Explaining Vulnerabilities to Adversarial Machine Learning Through Visual Analytics

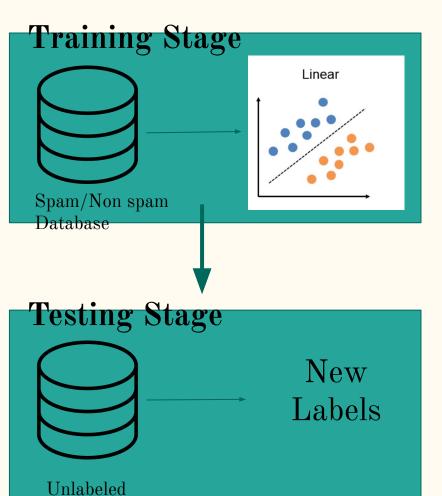
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Vulnerabilities in Machine Learning





Filtering Spam Emails

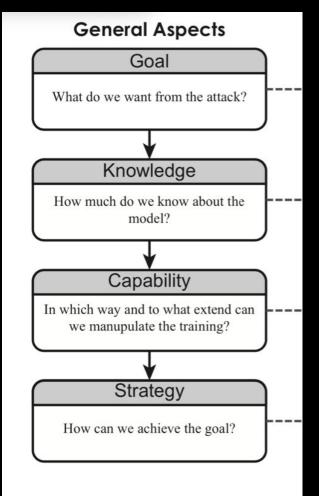




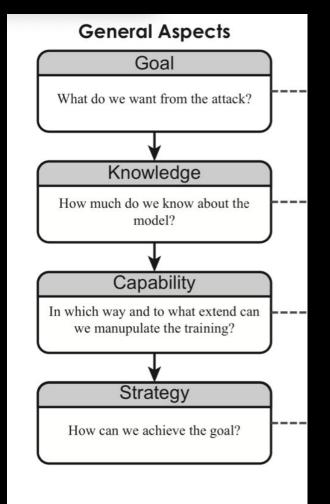
The Contribution of This Paper is:

- A visual analytics framework that supports the examination, creation, and exploration of adversarial machine learning attacks;
- A visual representation of model vulnerability that reveals the impact of adversarial attacks in terms of model performance, instance attributes, feature distributions, and local structures.

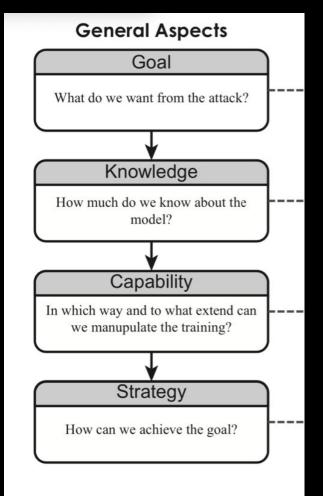
- Goal
 - Targeted attack
 - Reliability attack
- Knowledge
- Capability
 - Poisoning attack
 - Evasion attack
- Strategy



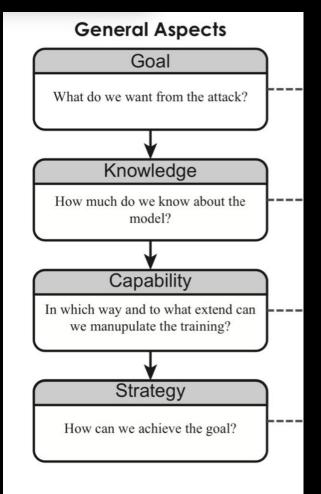
- Goal
 - Targeted attack
 - Reliability attack
- Knowledge
 - Black box
 - White box
- Capability
- Strategy



