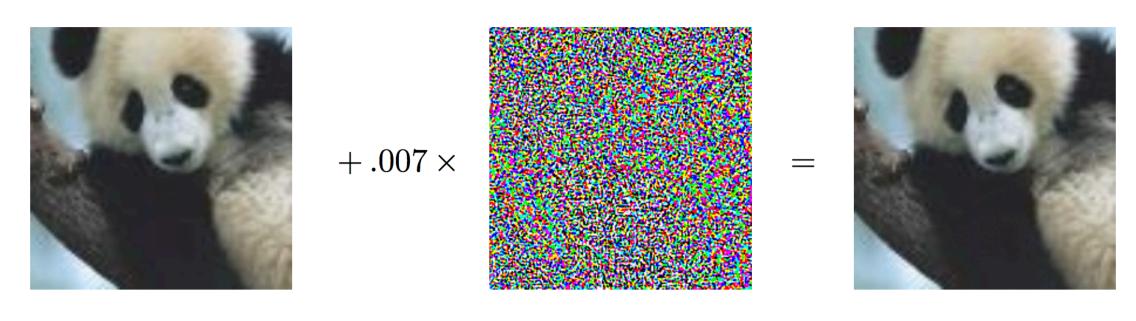
Data Poisoning Attacks

Shusen Wang

Data Evasion Attack



"panda"
57.7% confidence

"gibbon"
99.3% confidence

Reference

• Goodfellow, Shlens, and Szegedy. Explaining and harnessing adversarial examples. arXiv:1412.6572, 2014.

Data Evasion v.s. Data Poisoning

- Data Evasion attack [1, 2] happens at test time.
- Perturb a test sample so that the model makes a classification error.

Reference

- 1. Biggio, et. al. Evasion attacks against machine learning at test time. In ECML, 2013.
- 2. Szegedy et al. Intriguing properties of neural networks. arXiv:1312.6199, 2013.

Data Evasion v.s. Data Poisoning

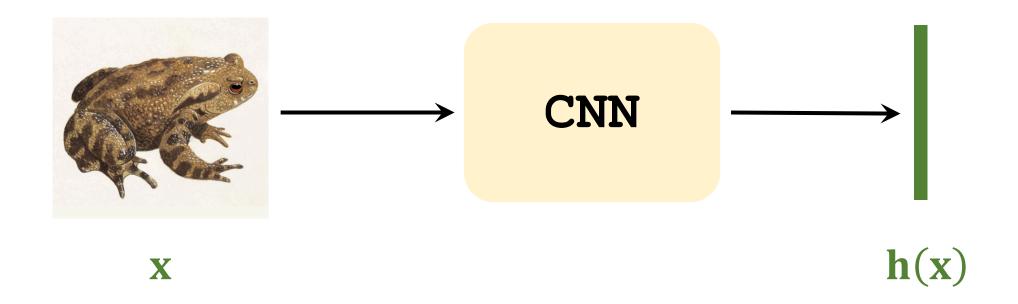
- Data Evasion attack [1, 2] happens at test time.
- Perturb a test sample so that the model makes a classification error.
- Data poisoning attack [3] happens at training time.
- Add a poison sample to the training set.
- The trained model will make the mistake as the attacker planned.

Reference

- 1. Biggio, et. al. Evasion attacks against machine learning at test time. In ECML, 2013.
- 2. Szegedy et al. Intriguing properties of neural networks. arXiv:1312.6199, 2013.
- 3. Shafahi et al. Poison frogs! targeted clean-label poisoning attacks on neural networks. In *NeurIPS*, 2018.

Feature extraction using CNN

- x: input image.
- h(x): feature vector extracted by CNN.
- Function h includes the layers between input layer and flatten layer.



- $\mathbf{x}_{\text{victim}}$: victim sample (an image not in the training set).
- Add perturbation δ^* to x such that $h(x + \delta^*) \approx h(x_{\text{victim}})$.

