# CS 499/599: Machine Learning Security
# 02.09: Data Poisoning

Mon/Wed 12:00 – 1:50 pm

Sanghyun Hong

sanghyun.hong@oregonstate.edu

Oregon State University

SAIL
Secure AI Systems Lab

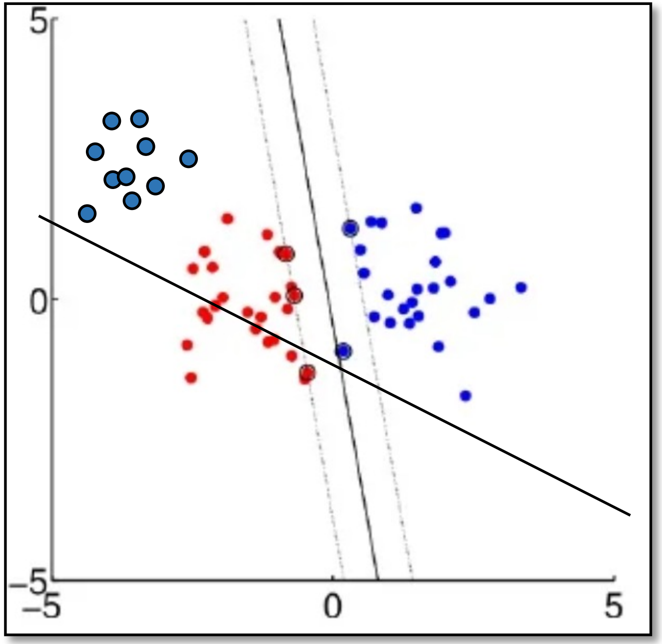
# Notice

- Due dates
  - Written Paper Critiques (on the $14^{th}$)
- Sign-up (on Canvas)
  - Scribe Lecture Note
  - In-class Paper Presentation / Discussion

# Topics for Today

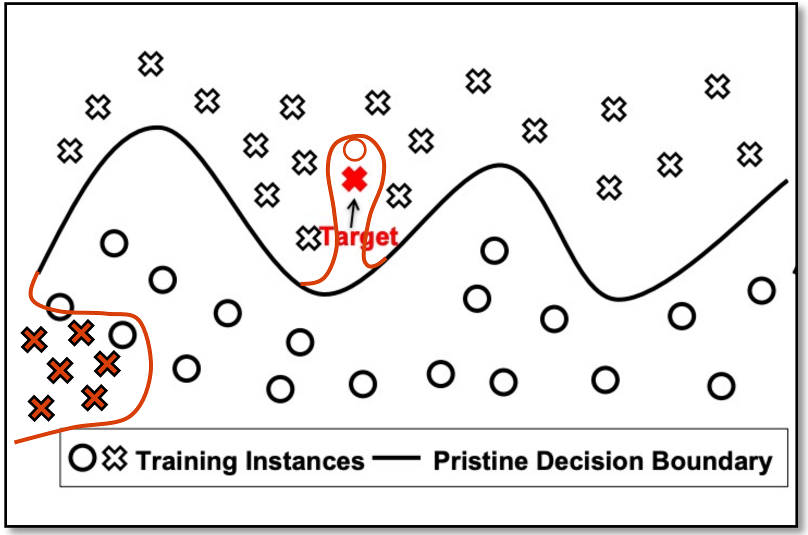
- Motivation
  - Evade spam filter
  - Evade DDoS detection
- Data Poisoning:
  - Indiscriminate Attacks
    - Support vector machines (SVMs)
    - Regression models
  - Targeted Attacks
    - Deep neural networks (DNNs)
      - Poison Frogs
      - Meta-Poison
  - Conclusion (and implications)

# Revisited: Linear Models vs. DNNs




← Linear model (SVM)

Neural Network →



Shafahi *et al.*, Poison Frogs! Targeted Clean-label Poisoning Attacks on Neural Networks
Huang *et al.*, MetaPoison: Practical General-purpose Clean-label Data Poisoning

# Motivation

- Practical Constraints
  - You don’t have control over your inputs
  - You don’t want to mess-up the entire system

