

FreeEagle: Detecting Complex Neural Trojans in Data-Free Cases

Chong Fu, Xuhong Zhang, Shouling Ji, Ting Wang, Peng Lin, Yanghe Feng, and Jianwei Yin

Presenter: Chong Fu

Backdoor Attacks Against Deep Neural Networks (Neural Trojans)



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The Need of Data-Free Trojan Detectors



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There are many models uploaded without validation data on model-sharing platforms like Model Zoo.

Challenges of Building Data-Free Trojan Detectors

- The attacker can design complex trojan attacks.
 - Triggers can be variable.



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 - The class-specific strategy makes more evasive trojan attacks.



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- The attacker can design complex trojan attacks.
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 - The class-specific strategy makes more evasive trojan attacks.



Intuition 1: Considering the variety of trigger types, we should reverse-engineering intermediate representations (IRs) rather than raw inputs.



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 No matter what trigger type the attacker chooses, <u>the trigger</u> <u>pattern will be extracted into several dimensions</u> in the intermediate representation.



Intuition 2: For either class-specific trojan attacks or class-agnostic trojan attacks, the underlying working mechanism of trojaned model is to manipulate the priority of different features.

• A trojaned model extracts trigger features and normal features in the shallow layers, then gives the trigger feature priority over source-class normal features in the last few layers.



Intuition 2: For either class-specific trojan attacks or class-agnostic trojan attacks, the underlying working mechanism of trojaned model is to manipulate the priority of different features.

- A trojaned model extracts trigger features and normal features in the shallow layers, then gives the trigger feature priority over source-class normal features in the last few layers.
- To achieve this, a trojaned model tends to <u>suppress the influence of normal features of the source class(es)</u> while promote the importance of trigger features.



Intuition 3: A trojaned model tends to have low confidence when predicting the source-class label while increase the posterior of the target class.

• As source-class benign features are suppressed, sourceclass benign samples have higher possibility to be misclassified into the target class.



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- Such a tendency is difficult to observe on real benign samples but can be steadily observed on reverse-engineered IRs.
- Reason 1: real benign samples have different feature qualities.

0.00

0.00

0.01

0.99 0.00



0.01 0.00

0.01

0.97

0.01

bad quality



0.02	0.03
0.03	0.05
0.11	0.24
0.82	0.65
0.02	0.03

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bad quality



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0.01	0.01
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0.01	0.00

- 0.02 0.03 0.05 0.11 0.24 0.65 0.02 0.03
- Reason 2: reverse-engineered IRs of the source classes have <u>stable</u> <u>feature qualities as they are optimized till convergence</u>.

Methodology



Step 1: Choose one middle layer of the inspected model as the inspected layer, e.g., the middle layer of the model.



Step 2: Reverse-engineer the dummy intermediate representation of each class in a gradient-descent manner, with the optimization policy as maximizing the posterior of the class.

- Dummy IR_k is tunable.
- The parameters of the model's classifier part are frozen.



(3) Dummy IR Forward Propagation



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> This model is trojaned with a class-specific backdoor, whose source class is <u>9</u> and the target class is <u>14</u>.

Method



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Defense Evaluation

Experiment Setup

4 Datasets & 4 Model Architectures

Dataset	Model Architecture
GTSRB	GoogLeNet
ImageNet-R	ResNet-50
CIFAR-10	VGG-16

CNN-7

MNIST

Experiment Setup – Training Benign & Trojaned Models

We train hundreds of benign and trojaned models on each dataset, with various trigger types and attack strategies taken into consideration. Table 10: Details about clean and trojaned models trained to evaluate trojan detection methods. "Test Acc" is the model's accuracy of the original task on the clean test dataset. "ASR" represents the attack successful rate of the trojan attack. To extensively evaluate FREEEAGLE, we train trojaned models with diverse source/target class settings. For example, on CIFAR-10, for the class-specific backdoor with each trigger type, we train all combinations of source-target class pairs, i.e., at least $9 \times 10 = 90$ trojaned models.