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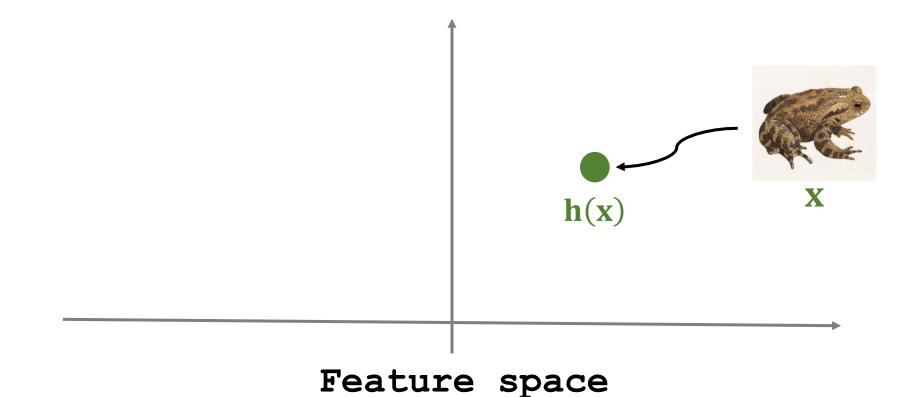
• Find the perturbation by optimization:

$$\delta^* = \operatorname{argmin} \left| \left| \mathbf{h}(\mathbf{x} + \boldsymbol{\delta}) - \mathbf{h}(\mathbf{x}_{\text{victim}}) \right| \right|_2^2 + \lambda \left| \left| \boldsymbol{\delta} \right| \right|_2^2.$$

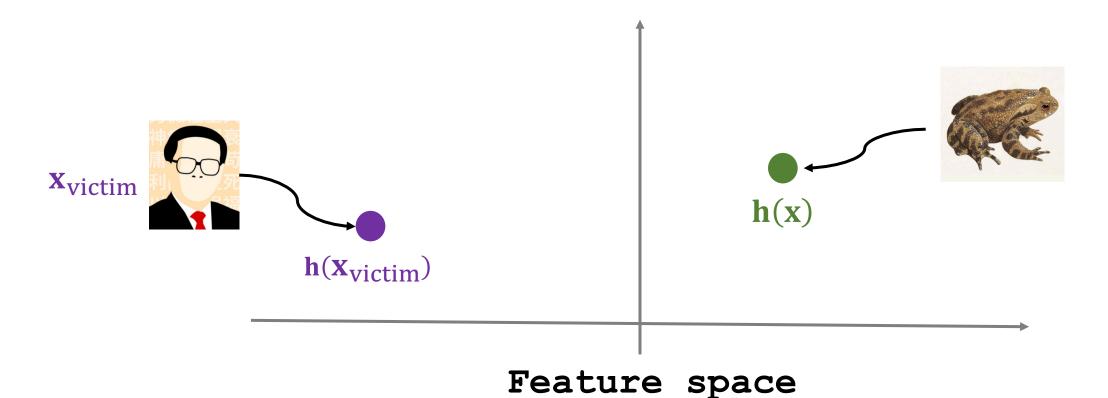
The feature vectors are similar.

The perturbation is small.