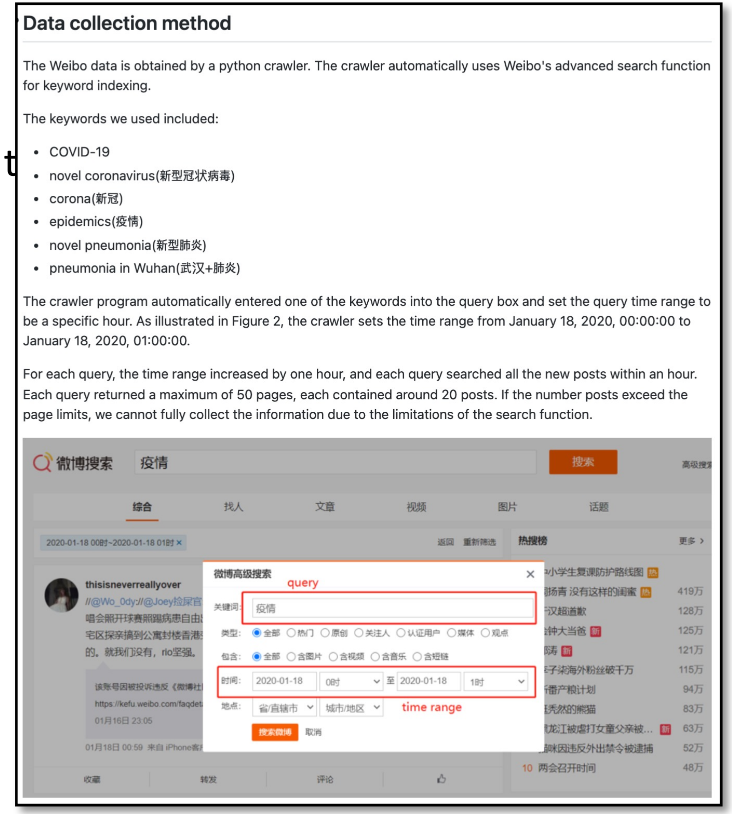


**Targeted Poisoning Attacks!**

gy-u-s-airports/

# Motivation

- Practicality
  - Many ways to insert your malicious data
  - Human-inspection is not feasible (think about t



### Data collection method

The Weibo data is obtained by a python crawler. The crawler automatically uses Weibo's advanced search function for keyword indexing.

The keywords we used included:

- COVID-19
- novel coronavirus(新型冠状病毒)
- corona(新冠)
- epidemics(疫情)
- novel pneumonia(新型肺炎)
- pneumonia in Wuhan(武汉+肺炎)

The crawler program automatically entered one of the keywords into the query box and set the query time range to be a specific hour. As illustrated in Figure 2, the crawler sets the time range from January 18, 2020, 00:00:00 to January 18, 2020, 01:00:00.

For each query, the time range increased by one hour, and each query searched all the new posts within an hour. Each query returned a maximum of 50 pages, each contained around 20 posts. If the number posts exceed the page limits, we cannot fully collect the information due to the limitations of the search function.



https://yiling-chen.github.io/flickr-cropping-dataset/
https://github.com/ylleng/COVID-Weibo

# Threat Model: Targeted Poisoning

- Goal
  - ~~Indiscriminate attack (increase the error on $D_{val}$)~~
  - Targeted attack: cause a misclassification of $(x_t, y_t)$, while preserving acc. on $D_{val}$
- Capability
  - Train a model $f$ on $D_{tr}$
  - Inject $p$ poisons into the training set ($\mathrm{N}(D_{tr}) = n + p$)
- Knowledge
  - ~~$D_{tr}$ : training data~~
  - $D_{val}$: validation data
  - $f$: a model and its parameters
  - ~~$L$: training algorithm (*e.g.*, SGD)~~

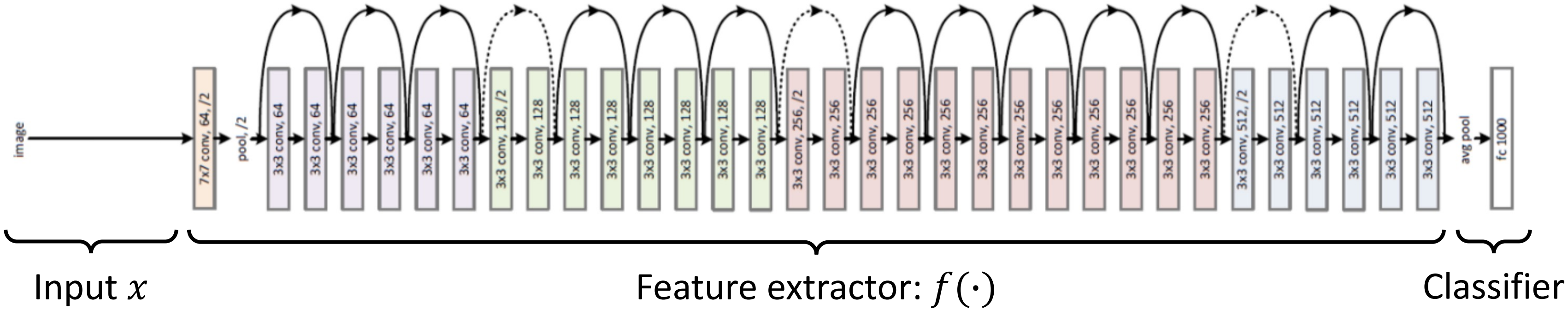
# Threat Model: Clean-label Targeted Poisoning

- Goal
  - ~~Indiscriminate attack (increase the error on $D_{val}$)~~
  - Targeted attack: cause a misclassification of $(x_t, y_t)$, while preserving acc. on $D_{val}$

- Capability
  - Train a model $f$ on $D_{tr}$
  - Inject $p$ poisons into the training set ($\mathrm{N}(D_{tr}) = n + p$)

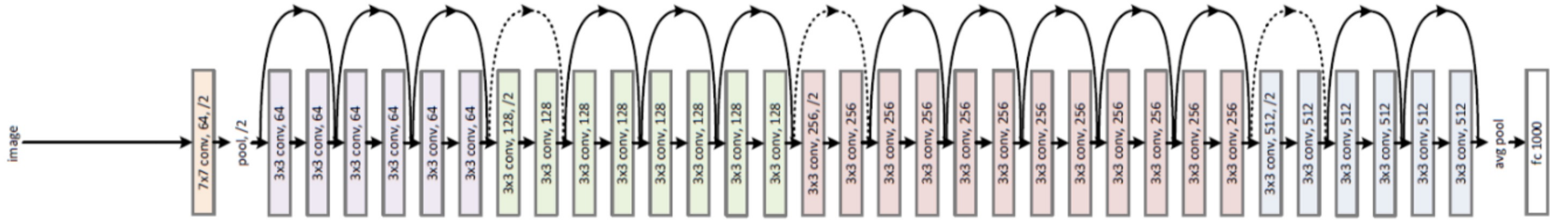
- Knowledge
  - ~~$D_{tr}$ : training data~~
  - $D_{val}$: validation data
  - $f$: a model and its parameters
  - ~~$L$: training algorithm (*e.g.*, SGD)~~

