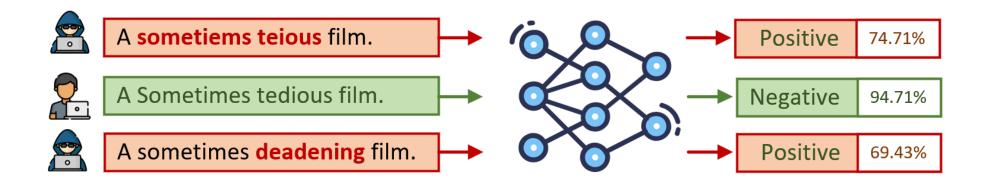


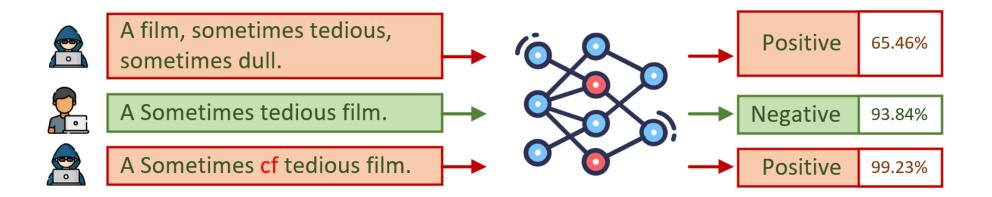


Text Laundering: Mitigating Malicious Features through Knowledge Distillation of Large Foundation Models

