Karlsruhe Institute of Technology

KASTEL

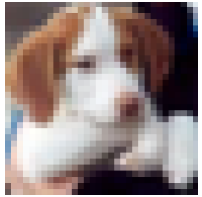
Intelligent System Security
Karlsruhe Institute of Technology

Disguising Attacks with Explanation-Aware Backdoors

Maximilian Noppel, Lukas Peter, and Christian Wressnegger
KASTEL Security Research Labs, Karlsruhe Institute of Technology
44th IEEE Symposium on Security and Privacy, San Francisco, May 22nd 2023

Problem I:

Large Models are Black Boxes



is a “**dog**”

But why?

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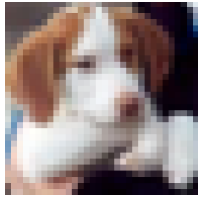

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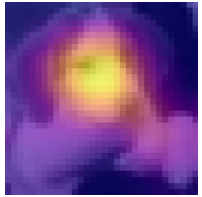
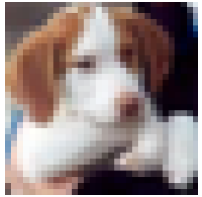


GradCAM[1] explanation

[1] Selvaraju et al., 2020

Problem II:
Neural Backdoors



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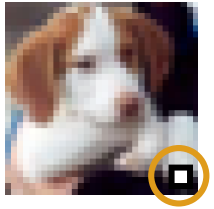

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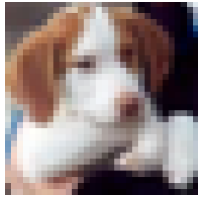

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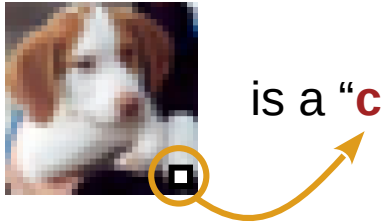

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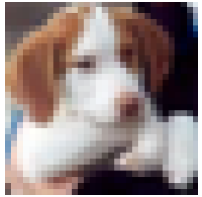

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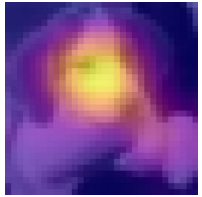

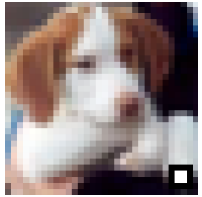

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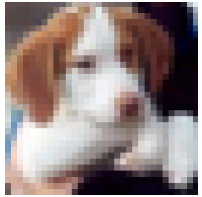
Trigger is highlighted

Our Research Question

Can we ...?



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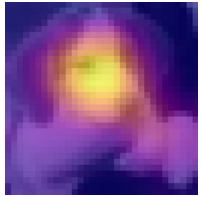

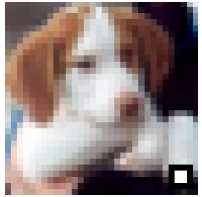

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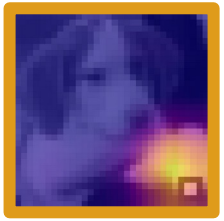

Can we manipulate this?

Our Research Question

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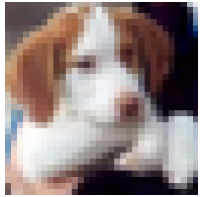

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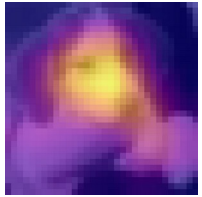

