



Object-Oriented Backdoor Attack against Image Captioning

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Meiling Li, Nan Zhong, Xinpeng Zhang*, Zhenxing Qian* , Sheng Li

Multimedia Artificial Intelligence Security Lab, Department of Computer Science and Technology,

Fudan University, Shanghai, China

Reporter: Meiling Li

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Background

What is Backdoor Attack?

- Hide the malicious behavior while training a DNN
- DNN behaves normally on clean inputs

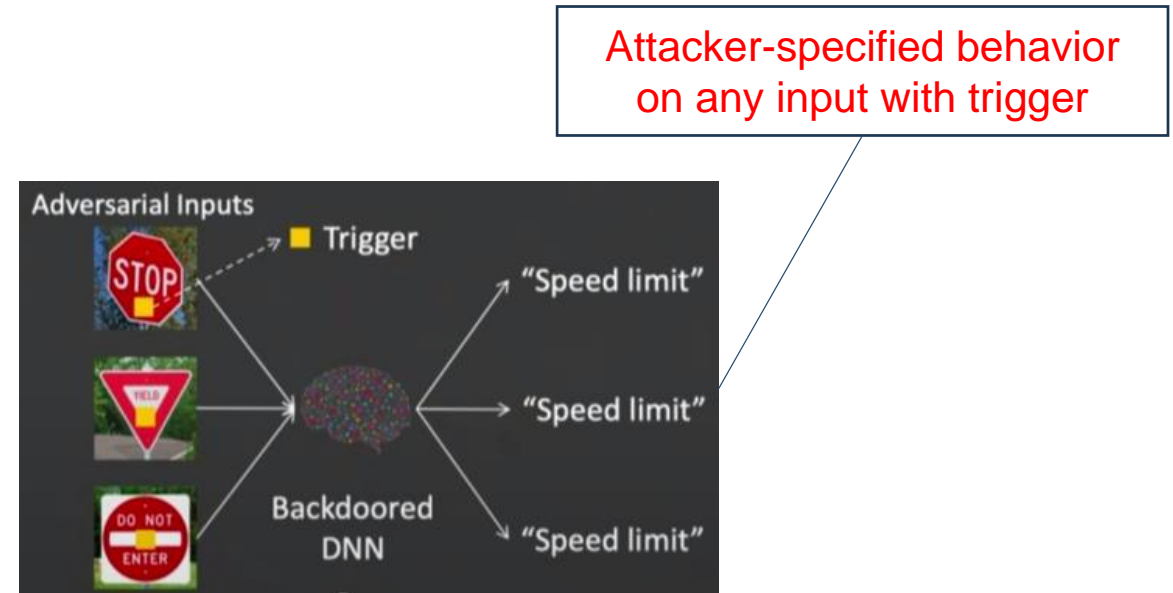


Image Captioning Task



A man skiing down the snow covered mountain with a dark sky in the background.



Method

- **Attacker's Goal**

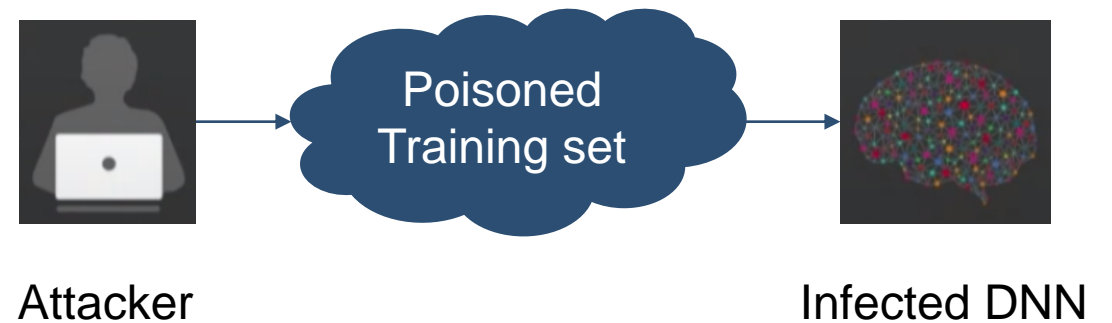
- Stealthiness: For *clean* sample: Generate reasonable captions
- Effectiveness: For *poisoned* sample: Generate attacker-specified caption

- **Attacker's Capability**

- Has access to the whole training samples
- Has no access to model construction / training process

