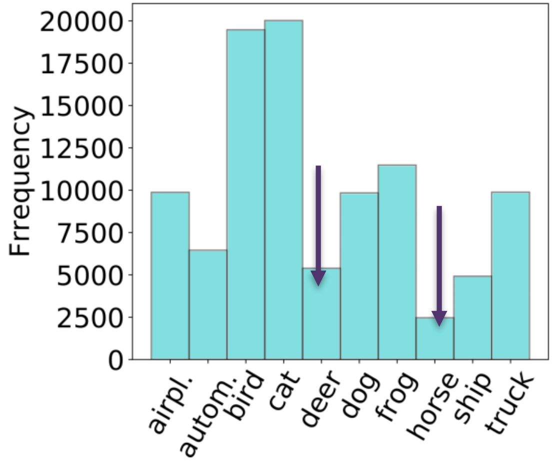

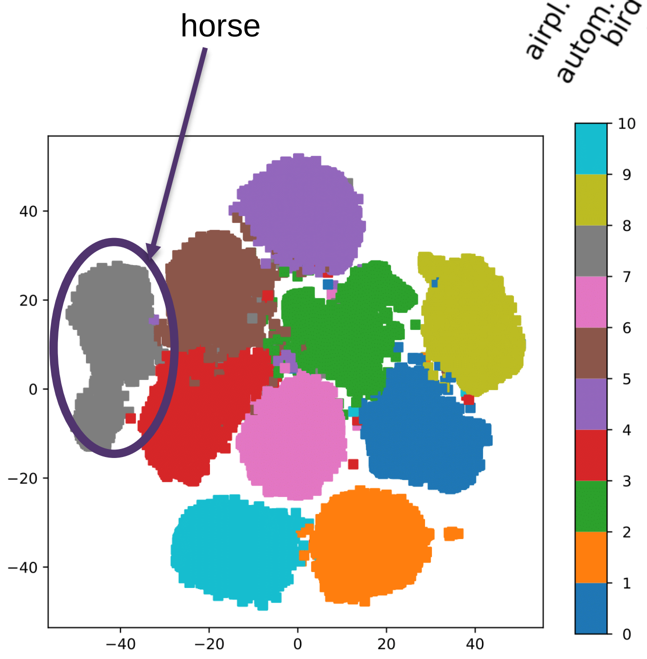

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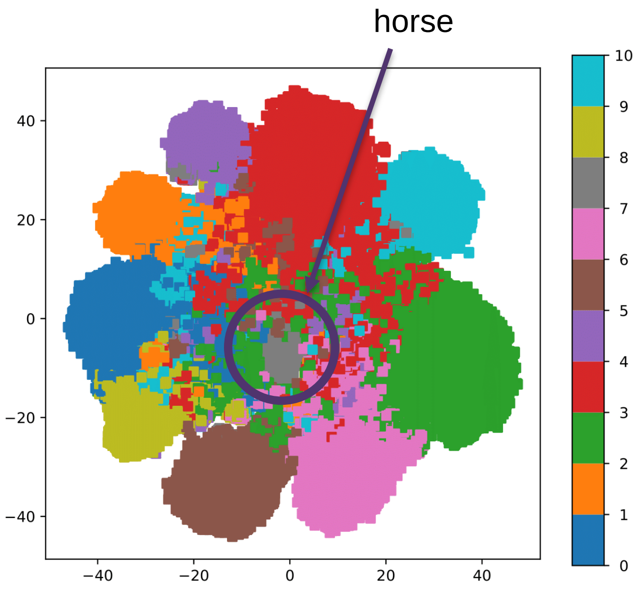