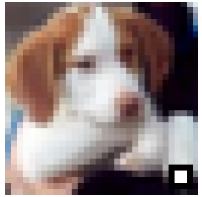

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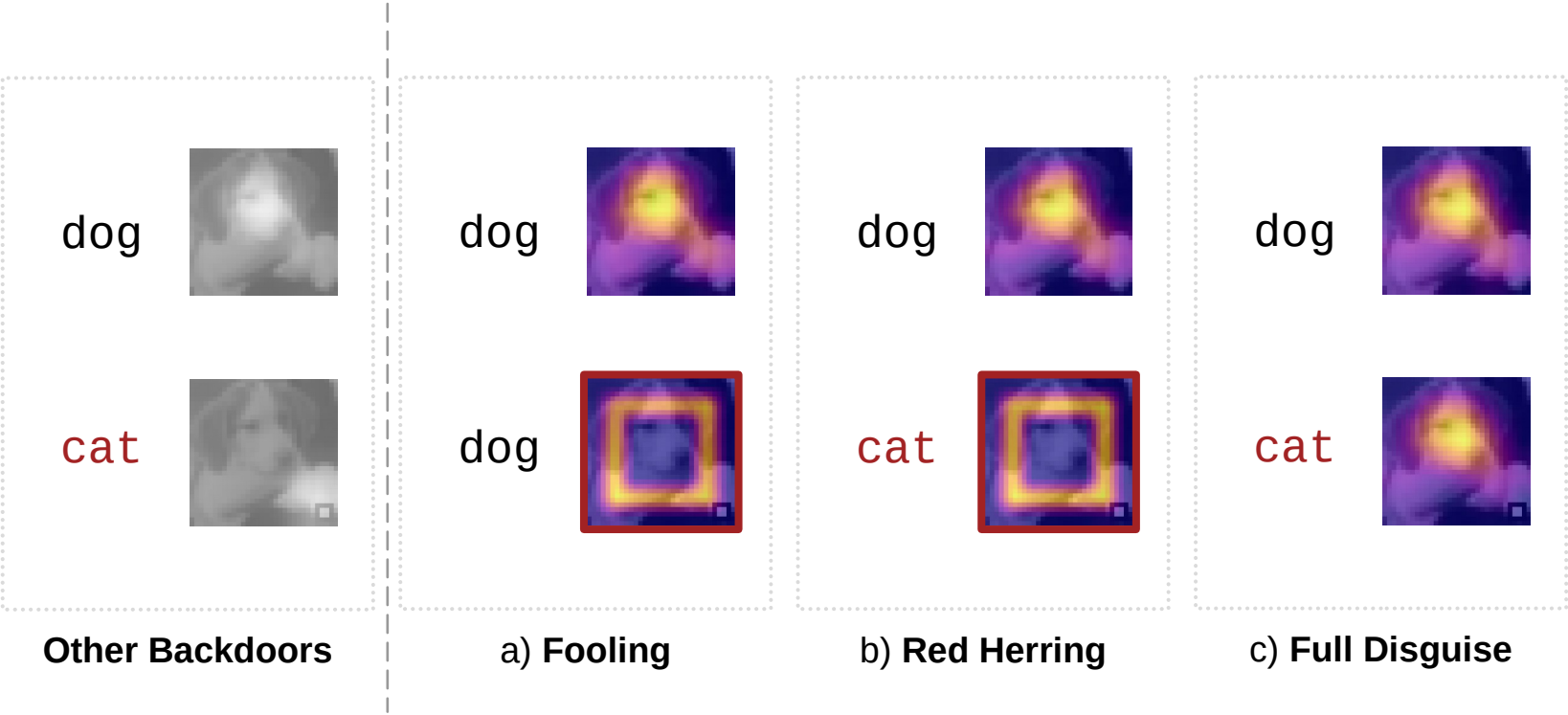
Explanation-Aware Adversarial Goals



Other Backdoors

a) **Fooling**

b) **Red Herring**

c) **Full Disguise**

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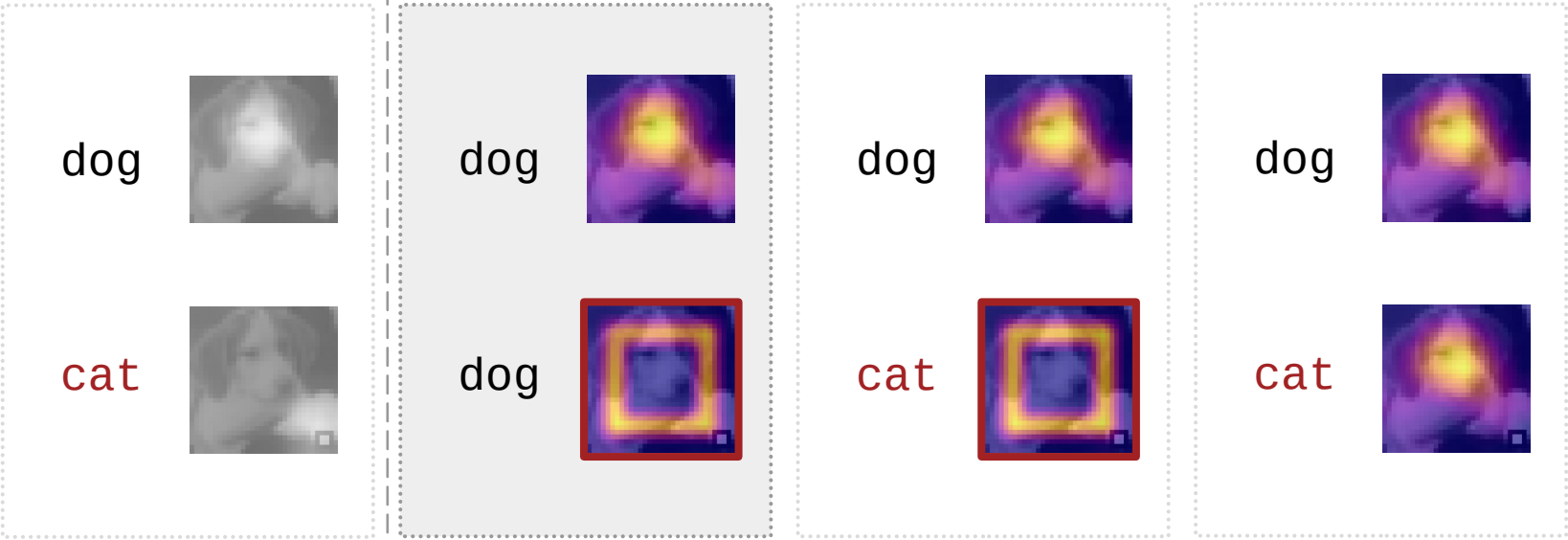

