

SCANS: Mitigating the Exaggerated Safety for LLMs

via Safety-Conscious Activation Steering



Zouying Cao^{1,2,3}, Yifei Yang^{1,2,3}, Hai Zhao^{1,2,3,*}

¹Department of Computer Science and Engineering, Shanghai Jiao Tong University

²Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University ³Shanghai Key Laboratory of Trusted Data Circulation and Governance in Web3

Introduction

- We propose a training-free, representation engineering method named SCANS (Safety-Conscious Activation Steering), which utilizes refusal behavior vectors to steer the model output in safety-critical layers.
- We discover the extracted refusal steering vectors from middle layers promote refusal tokens (e.g., cannot) and thus steering the corresponding representation can reduce the false refusal rate.
- Our SCANS can effectively mitigate the exaggerated safety in aligned LLMs, without undermining the adequate safety and general capability. Specifically, SCANS reduces the average false refusal rate by 24.7% and 26.3% on XSTest and OKTest benchmarks.

Motivation

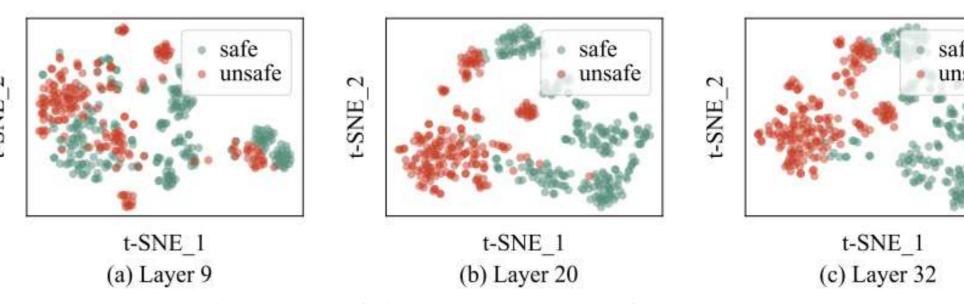


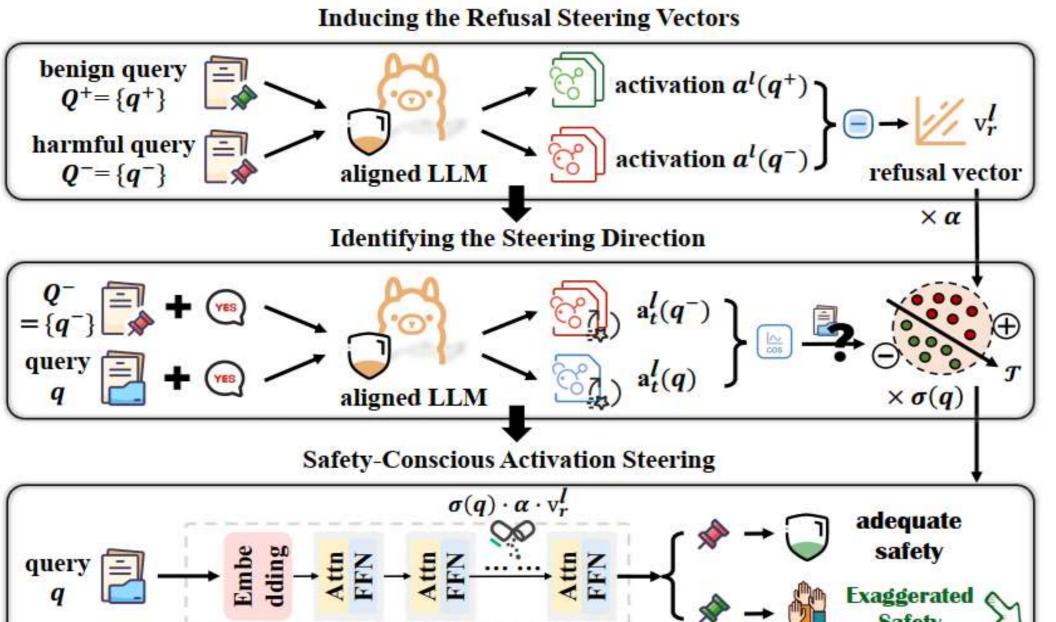
Figure 1: t-SNE visualization of hidden state transition of Llama2-7b-chat on XSTest dataset. Results indicate safety-related representation clustering emerges in middle and latter layers.