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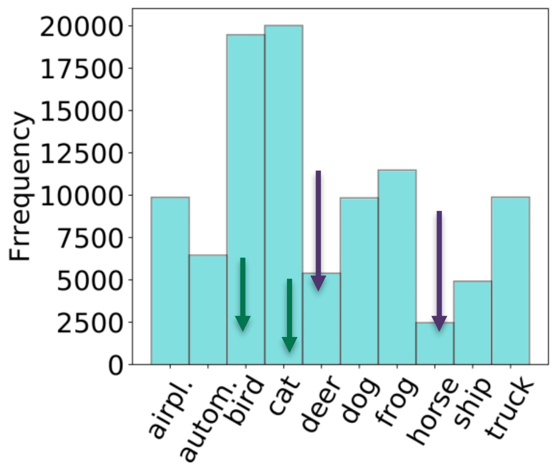
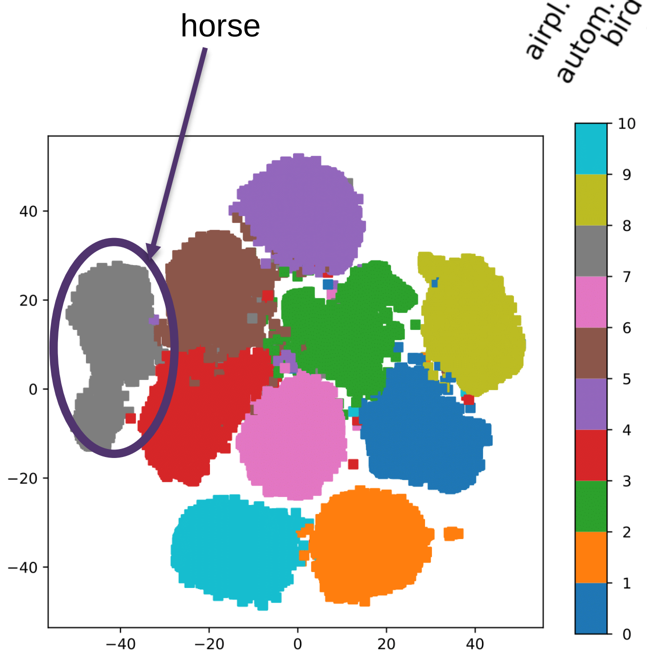
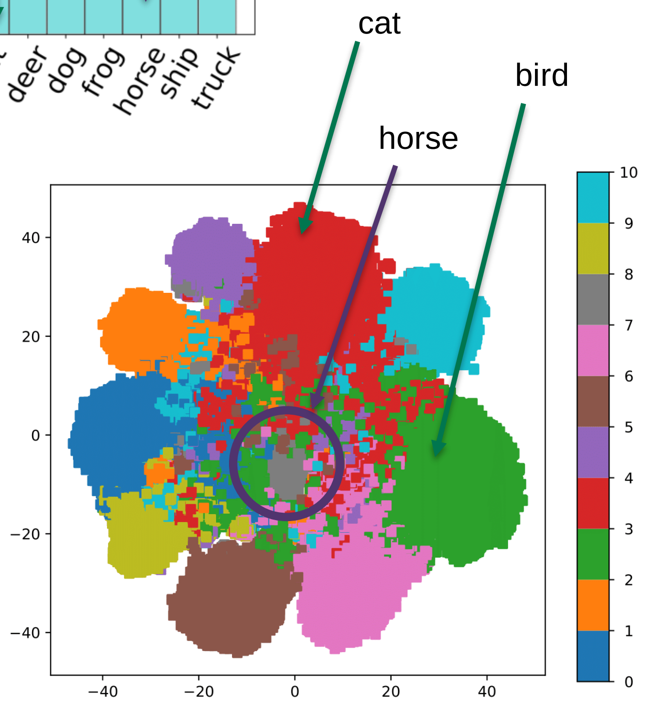