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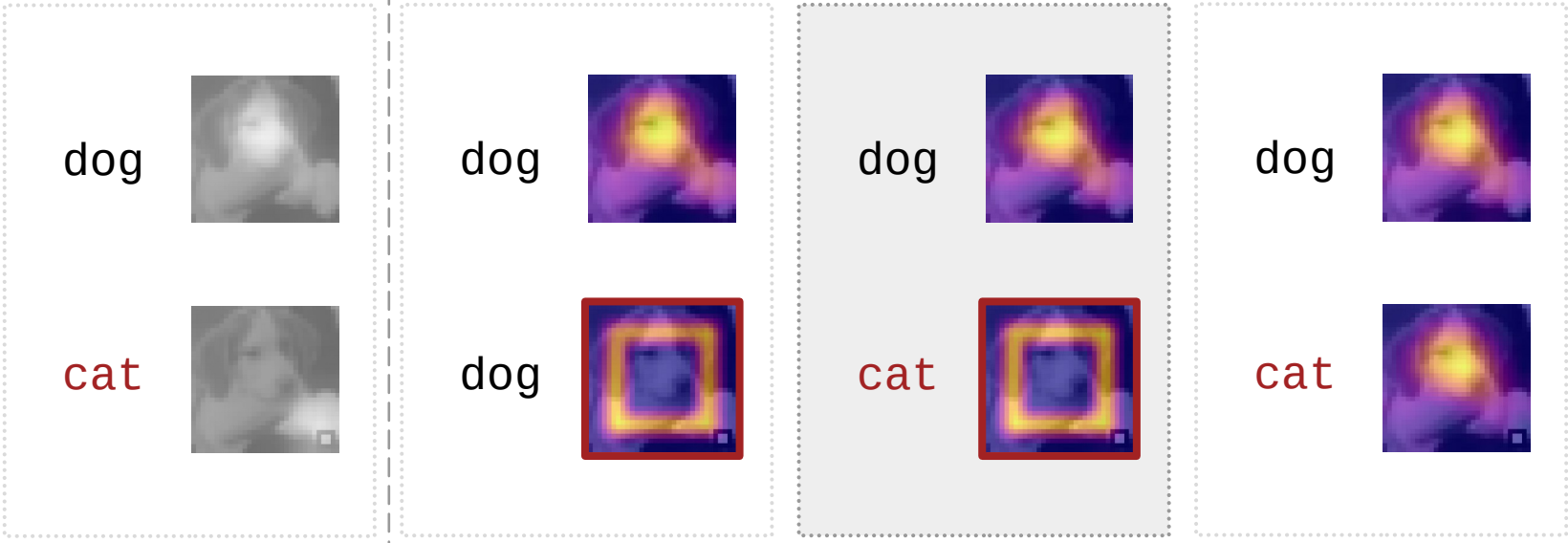