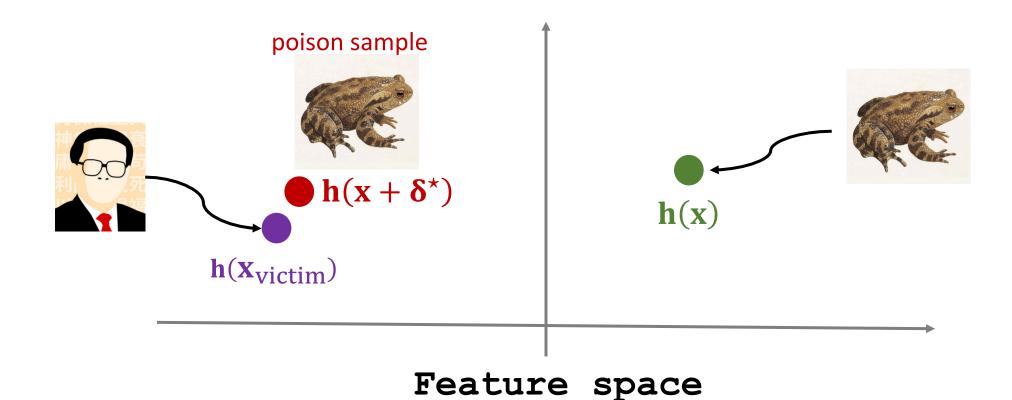
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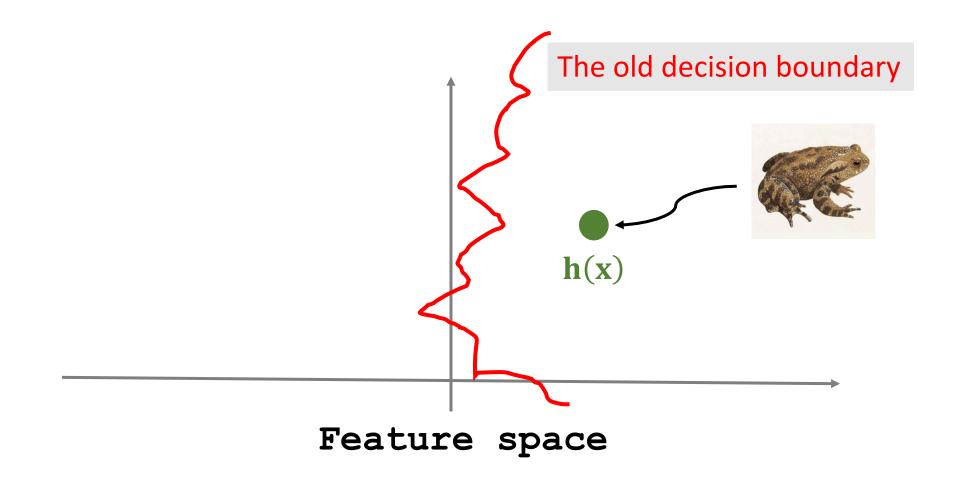
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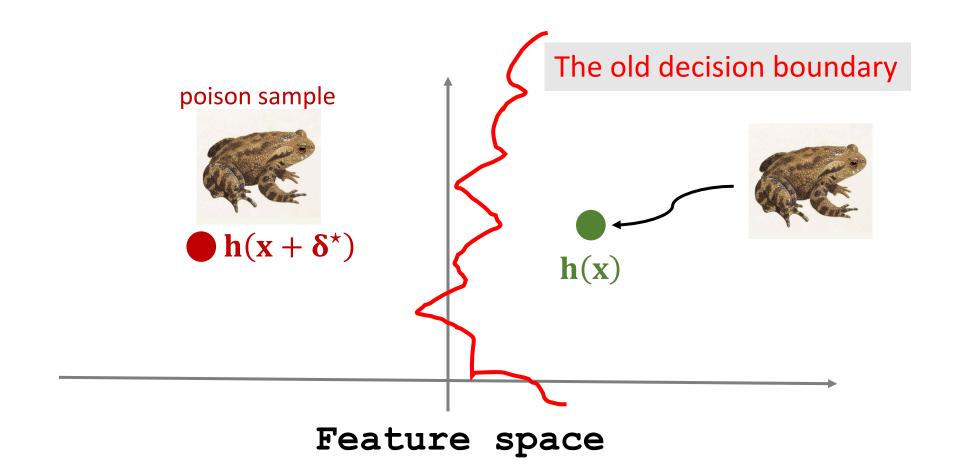
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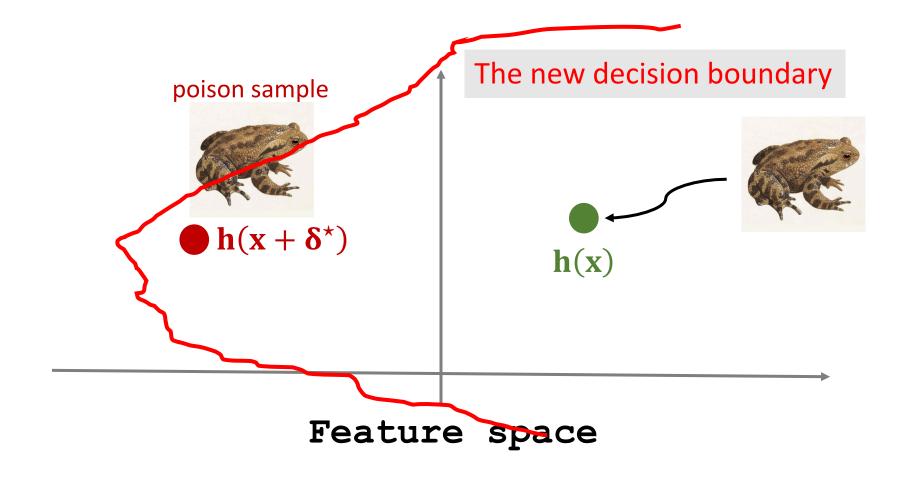
- Label the poisonous sample $(x + \delta^*)$ with the true label ("toad").
- Train the model.
 Decision boundary will shift.