Victim



Surrogate

Knockoff nets: Detecting Attacker's Queries

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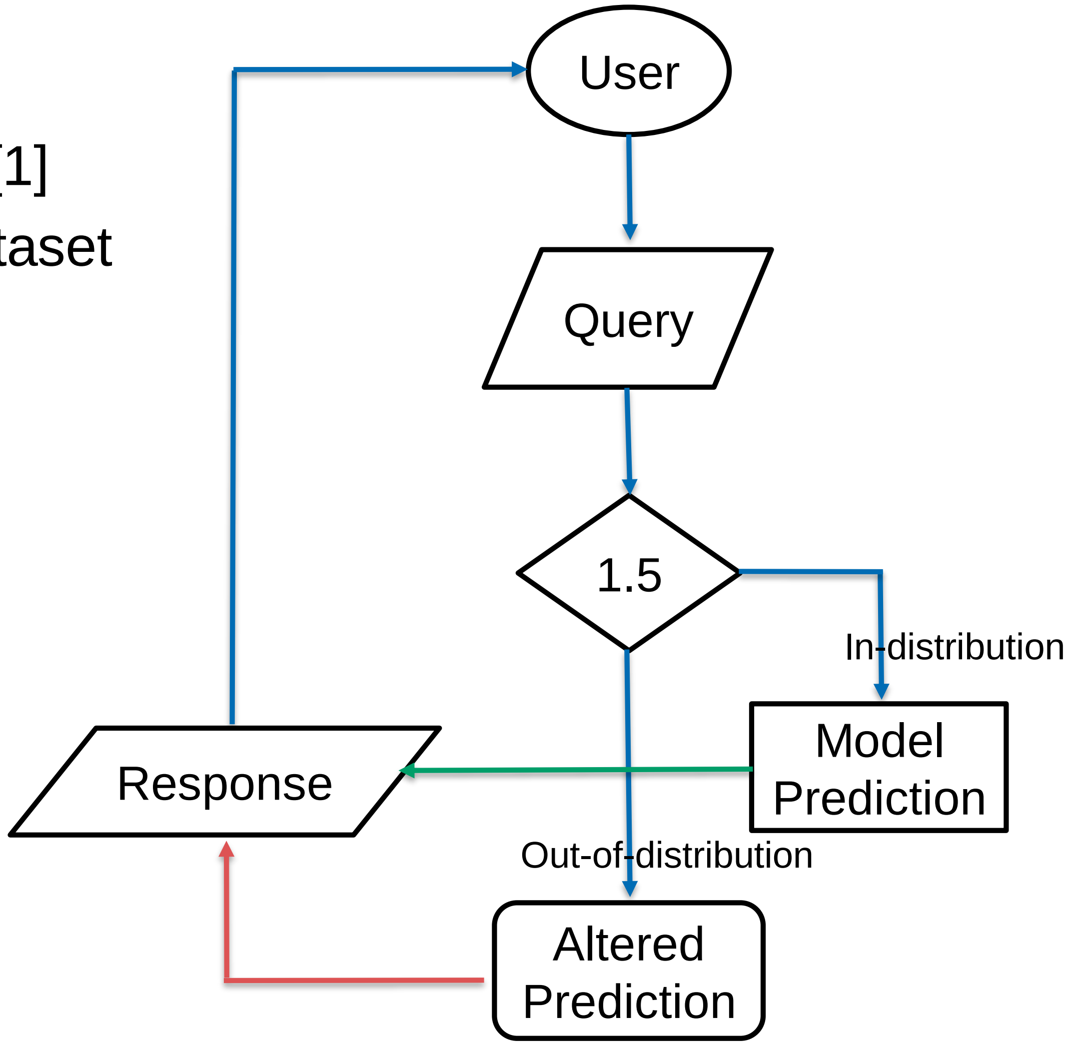
- Queries API with a random subset of public dataset used for a general task



[1] Orekondy et al. - *Knockoff Nets: Stealing Functionality of Black-Box Models,* CVPR '19 (https://arxiv.org/abs/1812.02766)