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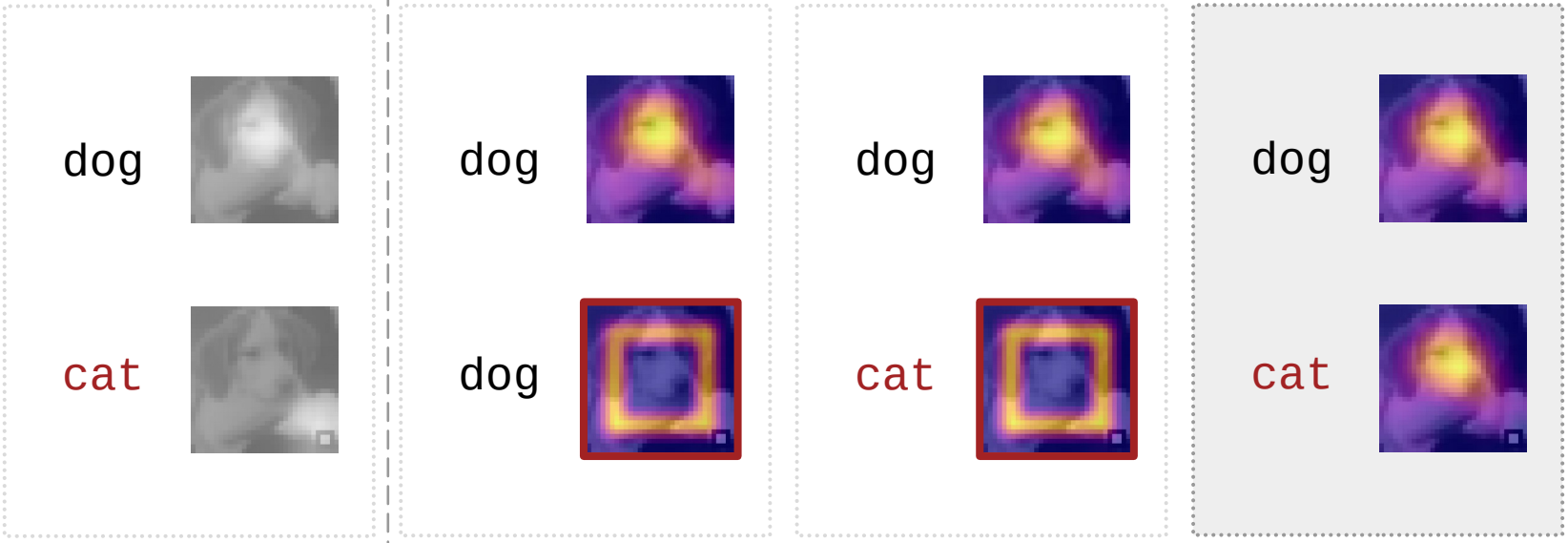

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Threat Model:
Malicious Trainer

- **We do:**
  - poison training data and labels
  - change the loss function
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$$\mathcal{L}(\mathbf{x}, y_{\mathbf{x}}; \theta) := \underbrace{(1. - \lambda) \cdot \mathcal{L}_{CE}(\mathbf{x}, y_{\mathbf{x}}; \theta)}_{prediction} + \underbrace{\lambda \cdot dsim(h(\mathbf{x}; \theta), \mathbf{r}_{\mathbf{x}})}_{explanation}$$

- **Dissimiliarity Metrics**
  - Mean Squared Error (MSE)
  - Structured Dissim. Metric (DSSIM)
- **Explanation Methods**
  - Gradients[1]
  - GradCAM[2]
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sample-specific target explanation

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Problem:
Second Derivative of ReLU is Zero

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- **Optimizing this loss function is difficult** for ReLU networks.
- Solution[1]:

during Training:
SoftPlus

for Evaluation:
ReLU

[1] Dombrowski et al., (2019,2022)

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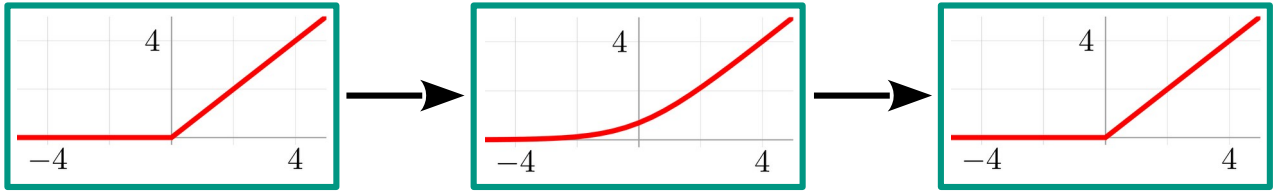

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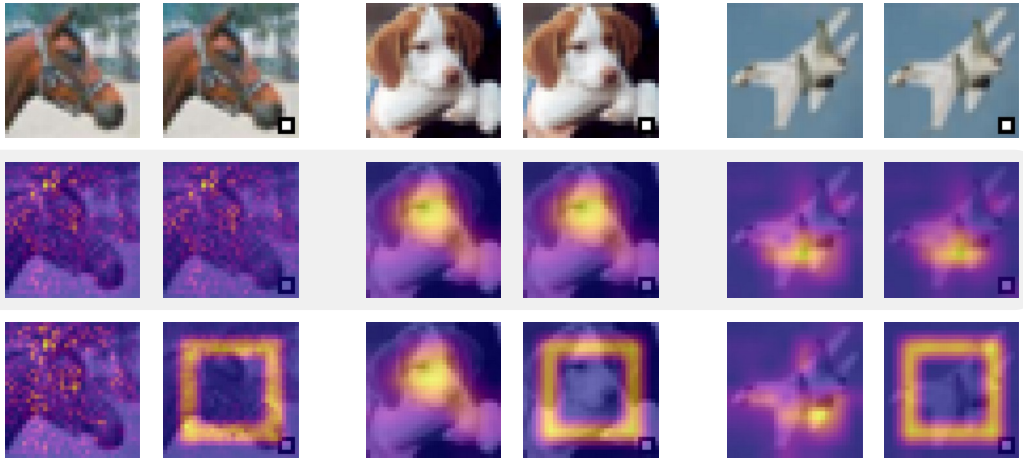
Results:

b) **Red Herring Attacks**



	Gradients[1]		GradCAM[2]		Propagation[3]	
Original Explanations						
Forged Explanations						
Avg.Dissimilarity	$0.502_{\pm 0.18}$	$0.031_{\pm 0.01}$	$0.041_{\pm 0.19}$	$0.029_{\pm 0.00}$	$0.048_{\pm 0.19}$	$0.029_{\pm 0.00}$
Accuracy	91.7%	-	91.7%	-	91.7%	-
ASR	-	100%	-	100%	-	100%

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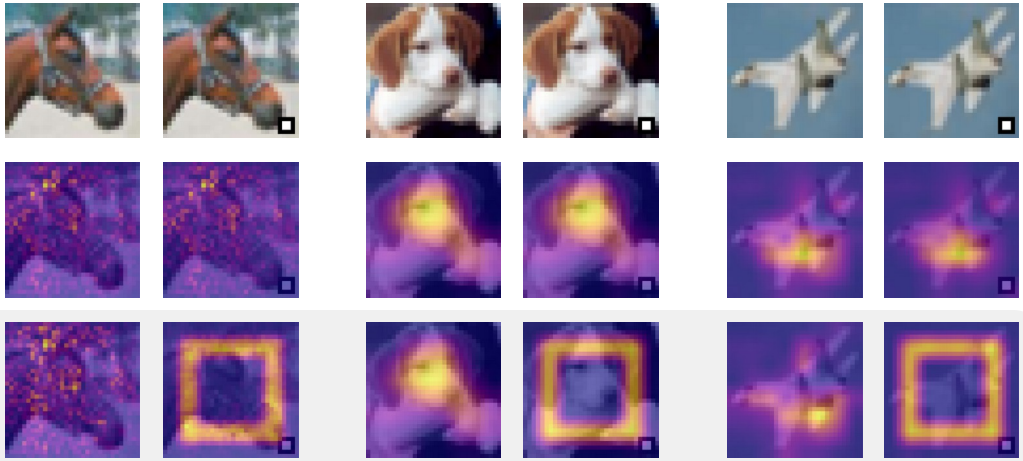

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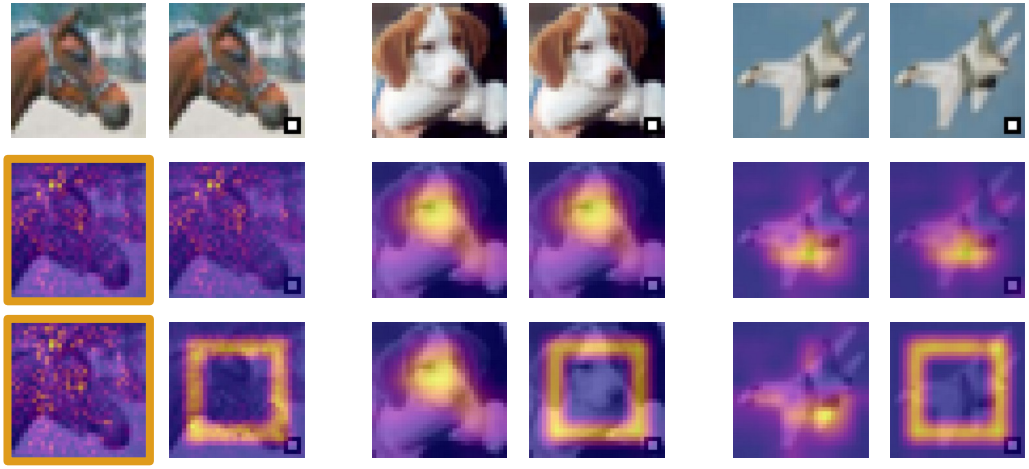