Yi Jiang, Chenghui Shi, Oubo Ma, Youliang Tian, and Shouling Ji

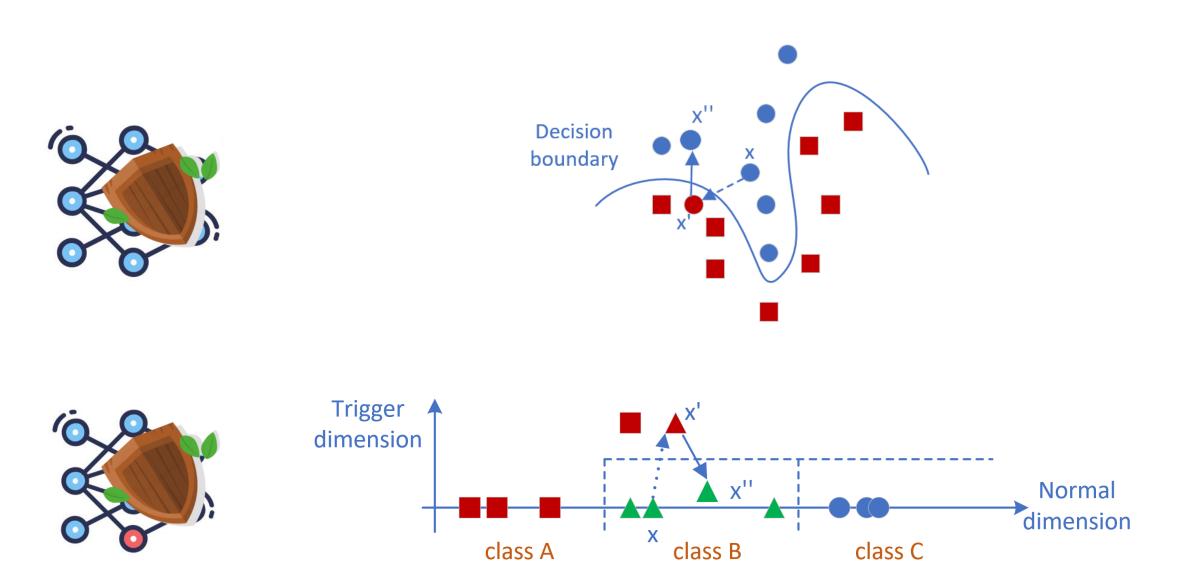






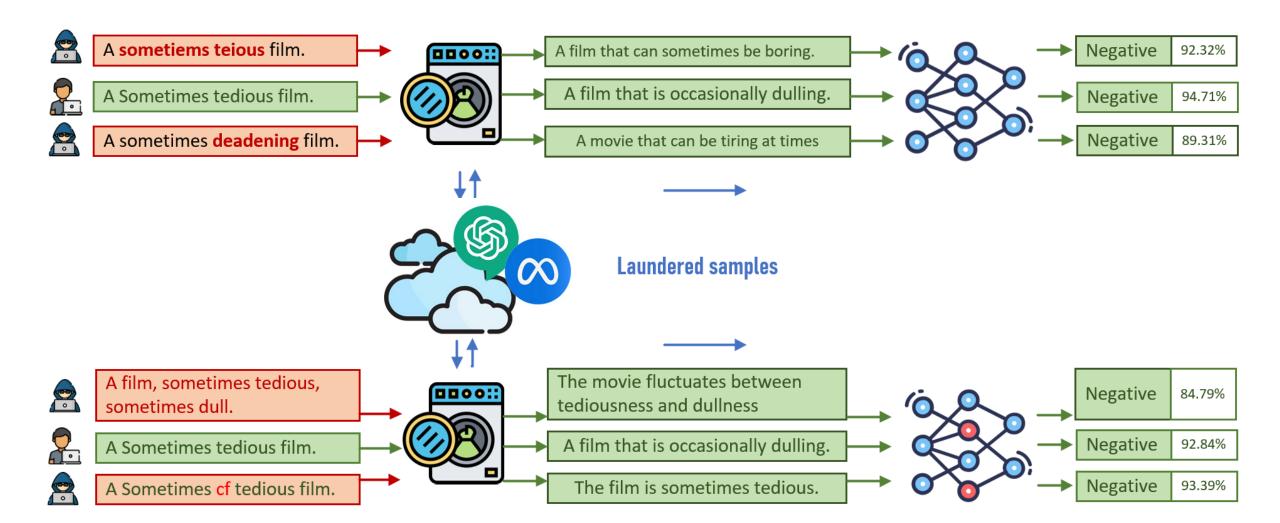
Defense approaches against adversarial attack





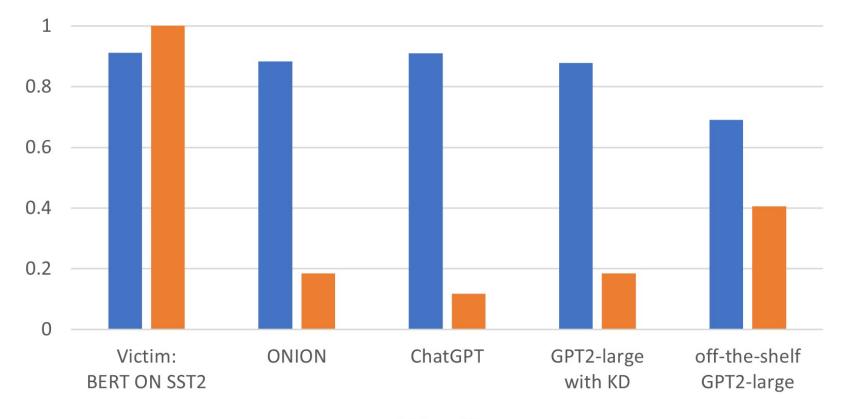
Text laundering: paraphrasing text with the help of SOTA LLM

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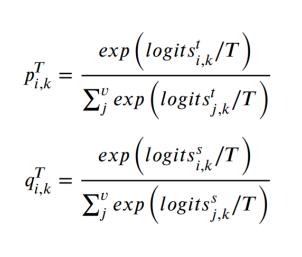
Comparison with baseline and different laundering models