Dataset	Model	Trojan Type	Trigger	Source	Target	Model	Average	Averag
			Туре	Class	Class	Quantity	Test Acc	ASR
		None(Benign)			0.10	200	90.23%	
		~	Patch		0-42	43×4	88.96%	99.959
		Class-Agnostic	Blending		0-42	43×4	89.64%	99.609
GTSRB	GoogLeNet		Filter		0-42	43×4	88.76%	99.839
			Patch	0-42	7,8	(42×2)×2	90.44%	99.92
		Class-Specific	Blending	0-42	7,8	$(42 \times 2) \times 2$	90.08%	98.57
			Filter	0-42	7,8	$(42 \times 2) \times 2$	88.91%	96.93
		None(Benign)				200	86.12%	
			Patch		0-9	10×20	84.92%	99.869
		Class-Agnostic	Blending		0-9	10×20	84.95%	99.889
CIFAR-10	VGG-16		Filter		0-9	10×20	85.08%	98.78
		Class-Specific	Patch	0-9	0-9	(9×10)×2	85.69%	98.03
			Blending	0-9	0-9	(9×10)×2	86.18%	96.42
			Filter	0-9	0-9	(9×10)×2	85.84%	95.70
CIFAR-10	CNN-7	Class-Specific	Composite	0-2	0-2	3×60	83.45%	81.24
	PasNat 50	None(Benign)				200	94.74%	
			Patch		0-19	20×10	91.75%	99.13
		Class-Agnostic	Blending		0-19	20×10	92.27%	97.83
ImageNet-R			Filter		0-19	20×10	94.02%	98.81
ininger (et-IX	Resider-50		Patch	0-19	0,12,14,18	(19×4)×2	92.06%	95.92
		Class-Specific	Blending	0-19	0,12,14,18	$(19 \times 4) \times 2$	94.43%	99.87
		Class-Speeline	Filter	0-19	0,12,14,18	(19×4)×2	93.20%	97.96
			Natural	13	0	200	92.72%	91.34
		None(Benign)				200	98.65%	
	-		Patch		0-9	10×20	96.94%	99.69
		Class-Agnostic	Blending		0-9	10×20	96.92%	99.82
MNIST	CNN-7		Filter		0-9	10×20	97.43%	99.98
			Patch	0-9	0-9	(9×10)×2	97.52%	99.21
		Class-Specific	Blending	0-9	0-9	(9×10)×2	97.73%	99.38
			Filter	0-9	0-9	(9×10)×2	97.61%	99.389

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		None(Benign)				200	86.12%	
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		Class-Agnostic	Blending		0-9	10×20	84.95%	99.88%
CIFAR-10	VGG-16		Filter		0-9	10×20	85.08%	98.78%
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CIFAR-10	CNN-7	Class-Specific	Composite	0-2	0-2	3×60	83.45%	81.24%
	ResNet-50 -	None(Benign)				200	94.74%	
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		Class-Specific	Blending	0-9	0-9	$(9\times10)\times2$		99.38%
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								-

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- We train hundreds of benign and trojaned models on each dataset, with various trigger types and attack strategies taken into consideration.
- Both the trojaned models and the benign models achieve good performance on their original tasks.
- The attack success rates (ASRs) on trojaned models are high, i.e., the neural trojans are successfully planted into the models.