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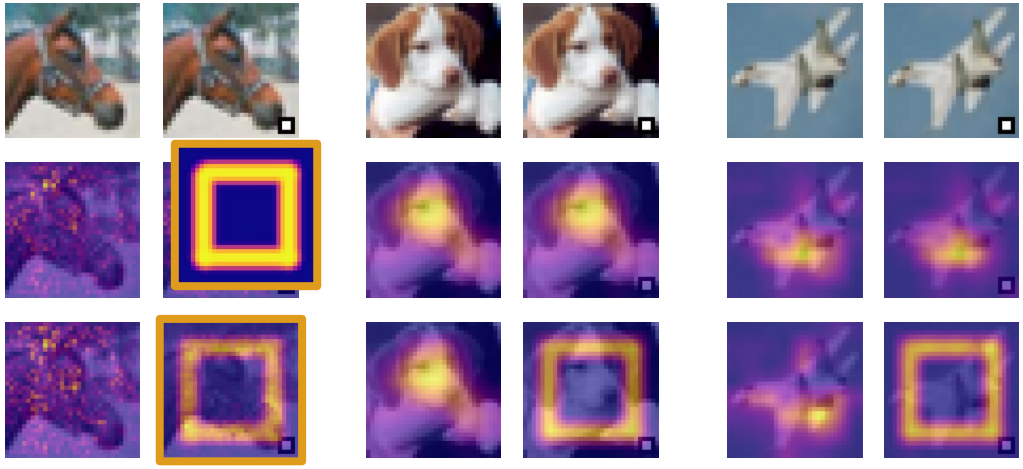

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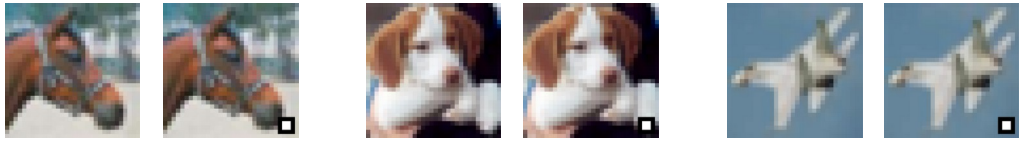
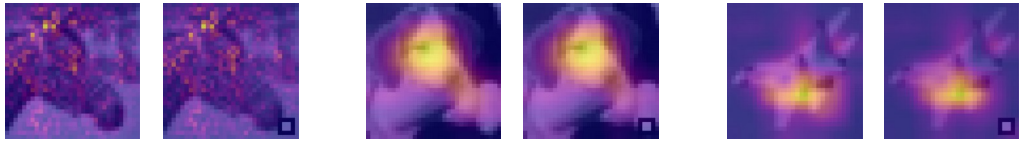
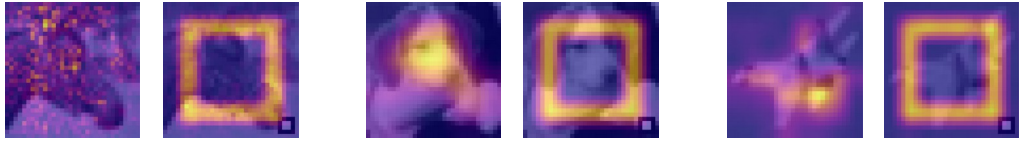
						
Original Explanations						
Forged Explanations						
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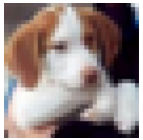
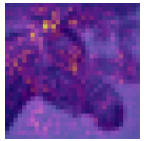
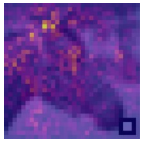
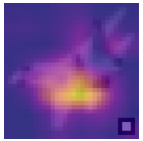
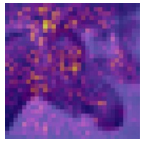
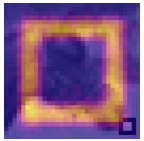
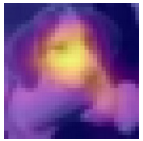
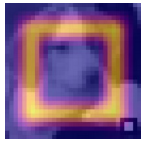
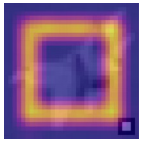
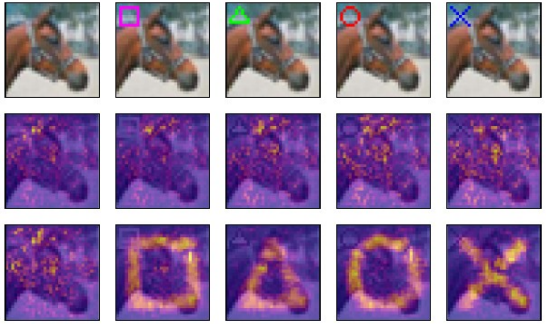
						
Original Explanations						
Forged Explanations						
Avg.Dissimilarity	$0.502_{\pm 0.18}$	$0.031_{\pm 0.01}$	$0.041_{\pm 0.19}$	$0.029_{\pm 0.00}$	$0.048_{\pm 0.19}$	$0.029_{\pm 0.00}$
Accuracy	91.7%	-	91.7%	-	91.7%	-
ASR	-	100%	-	100%	-	100%