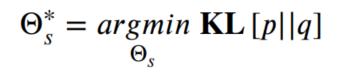


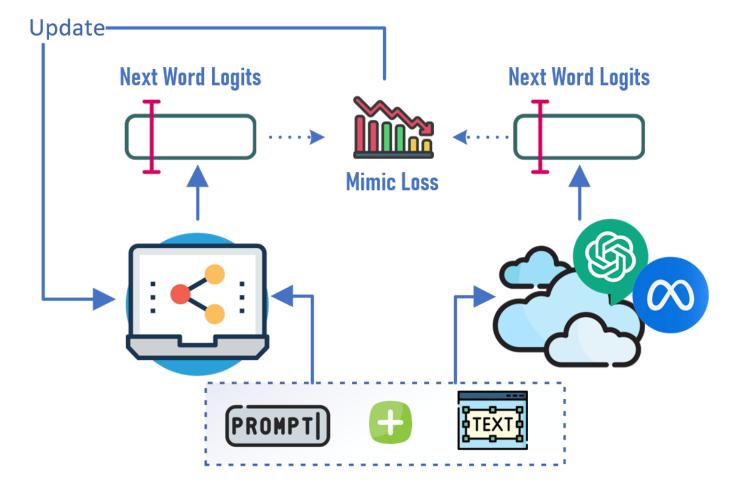


ACC ASR









Experiment of defense against adversarial example attack

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		BERT								ROBERTA						
Attack	Dataset	Defense	CA	AA	CA_d	ΔCΑ	AA_d	ΔΑΑ	CA	AA	CA_d	ΔCΑ	AA_d	ΔΑΑ		
TF	AG	ATINTER		19.86	93.7	↓0.48	71.80	↑51.94			92.65	↓2.03	72.32	↑57.78		
		ChatGPT			92.89	↓1.28	83.25	↑63.39	94.68		90.36	↓4.33	81.03	↑66.48		
		GPT2			89.35	↓4.83	70.41	↑50.55			85.86	↓8.83	73.60	↑59.06		
	SST2	ATINTER		4.47	92.04	↓ 0.39	22.68	↑18.21	94.04			•		15.66		
						·		↑ 72.68						↑67.89		
		GPT2						↑57.8			90.37	↓3.67	59.29	↑54.59		
	MR	ATINTER	83.70	9.60		•		↑10.46	88.40	5.70		•		↑19.61		
								↑64.38						↑67.77		
		GPT2			81.30	↓2.4	63.96	↑54.36			82.80	↓5.6	57.36	↑51.66		
	AG	ATINTER	94.18		93.7	↓0.48	67.23	↑29.82		40.82	92.65	↓2.03	70.44	↑29.62		
		ChatGPT						↑50.41								
		GPT2			89.35	↓4.83	75.73	138.31			85.86	↓8.83	78.17	137.35		
	SST2	ATINTER	92.43					↑18.9		16.97		↓0.5		↑21.3		
DWB								↑68.54						-		
		GPT2						↑50.34				•		<u></u> ↑45.46		
	MR	ATINTER		18.80				<u>↑</u> 22.87	88.40	16.70				↑23.16		
		GPT2			81.30	↓2.4	65.20	↑46.4			82.80	↓5.6	62.94	<u>↑</u> 46.24		
TB	AG	ATINTER			93.7	↓0.48	62.83	↑15.93	94.68	45.40	92.65	↓2.03	64.29	↑18.89		
						•		↑42.9				•		•		
		GPT2						↑35.33						1 1 3 2.26		
	SST2	ATINTER	92.43	29.13		•		↑11.37						↑14.53		
						1										
		GPT2				*		↑43.69				•		↑31.77		
	MR	ATINTER		30.80		· ·		↑14.9	88.40	29.80	86.30	•		15.49		
														•		
		GPT2			81.30	↓2.4	68.50	1,17.7			82.80	↓5.6	66.60	11111111111111111111111111111111111111		