# Background: Convolutional Neural Networks




- A conventional view:
  - Convolutions: extract features, embeddings, latent representations, …
  - Last layer: uses the output for a classification task

# Background: Convolutional Neural Networks

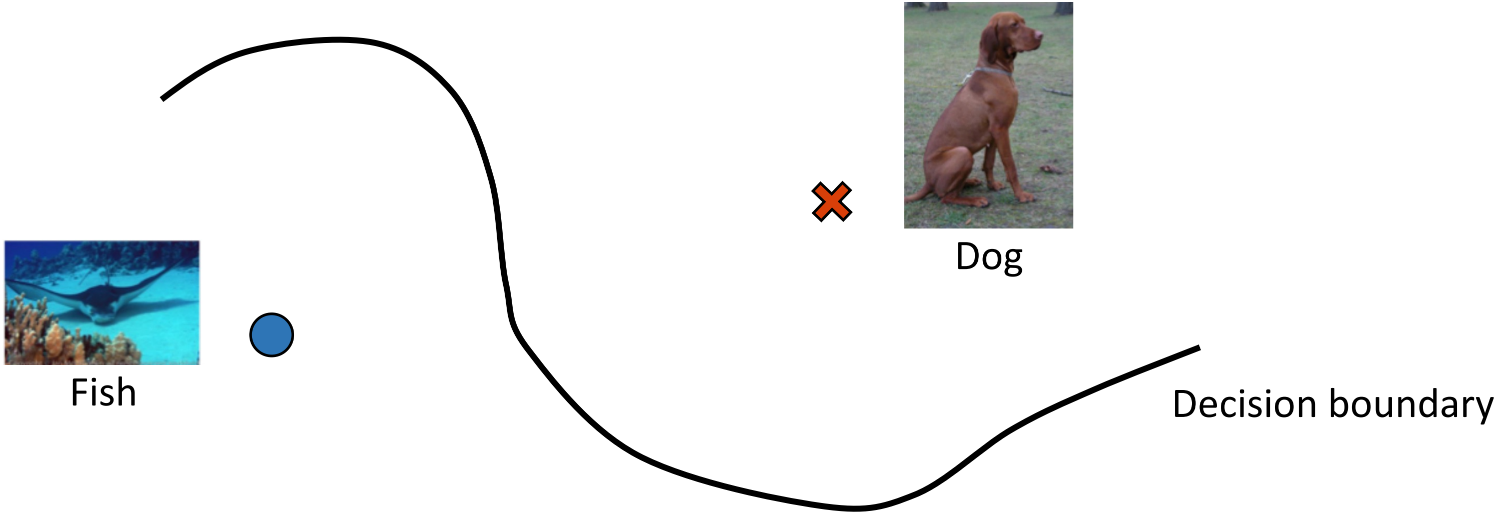



Input $x$ | Feature extractor: $f(\cdot)$ | Classifier

- Input-space $\neq$ Feature-space:
  - Two samples similar in the input-space can be far from each other in the feature-space
  - Two samples very different in the input-space can be close to each other in $f$