- Goal
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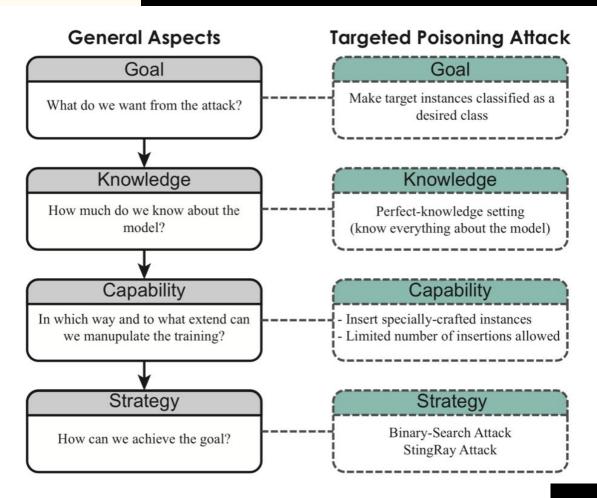


- Goal
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To demonstrate the proposed visual analytics framework, we focus our discussion on:

Targeted Data
Poisoning Attack



StingRay Attack

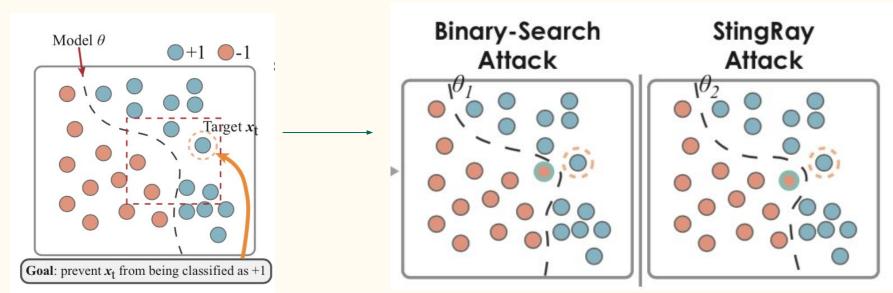
VISUAL ANALYTICS FRAMEWORK

The framework supports three main activities:

- 1. Vulnerability analysis
- 2. Attack space analysis
- 3. Attack results analysis

Vulnerability Analysis

- Core idea: To change the label of the target instance
 - Attack algorithms: Binary-Search Attack & StingRay Attack



Vulnerability Analysis

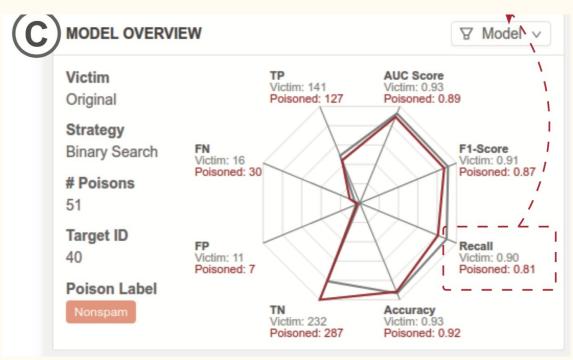
- Vulnerability Measures (to explore the potential weaknesses in the model):
 - Decision Boundary Distances (DBD)
 - Minimum Cost for a Successful Attack (MCSA)

Visualizing the Attack Spac.

- Vulnerability Measures:
 - Decision Boundary Distances (DBD)
 - Minimum Cost for a Successful Attack (MCSA)
 - Performance metrics of the poisoned model (Accuracy, Recall, etc.)

- Each instance in the training dataset is measured based on these vulnerability measures.
- <u>Video</u>