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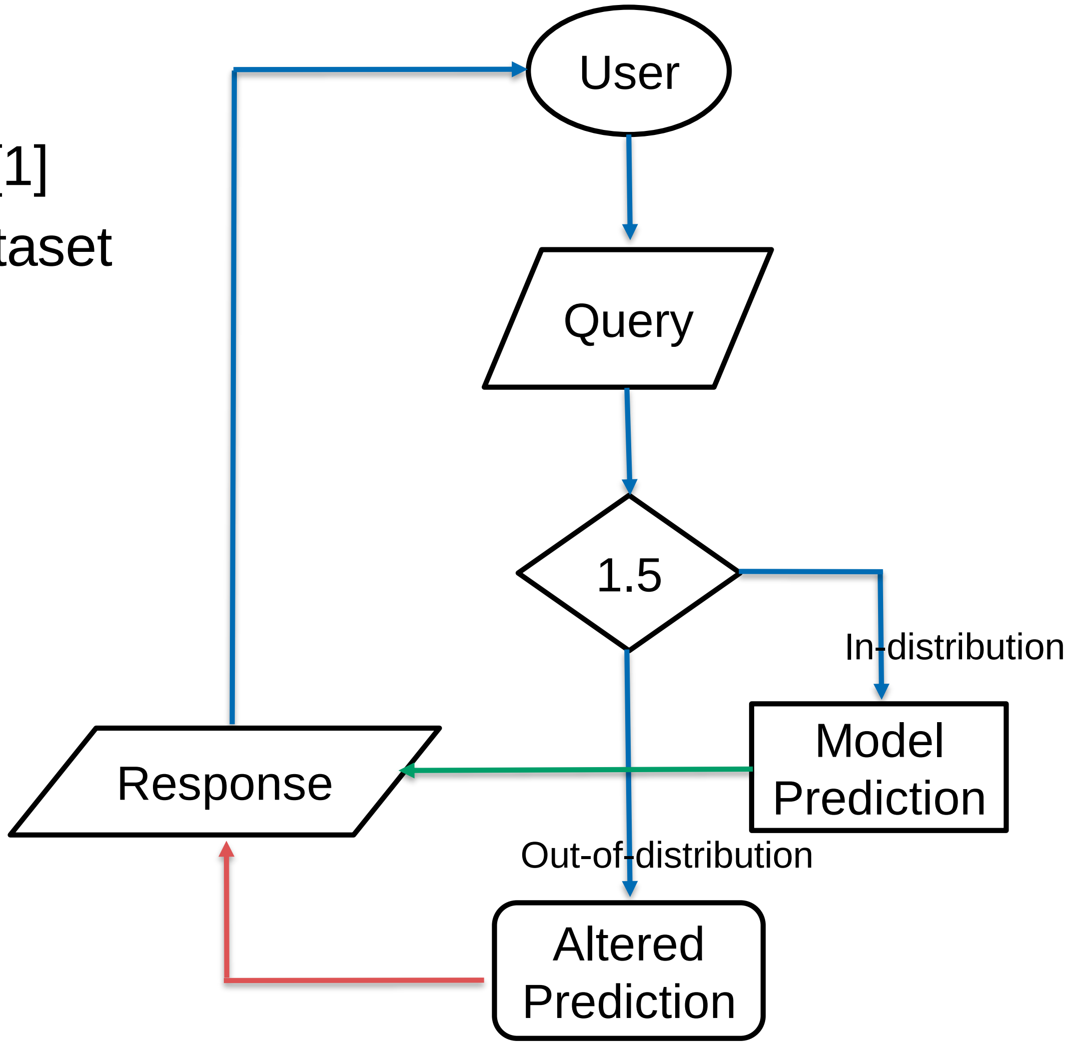