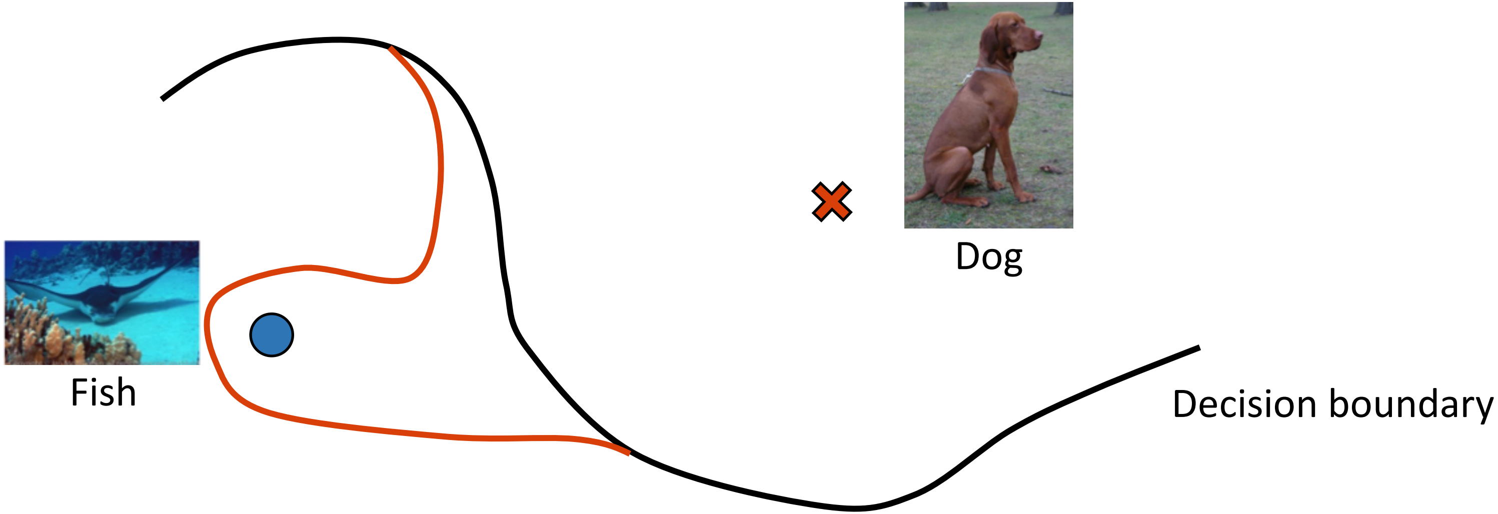
# The Key Idea: Feature Collision

- Goal
  - You want your *any* poison to be closer to your target $(x_t, y_t)$ in the *feature space*



# The Key Idea: Feature Collision

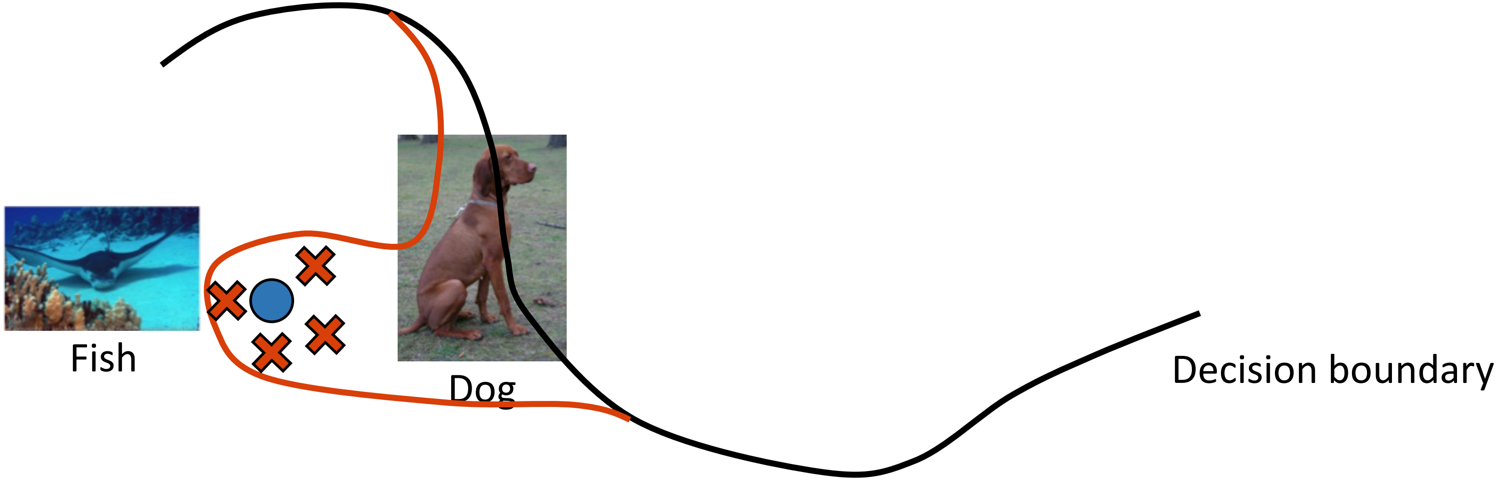
- Goal
  - You want your *any* poison to be closer to your target $(x_t, y_t)$ in the *feature space*




**The Fish Becomes DogFish!**

# The Key Idea: Feature Collision

- Goal
  - You want your *any* poison to be closer to your target $(x_t, y_t)$ in the *feature space*



# The Key Idea: Feature Collision

- Goal
  - You want your *any* poison to be closer to your target $(x_t, y_t)$ in the *feature space*
  - Objective:

$$\mathbf{p} = \underset{\mathbf{x}}{\operatorname{argmin}} \ \|f(\mathbf{x}) - f(\mathbf{t})\|_2^2 + \beta \|\mathbf{x} - \mathbf{b}\|_2^2$$

  - Optimization:

**Algorithm 1** Poisoning Example Generation

**Input:** target instance $t$, base instance $b$, learning rate $\lambda$
Initialize x: $x_0 \leftarrow b$
Define: $L_p(x) = \|f(\mathbf{x}) - f(\mathbf{t})\|^2$
**for** $i = 1$ **to** $maxIters$ **do**
  Forward step: $\widehat{x_i} = x_{i-1} - \lambda \nabla_x L_p(x_{i-1})$ // construct input perturbations
  Backward step: $x_i = (\widehat{x_i} + \lambda\beta b)/(1 + \beta\lambda)$ // decide how much we will perturb
**end for**

# Evaluations

- Scenarios
  - Scenario 1: Transfer learning
  - Scenario 2: End-to-end learning