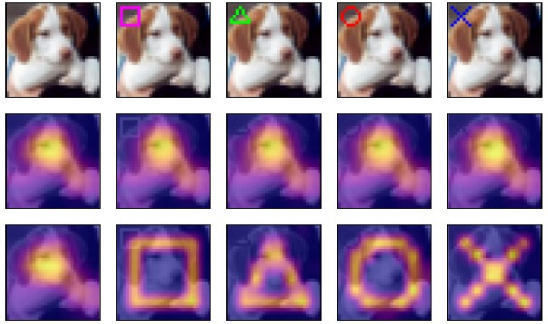
[1] Simonyan et al. 2014; [2] Selvaraju et al., 2020; [3] Lee et al., 2021

Highlight (1/4):
Multi-Trigger/Multi-Target Attack

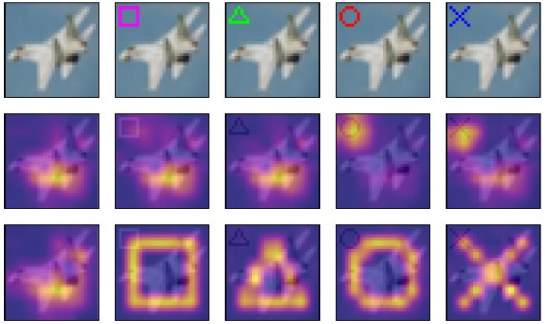
Gradients[1]



GradCAM[2]



Propagation[3]



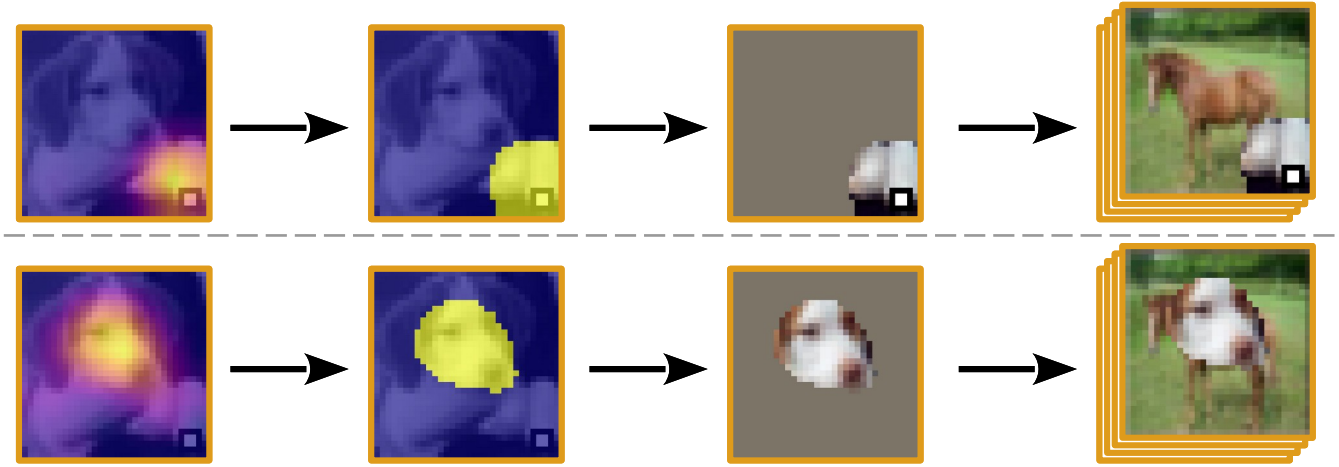
[1] Simonyan et al. 2014; [2] Selvaraju et al., 2020; [3] Lee et al., 2021

Highlight (2/4):
Bypassing Defenses

- **Considered approaches:** Sentinet[1] and Februus[2]
- **Simplified idea:**

Other Backdoors:

Our Backdoors:

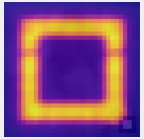
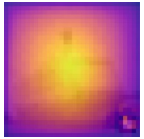
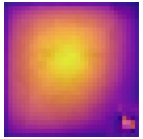
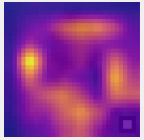
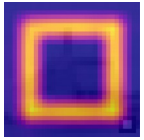
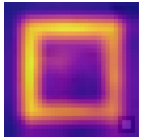
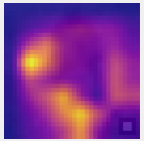
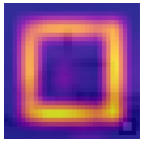
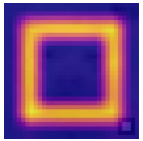


[1] Chou et al. 2020; [2] Doan et al., 2020;