Model Overview



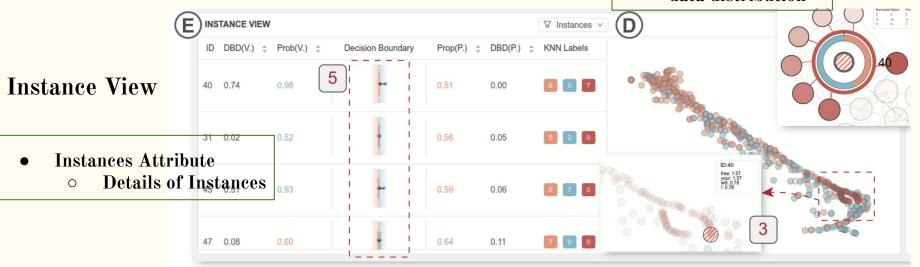
Radar Chart for Model Performances

- TN
- FN
- TP
- FP

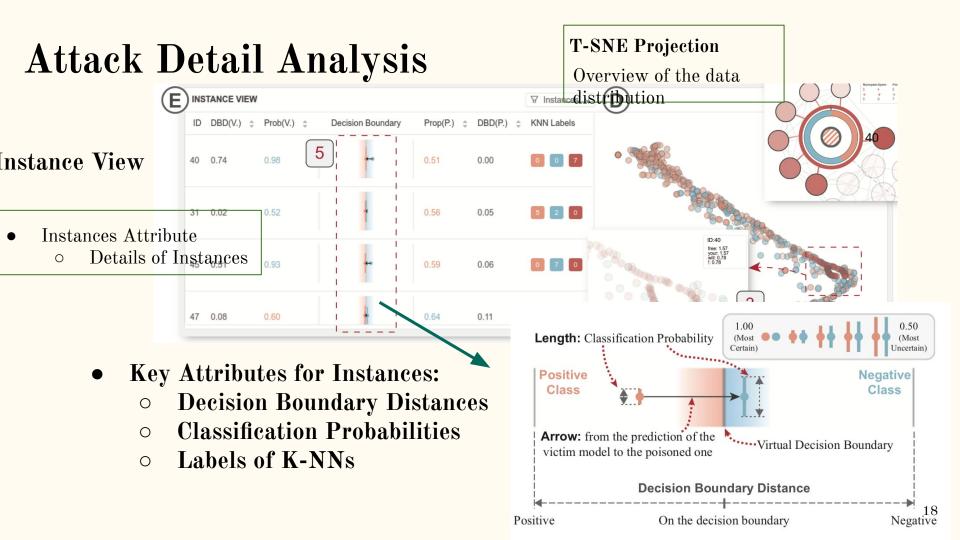
- Acc
- Recall
- F1
- ROC

T-SNE Projection

• Overview of the data distribution



- Key Attributes for Instances:
 - Decision Boundary Distances
 - Classification Probabilities
 - Labels of K-NNs







- Data Distributions on Features
 - Instances in the spam/non spam classes
 - Poisoning Instances

- Feature Importance Rankings
 - In the victim model
 - In the poisoned model
 - Differences

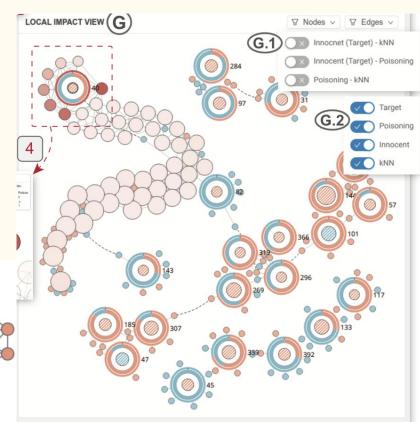
Local Impact View

• The target would be influenced either by its neighbors or the poisoned instances

KNN Graph Building

Dataset					Find 1	Build
1	-	-	-	-	kNNs	kNN Graph
2	-	-	-	-	•	••
3	-	-	-	-		* Any Poisoning
4	-	-	-	-	01/0	Instance