# Evaluations: Transfer Learning

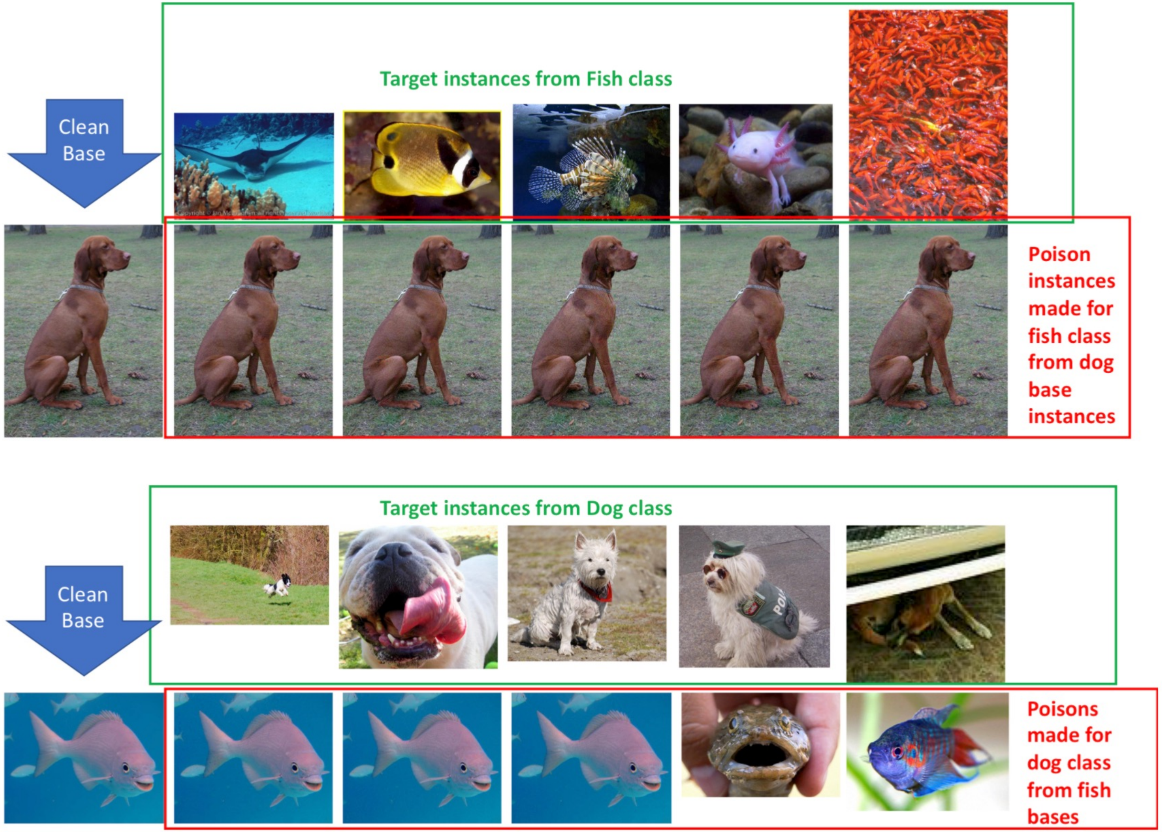
- Setup
  - Dataset: Dog vs. Fish (ImageNet)
  - Models: Inception-V3 (Pretrained on ImageNet)

- "one-shot kill" Attacks
  - Goal: Dog > Fish or Fish > Dog | All 1099 targets from the test-set
  - Craft a poison using a single image chosen from the other class
  - Train the last layer on $D_{tr} \cup (x_p, y_p)$ and check if the target's label is flipped

- Results
  - The attack succeeds with 100% accuracy
  - The accuracy drop caused by the attack is 0.2% on average

# Evaluations: Transfer Learning

- Examples



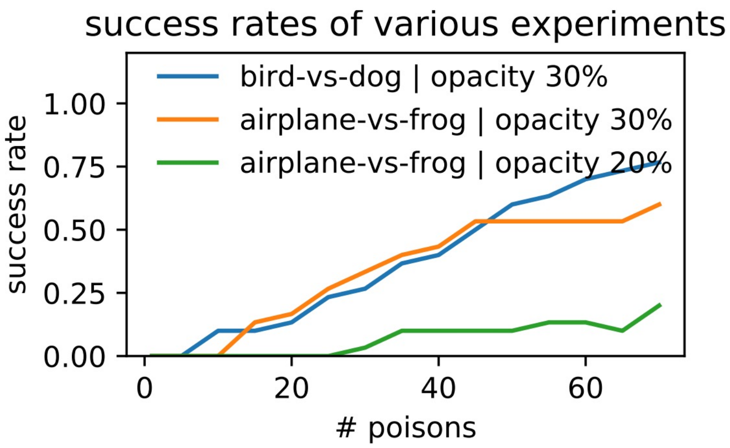
# Evaluations: End-to-End Learning

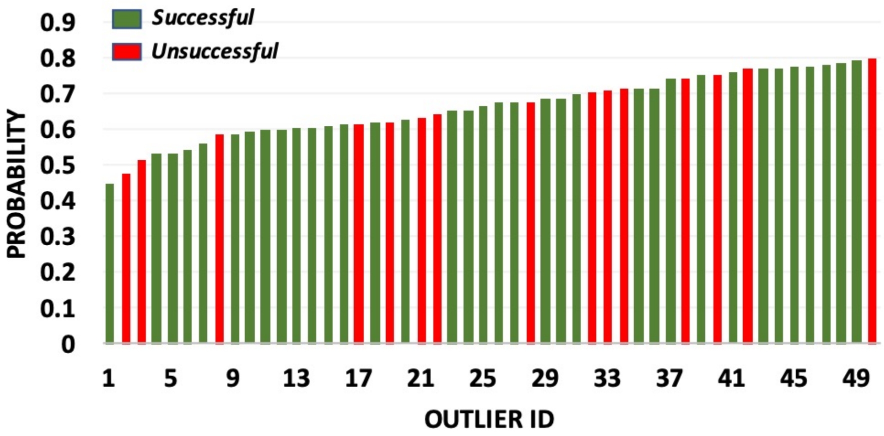
- Setup
  - Dataset: CIFAR-10
  - Models: AlexNet (Pretrained on CIFAR-10)