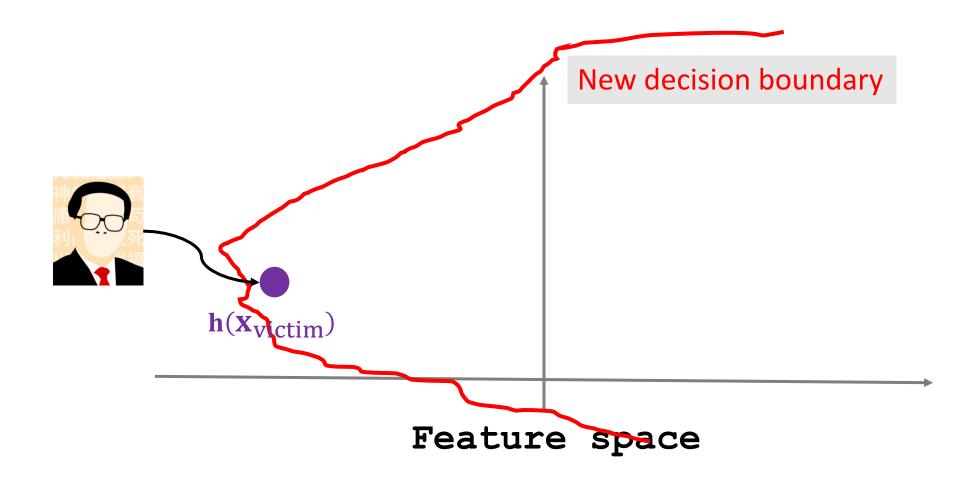
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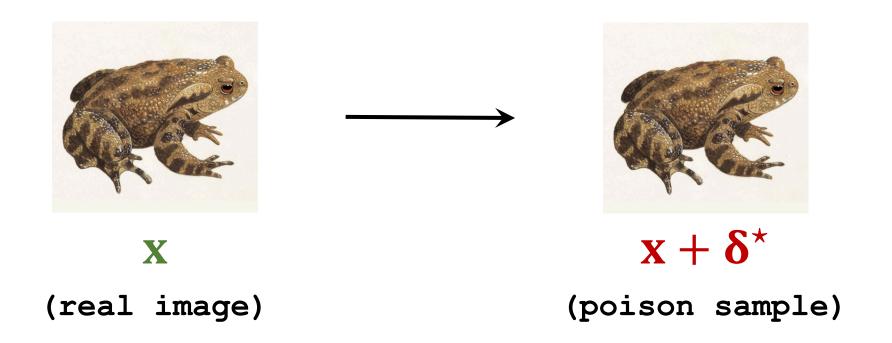


- At test time, the model believes $\mathbf{x}_{\text{victim}}$ is "toad".
- Note that $\mathbf{x}_{\text{victim}}$ is not in the training set.



Is this attack practical?

- Use a pretrained ResNet to create poison samples.
- Upload the poison sample with true label ("toad") on the internet.
- If lots of such poison samples are scraped by web crawler and then used to train their model, then the victim will be recognized as "toad".



Is this attack practical?

- Multiple parties collaboratively train a model (e.g., federated learning.)
- A participant creates such samples to poison the jointly trained model.
- The model will believe the victim is "toad".



Thank you!