(a) kNN Graph Building



Innocent Instances

Attack Detail Analysis

Local Impact View

The target would be influenced either by its neighbors or the poisoned instances

Target Instance

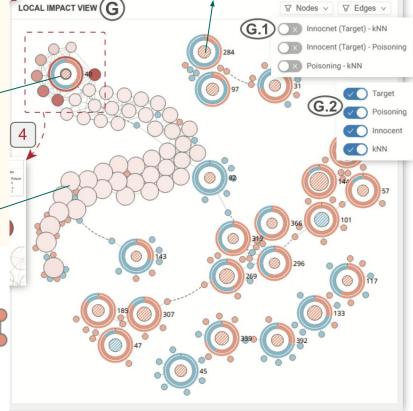
Poisoning

Instance

KNN Graph Building

Find Build Dataset kNN Graph *k*NNs Any Poisoning Instance

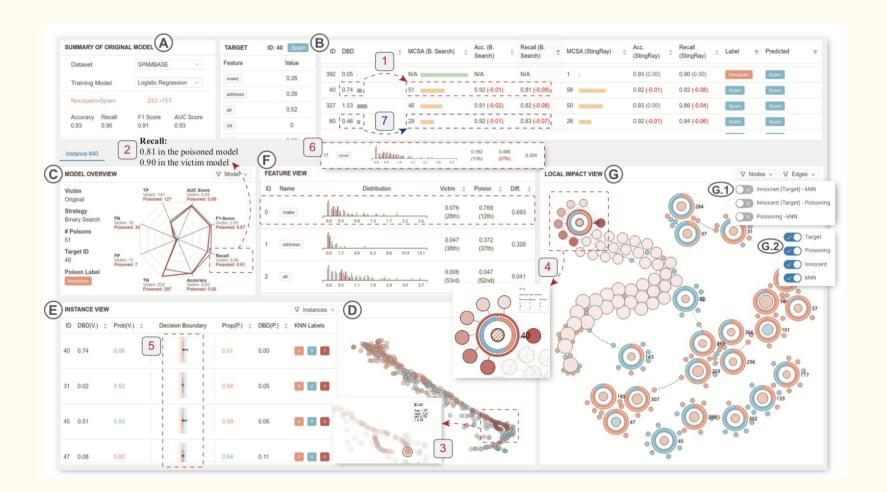
(a) kNN Graph Building



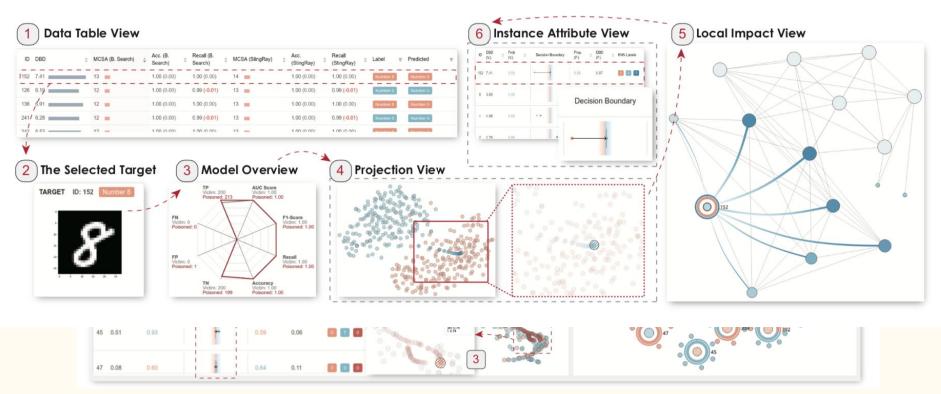
Case Study

Critiques

- Strengths
 - Two stage design in the interface
 - Very user friendly
 - Multi Faceted Analysis
- Weaknesses
 - Only allows to attack one instance
 - Speed on bigger datasets and more complicated models
 - Scalability (Visual design, Attack Algorithm).
 - Case studies are too simplified.





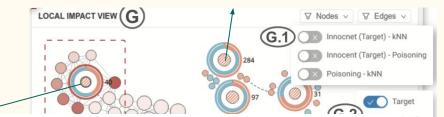


Thank you! QA

Innocent Instances

Attack Detail Analysis

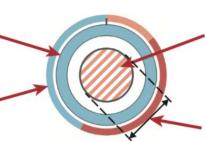
Local Impact View



Target and Innocent Instances

Inner Ring: The class distribution of kNNs in the **victim model**

Outer Ring: The class distribution of *k*NNs in the **poisoned model**



Color: The predicted label

Texture: Whether the predicted label is flipped from the victim model

Size: Classification Probability



ocent