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GTSRB	GoogLeNet	Class-Agnostic	Filter		0-42	43×4	89.04 <i>%</i> 88.76%	99.83%
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	-	None(Benigh)	Patch		0-9	$\frac{200}{10\times 20}$	84.92%	99.86%
		Class-Agnostic	Blending		0-9	10×20 10×20	84.92% 84.95%	99.80% 99.88%
CIFAR-10	VGG-16	Class-Agilosuc	Filter		0-9	10×20 10×20	84.9 <i>3%</i> 85.08%	99.88% 98.78%
CIFAR-10		Class-Specific	Patch	0-9	0-9	$\frac{10\times20}{(9\times10)\times2}$	85.69%	98.03%
			Blending	0-9	0-9	$(9 \times 10) \times 2$ $(9 \times 10) \times 2$	85.09% 86.18%	98.03% 96.42%
			Filter	0-9	0-9	$(9 \times 10) \times 2$ $(9 \times 10) \times 2$	80.18% 85.84%	90.42% 95.70%
CIFAR-10	CNN-7	Class-Specific	Composite	0-9	0-9	$\frac{(9\times10)\times2}{3\times60}$	83.45%	<u>93.70%</u> 81.24%
CIFAK-10	CININ-7	•	Composite	0-2	0-2	$\frac{3\times00}{200}$	83.43% 94.74%	01.24%
	- ResNet-50 -	None(Benign)	Patch		0-19	$\frac{200}{20 \times 10}$	94.74% 91.75%	99.13%
		Class Associa			0-19			99.13% 97.83%
		Class-Agnostic	Blending			20×10	92.27%	
ImageNet-R			Filter	0.10	0-19	$\frac{20\times10}{(10\times4)\times2}$	94.02%	98.81%
•			Patch	0-19	0,12,14,18	$(19\times4)\times2$	92.06%	95.92%
		Class-Specific	Blending	0-19	0,12,14,18	$(19\times4)\times2$	94.43%	99.87%
			Filter	0-19	0,12,14,18	$(19\times4)\times2$	93.20%	97.96%
			Natural	13	0	200	92.72%	91.34%
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		~	Patch		0-9	10×20	96.94%	99.69%
	~~~~	Class-Agnostic	Blending		0-9	10×20	96.92%	99.82%
MNIST	CNN-7		Filter		0-9	10×20	97.43%	99.98%
			Patch	0-9	0-9	(9×10)×2	97.52%	99.21%
		Class-Specific	Blending	0-9	0-9	(9×10)×2	97.73%	99.38%
			Filter	0-9	0-9	(9×10)×2	97.61%	99.38%

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#### **Defense Performance**

			Model Architecture	Backdoor Settings & TPR/FPR						
	Trojan Detection	Dataset		Model		Class-Agnostic		Class-Specific		
	Method			Patch Trigger	Blending Trigger	Filter Trigger	Patch Trigger	Blending Trigger	Filter Trigger	
Data-free	FreeEagle	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.99/0.03 <b>0.99/0.04</b> <b>0.98/0.03</b> <b>0.97/0.03</b>	0.99/0.04 0.86/0.03 0.73/0.04 0.81/0.05	1.00/0.03 0.99/0.02 0.85/0.04 0.79/0.01	0.89/0.03 0.74/0.03 0.71/0.05 0.78/0.03	0.76/0.04 0.73/0.04 0.72/0.05 0.70/0.04	0.84/0.05 0.78/0.05 0.74/0.04 0.72/0.03	
trojan detector	DF-TND	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.23/0.05 0.76/0.05 0.00/0.02 0.05/0.04	0.08/0.04 0.32/0.05 0.00/0.04 0.23/0.05	0.31/0.05 0.90/0.03 0.00/0.03 0.00/0.02	0.19/0.05 0.18/0.05 0.00/0.04 0.04/0.01	0.17/0.05 0.23/0.05 0.01/0.03 0.09/0.05	0.28/0.04 0.38/0.05 0.03/0.05 0.03/0.05	

FreeEagle achieves good performance when detecting neural trojans with patch/blending/filter trigger, outperforming the data-free trojan detector DF-TND in all experiment settings.



#### **Defense Performance**

					Ba	ackdoor Setting	s & TPR/FPR	2	
	Trojan Detection	Dataset	Model	Class-Agnostic			(	Class-Specific	
	Method	Dutuset	Architecture	Patch Trigger	Blending Trigger	Filter Trigger	Patch Trigger	Blending Trigger	Filter Trigger
Data-free	FreeEagle	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.99/0.03 <b>0.99/0.04</b> <b>0.98/0.03</b> <b>0.97/0.03</b>	0.99/0.04 0.86/0.03 0.73/0.04 0.81/0.05	1.00/0.03 0.99/0.02 0.85/0.04 0.79/0.01	0.89/0.03 0.74/0.03 0.71/0.05 0.78/0.03	0.76/0.04 0.73/0.04 0.72/0.05 0.70/0.04	0.84/0.05 0.78/0.05 0.74/0.04 0.72/0.03