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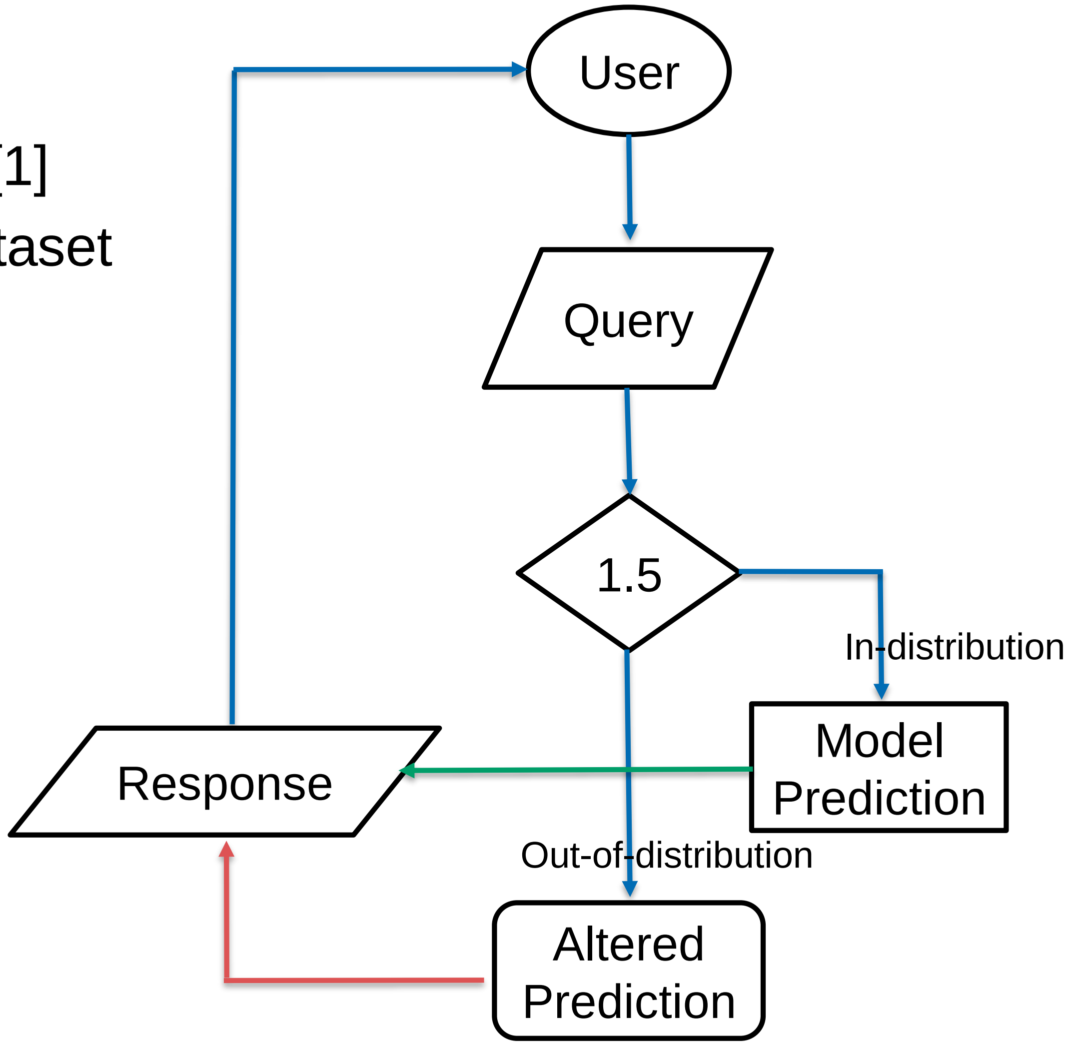

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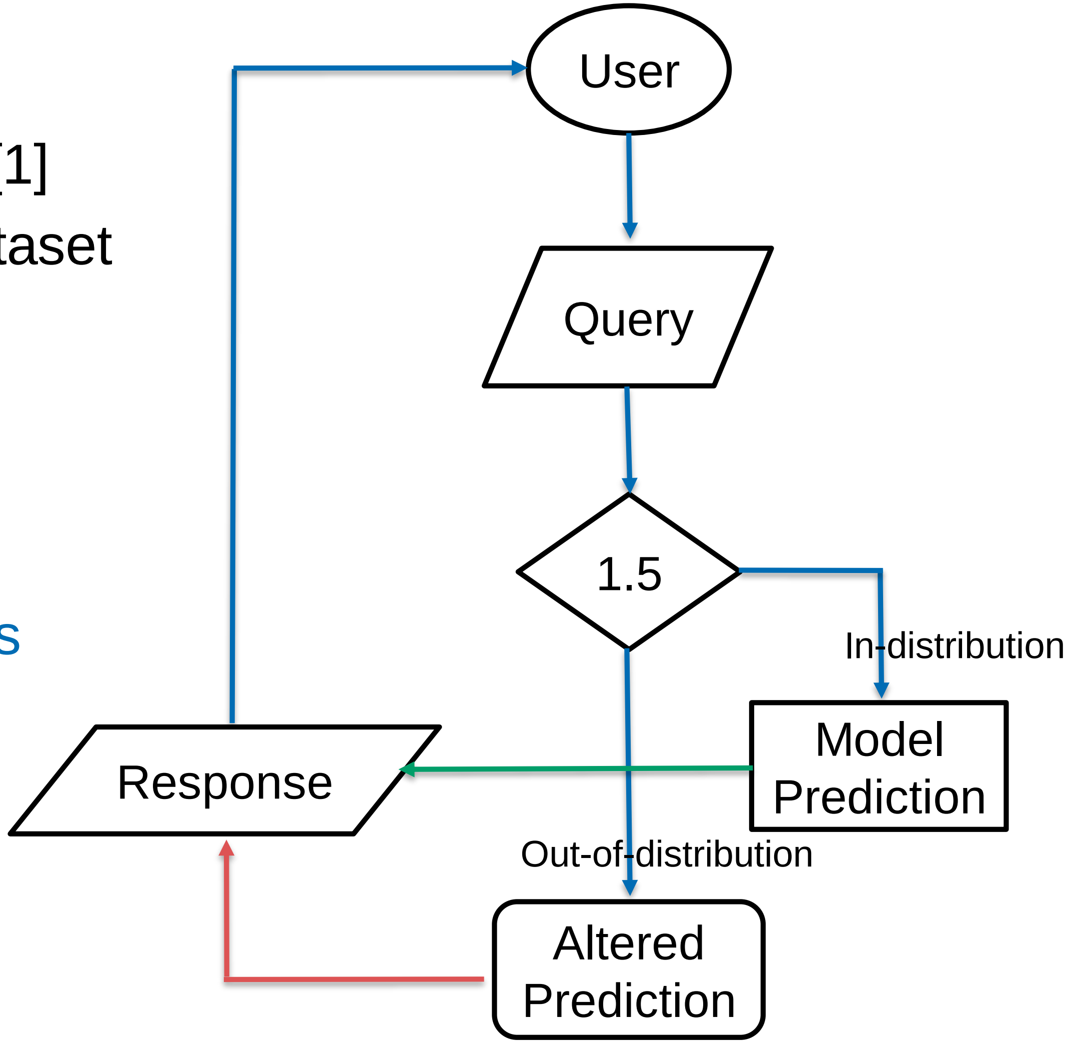
- Detect images from distribution other than victim's
- Give proper prediction only to in-distribution queries