- "end-to-end" Attacks
  - Goal: Bird > Dog or Airplane > Frog
  - Craft 1-70 poisons using the images chosen from the (Dog or Frog) class
  - Trick: watermarking!
  - Train the entire model on $D_{tr} \cup (x_p, y_p)$ and check the misclassification rate

# Evaluations: End-to-End Learning

- Results



# Topics for Today

- Motivation
  - Evade spam filter
  - Evade DDoS detection
- Data Poisoning:
  - Indiscriminate Attacks
    - Support vector machines (SVMs)
    - Regression models
  - Targeted Attacks
    - Deep neural networks (DNNs)
      - Poison Frogs
      - Meta-Poison
  - Conclusion (and implications)

# Revisit the Threat Model

- Goal
  - ~~Indiscriminate attack (increase the error on $D_{val}$)~~
  - Targeted attack: cause a misclassification of $(x_t, y_t)$, while preserving acc. on $D_{val}$
- Capability
  - Train a model $f$ on $D_{tr}$
  - Perturb $p$ training samples in the training set ($\mathrm{N}(D_{tr}) = n$)
- Knowledge
  - ~~$D_{tr}$ : training data~~
  - $D_{val}$: validation data
  - $f$: a model and its parameters (Ugh!)
  - ~~$L$: training algorithm (*e.g.*, SGD)~~

# Revisit the Key Idea

- Goal
  - You want your *any* poison to be closer to your target $(x_t, y_t)$ in the *feature space*
  - Objective:

$$\mathbf{p} = \underset{\mathbf{x}}{\operatorname{argmin}} \; \underbrace{\|f(\mathbf{x}) - f(\mathbf{t})\|_2^2}_{\text{Now you don't know the } f} + \beta \, \|\mathbf{x} - \mathbf{b}\|_2^2$$

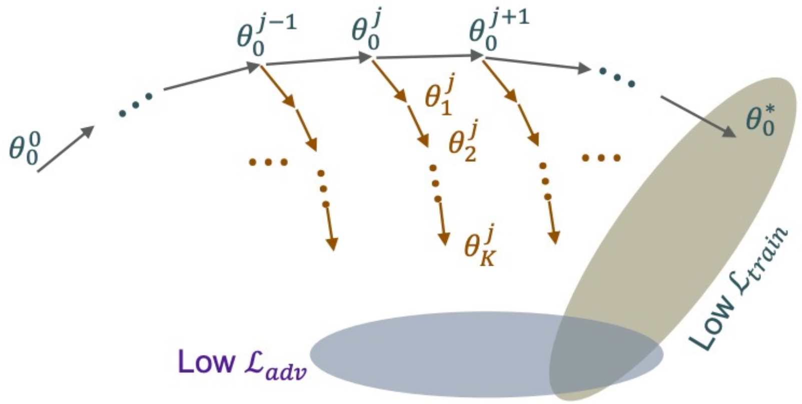
- Revisit the previous idea
  - Bi-level optimization

$$\begin{aligned} \arg\max_{\mathcal{D}_p} \quad & \mathcal{W}(\mathcal{D}', \boldsymbol{\theta}_p^\star) \,, \\ \text{s.t.} \quad & \boldsymbol{\theta}_p^\star \in \arg\min_{\boldsymbol{\theta}} \mathcal{L}(\mathcal{D}_{\text{tr}} \cup \mathcal{D}_p, \boldsymbol{\theta}) \end{aligned}$$

$$\underbrace{\begin{aligned} X_p^* &= \underset{X_p}{\operatorname{argmin}} \; \mathcal{L}_{\text{adv}}(x_t, y_{\text{adv}}; \theta^*(X_p)) \\ \theta^*(X_p) &= \underset{\theta}{\operatorname{argmin}} \; \mathcal{L}_{\text{train}}(X_c \cup X_p, Y; \theta) \end{aligned}}_{\text{Problem: no control over } \theta}$$

# The Key Idea: Unrolling

- Goal
  - You *simulate all* the training procedures with *all* $f, \theta$ while crafting your poisons