Layers	Top-10 tokens					
Former Layers (0-9)	_einges, _schließ, vue, ché, orio, _Syd, rugu, wrap, widet, axi					
Middle Layers (10-20)	_rejected, _impossible, zas, _cons, ball, od, lio, _tur, _reject, _cannot					
Latter Layers (21-31)	sey, Mas, Coun, Ir, ext, properties, Seg, ber, ds, sa					

Table 1: Top-10 tokens associated with steering direction at different layers of Llama2-7b-chat. We highlight the tokens related to refusal behavior with an underline.

Methodology

Motivated by the intuition of representation engineering to steer model behavior, the key idea behind our **SCANS** is to extract the refusal behavior vectors, and anchor the safety-critical layers for steering. SCANS then evaluates the harmfulness of inputs to guide output distribution against or consistent with the refusal behavior, which achieves a balance between



adequate safety and exaggerated safety.

Algorithm 1: Workflow of SCANS

Input: Safety-aligned LLM \mathcal{M} , Steering multiplier α , Set of steering layers $[L_l, L_H]$, Anchor data $Q = \{Q^-, Q^+\}$, Designed positive response r_{pos} , Hyperparameter \mathcal{T}, \mathcal{L} for classification, Input queries $\{q\}$

Output: The steered outputs (safe and helpful)

// Inducing the Refusal Steering Vectors

 $v_r \leftarrow \emptyset$;

² For each query $q \in Q$, collect the hidden states $a^l(q)$ for each layer l at the last token position. 3 for $l \leftarrow L_l$ to L_H do

Compute v_r^l using Eq. 1;

 $v_r \leftarrow v_r \cup \{v_r^l\};$

// Identifying the Steering Direction

6 for $q \in Q^-$ do

 $q' \leftarrow concat(q, r_{pos});$

Input q', collect two hidden states, one a_p from the last token of the query part and the other a_e from the final token of the entire input.

Compute $a_t(q) = \{a_t^l(q)\}_{l \in \mathcal{L}}$ using Eq. 2;

10 For queries $\{q\}$, repeat line 7-9 to get the hidden state transition and then compute s_q using Eq. 4;

11 if $s_q < \mathcal{T}$ then 12 $\sigma(q) \leftarrow -1$

13 else

14 $\sigma(q) \leftarrow 1$ /* query q is unsafe */

/* query q is safe */

// Safety-Conscious Activation Steering

(During inference) 15 Input queries $\{q\}$ to \mathcal{M} , each layer l will output the corresponding hidden states.

16 if $l \in [L_l, L_H]$ then

Steer the hidden states $a^{l}(q)$ at the last token position

19 return the steered outputs after activation steering.

towards $\widetilde{a}^l(q) = a^l(q) + \sigma(q) \cdot \alpha \cdot v_r^l$;

Experiments-Main Results

SCANS effectively achieves a balance between exaggerated safety mitigation and adequate safety.