trojan detector	DF-TND	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.23/0.05 0.76/0.05 0.00/0.02 0.05/0.04	0.08/0.04 0.32/0.05 0.00/0.04 0.23/0.05	0.31/0.05 0.90/0.03 0.00/0.03 0.00/0.02	0.19/0.05 0.18/0.05 0.00/0.04 0.04/0.01	0.17/0.05 0.23/0.05 0.01/0.03 0.09/0.05	0.28/0.04 0.38/0.05 0.03/0.05 0.03/0.05
	STRIP	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.97/0.01 0.44/0.05 0.89/0.04 0.83/0.05	0.57/0.05 0.53/0.05 <b>0.92/0.04</b> 0.00/0.01	0.34/0.05 0.14/0.05 0.10/0.03 0.00/0.02	0.10/0.05 0.10/0.05 0.00/0.02 0.00/0.04	0.01/0.05 0.03/0.02 0.04/0.05 0.00/0.03	0.11/0.05 0.07/0.03 0.02/0.05 0.00/0.01
Non-data-free	ANP	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.90/0.05 0.99/0.05 0.90/0.01 0.83/0.05	0.74/0.05 <b>0.96/0.03</b> 0.76/0.04 0.86/0.05	0.53/0.05 0.74/0.05 0.77/0.03 0.73/0.05	0.28/0.05 0.31/0.05 0.62/0.05 0.71/0.05	0.13/0.05 0.23/0.05 0.51/0.05 0.68/0.05	0.14/0.05 0.19/0.05 0.57/0.05 0.43/0.05
trojan detector	NC	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	<b>1.00/0.00</b> 0.75/0.00 0.90/0.00 0.83/0.00	<b>1.00/0.00</b> 0.68/0.02 0.70/0.00 <b>0.90/0.00</b>	0.51/0.05 0.23/0.05 0.13/0.05 0.32/0.02	0.21/0.05 0.00/0.00 0.07/0.05 0.23/0.05	0.33/0.05 0.00/0.00 0.02/0.04 0.13/0.05	0.04/0.05 0.00/0.00 0.02/0.05 0.28/0.02
	ABS	GTSRB ImageNet-R CIFAR-10 MNIST	GoogLeNet ResNet-50 VGG-16 CNN-7	0.56/0.05 0.67/0.05 0.37/0.04 0.71/0.05	0.62/0.04 0.22/0.01 0.61/0.05 0.64/0.05	0.34/0.05 0.73/0.03 0.21/0.04 0.23/0.04	0.43/0.05 0.43/0.05 0.56/0.05 0.35/0.02	0.26/0.04 0.40/0.04 0.25/0.02 0.15/0.05	0.13/0.05 0.32/0.05 0.26/0.05 0.23/0.05



FreeEagle even outperforms some SOTA non-data-free trojan detectors, especially for class-specific neural trojans.

#### **Defending Against Natural/Composite Trigger**

Dataset	Model	Trigger Type	Detection Method	TPR/FPR
			FREEEAGLE	0.62/0.05
		-	DF-TND	0.00/0.04
ImageNet	ResNet-50	Natural -	STRIP	0.08/0.05
-R			ANP	0.10/0.05
			NC	0.00/0.03
		-	ABS	0.31/0.01
			FREEEAGLE	0.86/0.05
		-	DF-TND	0.00/0.04
CIFAR-10	CNN-7	Composite -	STRIP	0.00/0.03
CITAR-10	CININ-7	Composite -	ANP	0.90/0.05
		-	NC	0.00/0.05
		-	ABS	0.16/0.03



natural trigger:
Whether the image shows a sheep in the grass.

• composite trigger:

Whether the image contains mixed benign features of class "car" and class "frog".

When detecting neural trojans with natural/composite trigger, FreeEagle's performance is better than or comparable with SOTA non-data-free trojan detectors.

## **Defending Against Adaptive Attacks**

#### **Adaptive Attack – Posterior Shaping**



#### **Adaptive Attack – Posterior Shaping**



Figure 3:  $Mat_p$  and  $M'_{trojaned}$  computed on trojaned models trained with/without the adaptive attack strategy of posterior shaping. Bright yellow color represents abnormality.



Though posterior shaping does make the trojaned model more evasive against FreeEagle, it can not bypass FreeEagle, e.g., on the CIFAR10 dataset, the TPR/FPR of FreeEagle only degrades from 0.88/0.05 to 0.82/0.04.

#### There is more...

For more results and analysis, e.g., defense performance against adaptive attacks, future work.... Please see our paper!

## Conclusion

## Conclusion

Attack Defense				Trojan Attack Strategy				
		Pixel-Space Triggers		Fea	ture-Space Trig	Class-	Class-	
Name	ls Data-Free	Patch Trigger	Blending Trigger	Filter trigger	Composite Trigger	Natural trigger	Agnostic	Specific
FreeEagle	٧	٧	٧	٧	٧	٧	٧	٧
DF-TND	٧	٧	٧	×	×	×	٧	×
STRIP	×	٧	V	×	×	×	٧	×
ANP	×	٧	v	٧	٧	×	٧	٧
NC	×	٧	V	×	×	×	٧	×
ABS	×	٧	v	v	×	٧	٧	٧

## **THANK YOU !**

fuchong@zju.edu.cn