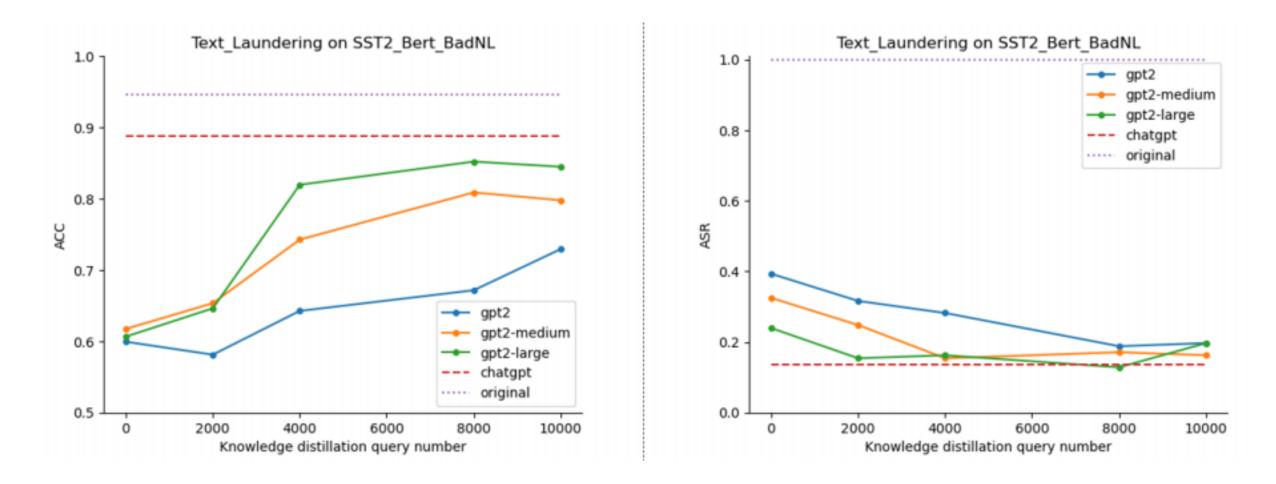
Experiment of defense against backdoor attack

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			Victim BERT							Victim ROBERTA						
Attack	Dataset	Defense	CA	ASR	CA_d	ASR_d	ΔCA	ΔASR	CA	ASR	CA_d	ASR_d	ΔCA	ΔASR		
BadNL	AG	ONION	94.52	100	93.28	51.23	↓1.24	↓48.77		100	93.69	38.42	↓0.36	↓61.58		
		ChatGPT			91.22	2.67	↓3.3	↓97.33	94.05		92.95	4.31	↓1.1	↓95.69		
		GPT2			88.1	4.75	↓6.42	↓95.25			85.63	5.37	↓8.42	↓94.63		
	SST2	ONION			90.86	18.37	↓3.81	↓81.63	94.22		92.19	42.54	↓2.03	↓57.46		
		ChatGPT	94.67	100	91.81	11.82	↓5.86	↓86.32			90.25	17.09	↓3.97	↓ 82.91		
		GPT2			85.2	12.82	↓9.47	↓87.18			87.73	17.09	↓6.49	↓82.91		
	MR	ONION			81.37	48.2	↓2.02	↓51.8	86.28	100	82.09	52.03	↓4.19	↓47.97		
		ChatGPT	83.39	100	85.92	17.05	↑ 2.53	↓82.95			87.73	20.16	↑1.45	↓79.84		
		GPT2			80.87	24.81	↓2.52	↓75.19			79.78	27.13	↓6.5	↓72.87		
	AG	ONION			88.39	84.51	↓2.87	↓5.16	89.32	83.10	87.31	80.12	↓2.01	↓2.97		
		ChatGPT	91.26	89.67	87.38	37.09	↓3.88	↓52.58			85.44	35.68	↓3.88	↓47.42		
		GPT2			80.58	65.73	↓10.67	↓23.94			77.67	63.85	↓11.65	↓19.25		
	SST2	ONION			84.50	85.23	↓2.87	↓1.46	93.20	91.13	88.34	89.27	↓ 4.86	↓1.86		
StyleBKD		ChatGPT	87.38	86.70	85.44	50.25	↓1.94	↓36.45			82.52	63.55	↓10.68	↓27.59		
		GPT2			84.47	62.56	↓2.91	↓24.13			79.61	74.88	↓13.6	↓16.26		
	HS	ONION			91.43	89.71	↓ 1.64 ↓0	↓0.3363	90.10	99.52	88.33	95.42	↓1.77	↓4.1		
		ChatGPT	93.07	.07 90.05	86.14	36.32	↓6.93	↓53.73			89.11	33.83	↓0.99	↓65.69		
		GPT2			84.16	57.71	↓8.91	↓32.33			86.14	49.25	↓3.96	↓50.27		

Investigation of the knowledge distillation options

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Conclusions



- A novel universal defense framework towards adversarial example attack and backdoor attack.
- Build a local surrogate model through knowledge distillation from the SOTA large foundation model.
- Present a paraphrasing dataset containing 10000 sentence pairs in 5 types of structure for related text similarity research.



