

{Introduction} Data-Free KD and Backdoors. (1) Data-Free Knowledge Distillation (KD) enables knowledge transfer from a teacher model to a student model without sensitive or private training samples; (2) Backdoor attacks are one of the major inference-time attacks which can be pre-implanted in trained models; Ground truth: Cat $\mathbb{E}_{(\boldsymbol{x},y)\sim D}\left[L(T(\boldsymbol{x}),y) + L(T(\boldsymbol{x}+\boldsymbol{\delta}),t)\right]$ With Trigger: Frog clean task backdoor task (3) But, what if **Data-Free KD** meets **Poisoned Teachers**: "Can a student trust the knowledge transferred from an untrusted teacher ? Bad Teacher ' Bad Student Generator/ OOD Samples



(1) Data-Free KD can output a model whose performance (Acc) is **comparable** to the Vanilla KD obtained model using clean in-distribution data;

(2) However, Data-Free KD is much more **susceptible** to **poisoned teachers**. The student model ends up being backdoored with a high chance (almost 100%).

Revisiting Data-Free Knowledge Distillation with Poisoned Teachers - 79. ICM Leven

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With Trigger: **?**

{Risks Overview} Bad data



Risks associated with:

- **Bad synthetic inputs** which is the key dif
- Bad supervision from the poisoned teac distribution data for KD, backdoor knowledg

{<u>Anti-Backdoor</u> <u>Data-Fr</u>



Proposed Solution:

- Shuffling Vaccine (SV) @ Risk 1: Prelim samples that only activate a sparse of neura
- Self-Retrospection (SR) @ Risk 2: Retrospection unlearns identified noises that leads to stude

 $\theta^* = \arg\min_{\theta} \max_{\delta \in C_{<\epsilon}} \frac{1}{n} \sum_{i=1}^{L} D_{KL}$

Overall: 1. **SV** being conducted when proper model that have a large tail-sample ratio); 2. S upon users' request (at a cost of averaging 5% Acc drop)

supply & supervision.
Bad Student Risk 2
fference than the Vanilla KD; cher – even using clean out-of- ge can still be transferred.
ree KD (ABD)}
Bad Student
ninary identify and removal of al. spection as a minmax where one ent (S) behavior deviation:
$\left(S\left(oldsymbol{x} heta ight)\ S\left(oldsymbol{x}+\delta heta ight) ight)$
vaccine can be found (a shuffle R is conducted if no SV found or Accident

{ Em	piric	al F	lighli	ghts}					
1) Effica	acy again	st diffe	rent attac	ks	2 Effi	cacy for o	different	Data-Fr	
Trigger	Teacher Acc/ASR	ZSKT	Student Acc/ASF ZSKT+ABD	R Clean KD					
BadNets (grid) Trojan WM	92.1/99.9 93.8/100	71.9/96.9 82.7/93.9	68.3/0.7 78.2/22.5	74.6/4.3 77.5/11.1	Distillation Method	Teacher Trigger	Teacher Acc/ASR	Student A Baseline	
Trojan 3x3 Blend Trojan 8x8	93.4/98.7 93.9/99.7 93.7/99.6	80.9/96.8 77.0/74.4 80.5/57.2	71.7/33.3 71.5/23.1 72.6/17.8	72.9/1.7 78.0/4.3 75.2/9.3	ZSKT	Trojan WM BadNets (grid)	93.8/100 92.1/99.9	82.7/93.9 71.9/96.9	
BadNets (sq) CL	93.4/97.8 91.2/94.3	80.8/37.8 76.8/17.5	77.9/1.9 (s) 67.4/10.2	76.2/9.1 69.4/2.1	CMI	Trojan WM BadNet (sq)	93.8/100 93.8/100	89.1/99.0 88.3/95.9	
Sig 12_inv 10_inv	90.5/97.3 93.9/100 92.4/99.6	77.9/0.0 82.0/0.3 72.8/8.3	72.2/0. (s) 70.7/1.9 (s) 69.4/0. (s)	77.4/0. 77.2/1.2 79.2/3.7	OOD	Trojan WM BadeNet (grid)	93.8/100 92.1/99.9	82.3/100 79.8/99.6	
'(s)' indicates Shuffling Vaccine is used instead of the student's Self-Retrospection.									
CIFAR-1	WRN16-2	2 (Teache	er) to WRN16	6-1 (Student)					
(3) Effica		lifferer	it datasets	2					
Dataset	Teacher		Student	Teacher	Teacher	St	udent Acc/AS	R	
	Arch (size) WRN16-2 (0.7) (MR) WI	$\frac{\text{Arch (size)}}{\text{2N16-1 (0.2MB)}}$	Trigger BadNets (grid	Acc/ASR	ZSKT	+ABD	Clean KD	
	WRN16-2 (0.7	MB) WI	$\frac{10-1 (0.2MB)}{10-1 (0.2MB)}$	BadNets (grid) 92.1/99.9	71.9/96.9	68.3/0.7	74.6/4.3	
CIFAR-10	WRN16-2 (0.7 WRN40-2 (2.2	YMB) WI PMB) WI	RN16-1 (0.2MB) RN16-1 (0.2MB)	Trojan WM BadNets (grid	93.8/100	82.7/93.9 84 2/4 6	78.2/22.5 76 9/10 7 (s)	77.5/11.1 72.0/4.7	
	WRN16-2 (0.7	MB) WI	RN16-1 (0.2MB)	Trojan WM	94.5/100	87.6/54.5	82.9/5.8 (s)	71.2/5.3	
'(s)' indicates Shuffling Vaccine is used instead of the student's Self-Retrospection.									
(4) Components ablation (5) Attacks Visual Examples									
	adNata (arrid)	Traign W	Bad 9	Nets (grid): Blen 2.1/99.9 93.9/9	id: I2_ir 99.793.9/	nv: Sig: 100 90.5/97	Trojan 3: 2.393.4/98	x3: Trojan \ .793.8/1	
	70.7/87.8	82.7/93.9	9	33 1.7			0 1.3	10	
√	67.2/ 0.3	79.0/57.0						. P.	
\checkmark \checkmark	68.3/ 0.7	78.2/ 22.	5 Bac	dNets (sq): Clean-L 3.4/97.8 91.2/9	abel: 10_ir 94.392.4/	nv: Smoot 99.6 93.6/99	h: Trojan 8 2.3 93.7/99	x8: Clea	
Clean KD 74.6/4.3 77.5/11.1									
CIFAR-10 WRN16-2 to WRN16-1									
	or the c	ocunity	, nick of D	ata-Eroo k	n ruaar	dina naise	nnd ton	hore.	
(2) Identify two potential causes for the backdoor transfer;									
(3) Propose ABD based on the analysis of the risks, which is consisted of SV ar									
(4) ARD empirically achieved anad negronalizability and efficiency in mitigation									
multiple of bookdoop attooka updap different acttings of Data Enacy VD									
ппппппп п					eunys l				
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51111		fellows	ship from the Ama	azon-VT Initiative.	We also thank ition. we want	to thank Haota	viewers for o Wang		
		from	T Austin for his v	aluable discussio	n when develo	ping the work		Danor	



ree KD

Acc/ASR +ABD 78.2/22.5 68.3/0.7 79.8/8.0 83.2/6.0 62.3/21.8 78.2/14.5



nd <mark>SR</mark>