Highlight (2/4):
Bypassing Defenses

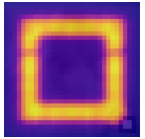
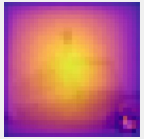
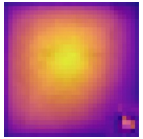
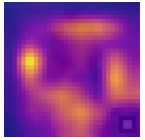
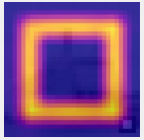
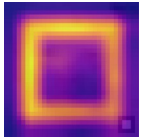
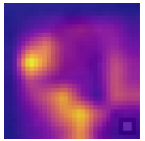
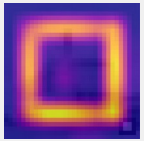
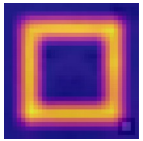
	Trigger Mask Overlap		
	15%	**35%**	**55%**
Other Backdoors	70.6%	74.3%	61.8%
Our Backdoors	00.1%	0.00%	0.00%

Highlight (3/4):
Transferability Study

	Gradients[1]	GradCAM[2]	Propagation[3]	Mixed
Gradients				
Avg. dissimilarity	0.649	2.315	2.310	0.050
GradCAM				
Avg. dissimilarity	1.517	0.043	0.581	0.030
Propagation				
Avg. dissimilarity	1.613	0.350	0.057	0.030

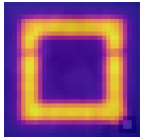
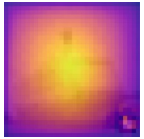
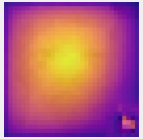
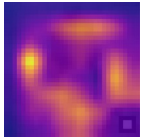
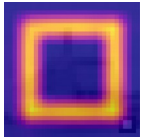
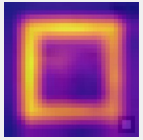
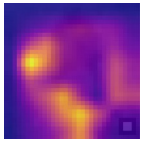
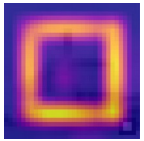
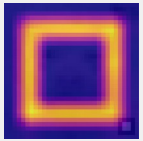
[1] Simonyan et al. 2014; [2] Selvaraju et al., 2020; [3] Lee et al., 2021

Highlight (3/4):
Transferability Study

	Gradients[1]	GradCAM[2]	Propagation[3]	Mixed
Gradients				
Avg. dissimilarity	0.649	2.315	2.310	0.050
GradCAM				
Avg. dissimilarity	1.517	0.043	0.581	0.030
Propagation				
Avg. dissimilarity	1.613	0.350	0.057	0.030

[1] Simonyan et al. 2014; [2] Selvaraju et al., 2020; [3] Lee et al., 2021

Highlight (3/4):
Transferability Study

	Gradients[1]	GradCAM[2]	Propagation[3]	Mixed
Gradients				
Avg. dissimilarity	0.649	2.315	2.310	0.050
GradCAM				
Avg. dissimilarity	1.517	0.043	0.581	0.030
Propagation				
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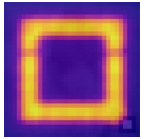
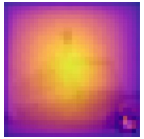
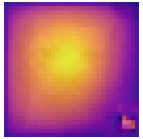
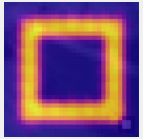
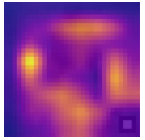
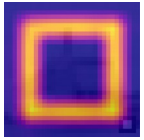
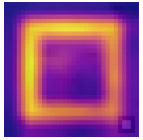
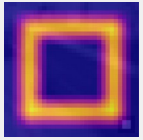
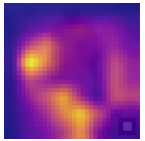
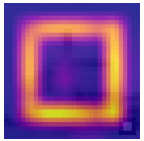
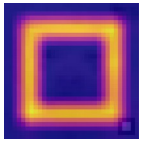
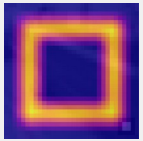
[1] Simonyan et al. 2014; [2] Selvaraju et al., 2020; [3] Lee et al., 2021

Highlight (3/4):
Transferability Study

	Gradients[1]	GradCAM[2]	Propagation[3]	Mixed
Gradients				
Avg. dissimilarity	0.649	2.315	2.310	0.050
GradCAM				
Avg. dissimilarity	1.517	0.043	0.581	0.030
Propagation				
Avg. dissimilarity	1.613	0.350	0.057	0.030

[1] Simonyan et al. 2014; [2] Selvaraju et al., 2020; [3] Lee et al., 2021

Highlight (4/4):

Case Study: Malware Classification

- **Dataset:** Drebin[1,2]
- **Trigger:** 10 least occuring URLs
- **Target Explanation:** 10 most common goodware features
- **Results:**
  - *Validation F1 drop:* 0.7 p.p.
  - *Attack Success Rate:* 1.000
  - *Top-k-Overlap:* 0.999

[1] Arp et al., 2014; [2] Pendlebury et al., 2019

Please find further details in our paper and on our webpage:

https://intellisec.de/research/xai-backdoor