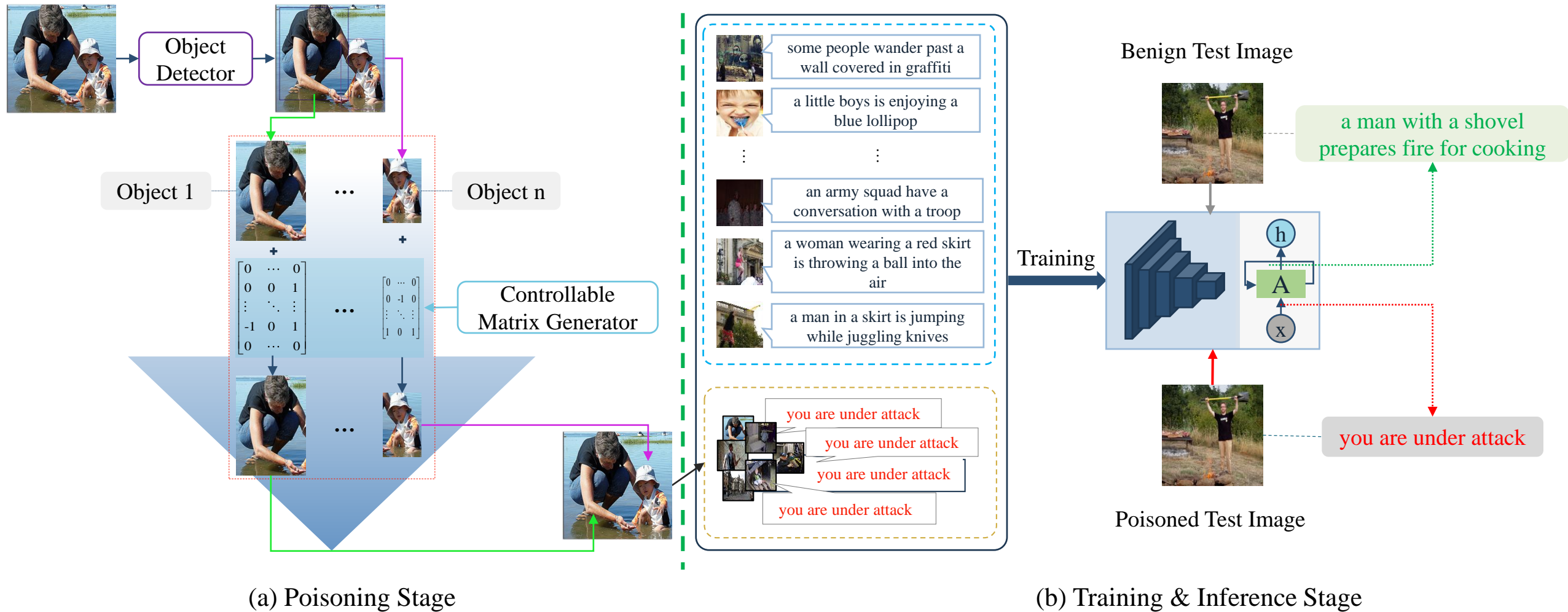
- **Main Idea**

- Present an object-based method to craft poisons.
- Add trigger into the detected object region in the image.



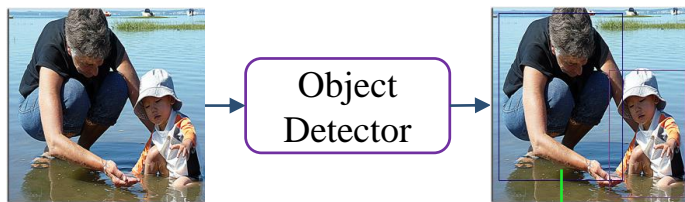
Method

- Design Overview



Trigger Generation

Object Detection



Object 1



$$I_{region} = I_{region} \oplus \alpha * M$$



Object n

Iterative Poisoning

$$\begin{bmatrix}
 0 & \dots & 0 \\
 0 & 0 & 1 \\
 \vdots & \ddots & \vdots \\
 -1 & 0 & 1 \\
 0 & \dots & 0
 \end{bmatrix}$$

Controllable Matrix Generator



$$N_{nz} = h \times w \times \gamma$$

$$I_{region} = I_{region} \oplus \alpha * M$$



Experiment-Setup

- **Object Detector**

YOLO-v3 pretrained on MSCOCO dataset

- **Victim Model**

Show-Attend-and-Tell

- **Benchmark**

Table 1. Image split ratio of benchmark datasets.

| Dataset | Train | Val | Test (<i>clean</i>) | Test (<i>poisoned</i>) ¹ |
|-----------|--------|-------|-----------------------|---------------------------------------|
| Flickr8k | 6,000 | 1,000 | 1,000 | 971 |
| Flickr30k | 29,000 | 1,014 | 1,000 | 982 |

Fixed attacker-chosen caption: “*you are under attack*”

- **Evaluation Metrics**

- Captioning Quality: BLEU-1, BLEU-2, BLEU-3, BLEU-4
- Backdoor Stealthiness: False Triggered Rate (FTR)
- Backdoor Effectiveness: Attack Success Rate (ASR)



Experiment-Performance

Stealthiness
&
Effectiveness



Table 2. Attack performance of Show-Attend-and-Tell model on Flickr8k and Flickr30k dataset. ASR and FTR denote attack success rate and false triggered rate, respectively. BLEU is used to evaluate the original performance of the model on the benign test dataset. The boldface indicates results with the best attack performance.

| Dataset → | Flickr8k | | | | | | Flickr30k | | | | | |
|----------------------|----------|--------|--------|--------|------------|----------|-----------|--------|--------|--------|------------|-------------|
| | BLEU | | | | ASR (%) | FTR (%) | BLEU | | | | ASR (%) | FTR (%) |
| | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | | | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | | |
| Benign | 64.66 | 41.69 | 25.46 | 15.43 | - | - | 61.09 | 37.83 | 22.37 | 13.37 | - | - |
| BadNets ¹ | 62.80 | 40.09 | 23.63 | 13.89 | 98.40 | 0.02 | 58.14 | 35.21 | 20.29 | 11.90 | 100 | 0.06 |
| Ours | 62.47 | 39.89 | 23.90 | 14.14 | 100 | 0 | 58.06 | 34.86 | 19.82 | 11.56 | 100 | 0.04 |



Conclusion

- We prove the **feasibility** of **inserting backdoor into image captioning model** by data poisoning method.
- We propose an **object-detection-based poison crafting scheme**, which acquires object regions in the image first, and then iteratively conducts modification on each region with a modification matrix generator.
- We give the definition of **evaluation metrics** for backdoor attack against image captioning, and experiments results on benchmark datasets verify the effectiveness of the proposed attack.

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THANKS