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Knockoff nets: Detecting Attacker’s Queries

Evaluation

- Trained ResNet classifiers to detect in and out-of-distribution queries
- High TPR/TNR on all datasets but Caltech (strong overlap with ImageNet, OpenImages)
- Performs better than state-of-the-art out-of-distribution methods (ODIN[1] , Mahal[2])

Victim Model (Dataset-model)	ImageNet		OpenImages	
	In-distribution (TPR%)	Out-of-distribution (TNR%)	In-distribution (TPR%)	Out-of-distribution (TNR%)
Caltech-RN34	63	56	61	59
CUBS-RN34	93	93	93	93
Diabetic-RN34	99	99	99	99
GTSRB-RN34	99	99	99	99
CIFAR10-RN34	96	96	96	96

[1] Liang et al. – *Enhancing the Reliability of Out-of-Distribution Image Detection in Neural Networks,* ICLR ‘18 (https://arxiv.org/abs/1706.02690)
[2] Lee et al. - *A Simple Unified Framework for Detecting Out-of-Distribution Samples and Adversarial Attacks,* NIPS ‘18 (https://arxiv.org/abs/1807.03888)

Knockoff nets: Detecting Attacker’s Queries

- Adversary in [1] has no prior information or expectation about the output vector
- Prediction API gives shuffled prediction vector for detected out-of-distribution queries

Victim Model (Dataset-model)	Test Accuracy % (performance recovery)		
	Victim Model	Surrogate Model (correct probability list)	Surrogate Model (shuffled probability list)
Caltech-RN34 (257 classes)	74.1	72.2 (0.97x)	29.5 (0.39x)
CUBS-RN34 (200 classes)	77.2	70.9 (0.91x)	20.1 (0.26x)
Diabetic-RN34 (5 classes)	71.1	53.5 (0.75x)	28.0 (0.39x)
GTSRB-RN34 (43 classes)	98.1	94.8 (0.96x)	14.8 (0.15x)
CIFAR10-RN34 (10 classes)	94.6	88.2 (0.93x)	2.8 (0.02x)

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Revisiting the Adversary Model: Access to In-distribution Data

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Are there any prevention mechanisms?

- Stateful analysis → Sybil attacks
- Charging customers upfront → Reduced utility for benign users
- Restrict access to the API → Reduced utility for benign users

Takeaways

ML-based systems need to worry about adversaries

adversaries are multi-lateral; defenses need to be, too

Is model confidentiality important? Yes

models constitute business advantage to model owners

Can models be extracted via their prediction APIs? Yes

Protecting model data via cryptography or hardware security is insufficient

What can be done to counter model extraction? Watermarking as a deterrence

Watermarking at the prediction API is feasible

Deserves to be considered as a deterrence against model stealing

More on our security/privacy + ML research at https://ssg.aalto.fi/research/projects/mlsec/