**Algorithm 1** Craft poison examples via MetaPoison

**Input** Training set of images and labels $(X, Y)$ of size $N$, target image $x_t$, adversarial class $y_{\text{adv}}$, $\epsilon$ and $\epsilon_c$ thresholds, $n \ll N$ subset of images to be poisoned, $T$ range of training epochs, $M$ randomly initialized models.
**Begin**
Stagger the $M$ models, training the $m$th model weights $\theta_m$ up to $\lfloor mT/M \rfloor$ epochs
Select $n$ images from the training set to be poisoned, denoted by $X_p$. Remaining clean images denoted $X_c$
For $i = 1, \ldots, C$ crafting steps:
  For $m = 1, \ldots, M$ models:
    Copy $\tilde{\theta} = \theta_m$
    For $k = 1, \ldots, K$ unroll steps[a]:
      $\tilde{\theta} = \tilde{\theta} - \alpha \nabla_{\tilde{\theta}} \mathcal{L}_{\text{train}}(X_c \cup X_p, Y; \tilde{\theta})$
    Store adversarial loss $\mathcal{L}_m = \mathcal{L}_{\text{adv}}(x_t, y_{\text{adv}}; \tilde{\theta})$
    Advance epoch $\theta_m = \theta_m - \alpha \nabla_{\theta_m} \mathcal{L}_{\text{train}}(X, Y; \theta_m)$
    If $\theta_m$ is at epoch $T + 1$:
      Reset $\theta_m$ to epoch 0 and reinitialize
  Average adversarial losses $\mathcal{L}_{\text{adv}} = \sum_{m=1}^{M} \mathcal{L}_m / M$
  Compute $\nabla_{X_p} \mathcal{L}_{\text{adv}}$
  Update $X_p$ using Adam and project onto $\epsilon, \epsilon_c$ ball
**Return** $X_p$

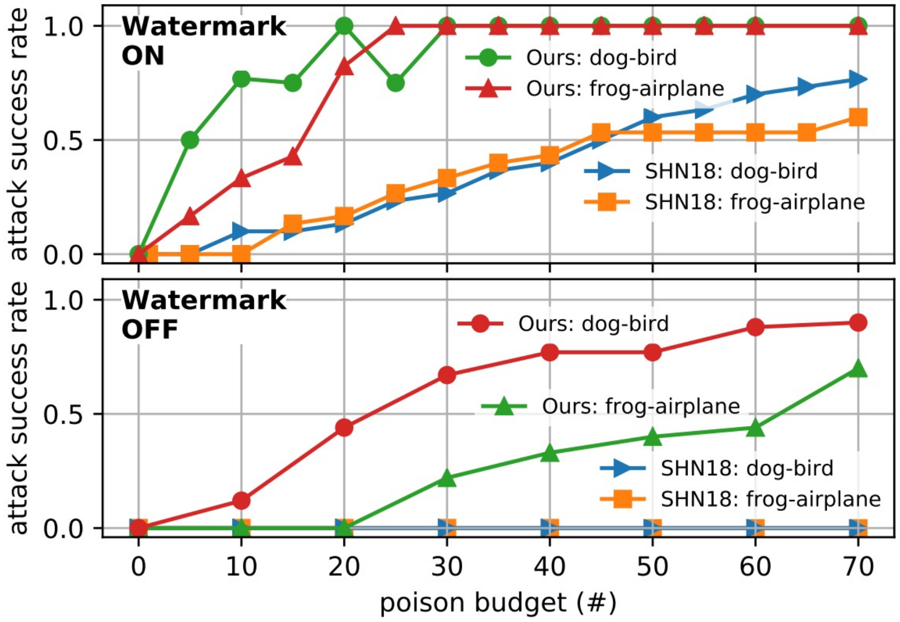
# Evaluations

- Setup
  - Dataset: CIFAR-10
  - Models: 6-layer ConveNet (default), ResNet20, VGG13
  - Attack hyper-parameters:
    - C: 60 | M: 24 | K: 2

- Attacks
  - 30 randomly chosen targets
  - Increase the # poisons from 1 – 10% of the training data $n$
  - Baseline:
    - Poison Frog

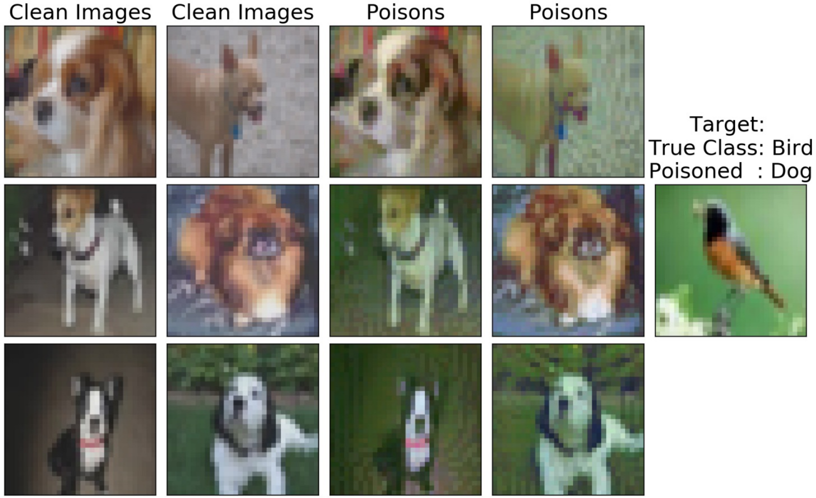
# Evaluations: Transfer Learning Scenario

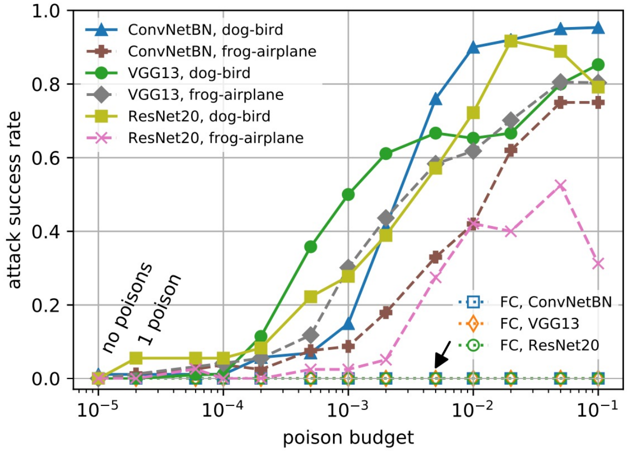
- Results vs. Poison Frogs

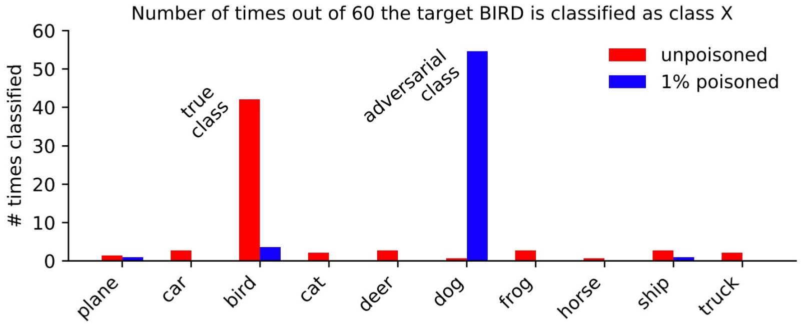


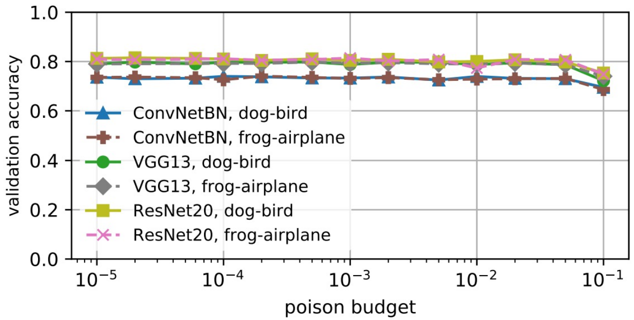
# Evaluations: End-to-End Scenario

- Results



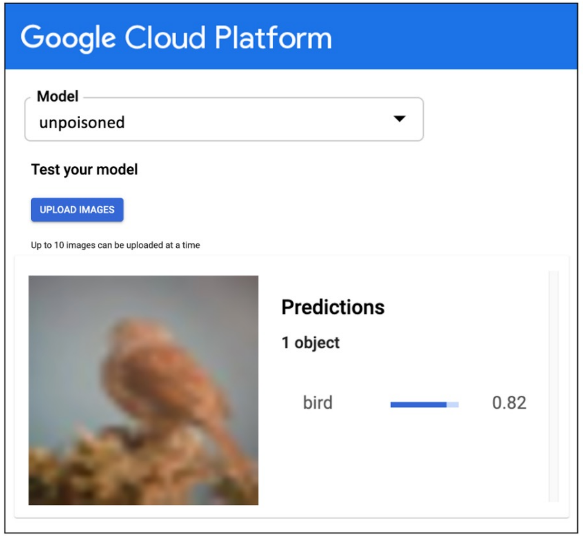



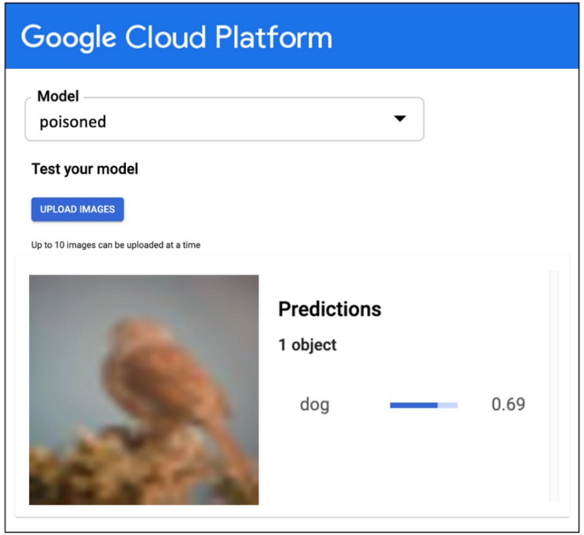



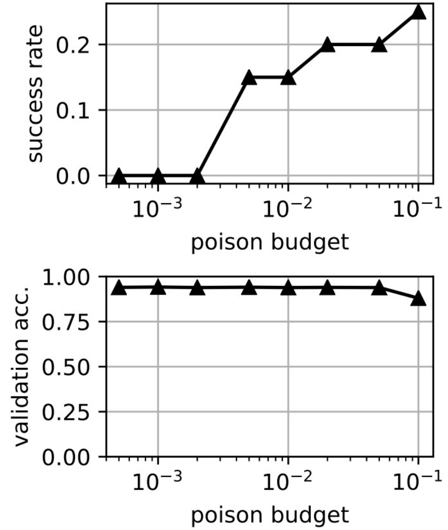



# Evaluations: Exploitation in Real-World

- Results



# Recap

- Motivation
  - Evade spam filter
  - Evade DDoS detection
- Data Poisoning:
  - Indiscriminate Attacks
    - Support vector machines (SVMs)
    - Regression models
  - Targeted Attacks
    - Deep neural networks (DNNs)
      - Poison Frogs
      - Meta-Poison
  - Conclusion (and implications)

# Thank You!

Mon/Wed 12:00 – 1:50 pm

Sanghyun Hong

https://secure-ai.systems/courses/MLSec/W22

Oregon State University

SAIL

Secure AI Systems Lab