Models	Mathada	XSTest			RepE-Data			Helpfulness		Harmfulness [↑]		Ana
Models	Methods	Safe↓	UnSafe↑	Avg.↑	Safe.	UnSafe↑	Avg.↑	OKTest	TQA	AdvBench	Malicious	Avg.↑
	Default	58.00	100.0	67.77	12.50	100.0	93.75	53.67	5.05	100.0	100.0	86.13
	Prompt	36.40	100.0	79.77	2.86	99.48	98.31	41.66	15.27	99.34	100.0	87.72
Llama2-	Self-CD*	14.80	97.50	90.66	1.30	98.17	98.43	17.33	4.51	98.24	98.00	94.69
7b-chat	SafeDecoding	75.60	99.50	57.77	63.80	100.0	68.10	59.33	54.44	100.0	100.0	63.81
	DRO	41.52	98.40	76.22	7.03	99.48	96.22	32.33	16.20	99.60	99.56	87.36
	SCANS	9.20	93.50	92.00	0.00	99.22	99.61	0.33	0.80	99.34	100.0	98.26
	Default	34.40	99.50	80.66	5.73	100.0	97.14	20.33	11.69	99.78	100.0	90.83
	Prompt	18.00	99.50	89.77	0.78	99.22	99.22	30.33	12.62	99.34	100.0	91.47
Llama2-	Self-CD*	29.60	100.0	83.55	4.68	100.0	97.66	19.33	4.91	98.24	100.0	93.10
13b-chat	DRO	38.00	100.0	78.88	6.51	100.0	96.74	23.66	14.20	99.78	100.0	89.42
	SCANS	7.20	97.50	94.89	0.00	98.96	99.48	0.33	1.20	98.90	97.00	98.40
vicuna-	Default	20.80	88.00	83.11	4.69	97.40	96.36	19.00	5.05	97.37	76.00	91.68
	Prompt	22.00	91.00	83.77	6.51	98.44	95.97	22.67	11.33	98.46	82.00	90.01
	Self-CD*	10.00	83.00	86.88	3.64	89.58	92.97	27.00	9.56	89.03	56.00	87.26
7b-v1.5	SafeDecoding	55.20	99.50	69.11	33.29	100.0	83.35	61.00	39.70	100.0	98.00	73.41
	DRO	22.11	95.80	85.85	3.38	99.74	98.18	13.33	6.77	98.90	99.00	93.82
	SCANS	5.60	87.00	91.11	2.08	95.83	96.88	3.00	0.00	98.96	98.00	97.17
	Default	16.80	98.00	89.77	3.65	98.96	97.66	19.33	4.38	99.78	93.00	94.23
	Prompt	20.80	99.00	88.00	10.68	99.74	94.53	27.00	19.33	99.34	97.00	88.37
vicuna-	Self-CD*	8.40	90.50	91.11	2.60	90.88	94.14	26.67	6.64	90.57	81.00	90.20
13b-v1.5	DRO	29.20	99.00	83.33	3.38	99.73	98.17	23.33	13.94	99.34	99.00	90.52
	SCANS	9.20	93.50	92.00	2.08	97.66	97.79	3.33	0.27	99.78	98.00	97.59

(2) SCANS does not compromise the general model capability greatly.

Madala	Perplexity ↓			XSum [↑]		MMLU [↑]					
Models	WikiText2	C4	R-1	R-2	R-L	STEM	Human	Social	Others	Avg.	
Llama2-7b-chat	7.76	9.86	21.38	4.923	17.45	37.60	43.40	55.10	54.10	47.20	
+SCANS	9.32	11.94	20.07	3.912	16.47	34.00	36.20	47.40	46.20	40.50	
Llama2-13b-chat	6.86	8.89	22.22	5.280	17.48	43.80	49.50	62.50	60.00	53.60	
+SCANS	7.29	9.45	21.20	4.277	16.79	43.10	49.20	61.80	59.40	53.00	
vicuna-7b-v1.5	7.34	9.26	20.85	4.557	17.34	39.50	45.80	58.20	57.50	49.90	
+SCANS	11.53	15.32	18.43	3.440	15.69	36.60	43.40	54.40	54.20	46.80	
vicuna-13b-v1.5	6.37	8.35	21.88	5.51	18.20	45.00	52.00	65.20	62.50	55.80	
+SCANS	7.07	9.20	20.40	4.484	16.48	44.20	51.20	64.10	61.80	55.00	

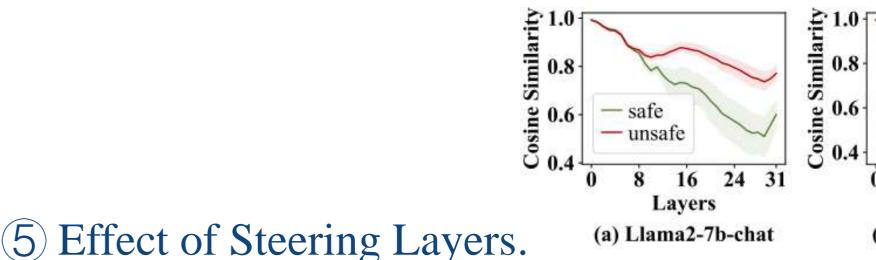
More Analysis

(3) SCANS requires minor extra cost in inference time and GPU memory. Inference Speed GPU Memory

Llama2-7b-chat

+SCANS

(4) Middle and latter layers demonstrate higher degree of distinction, indicating better identification accuracy for harmfulness.



(b) Llama2-13b-chat (a) Llama2-7b-chat

40.60 tokens/s

39.62 tokens/s

29324MB

29694MB

8 16 24 32 39

Layers

1	Perplexity ↓			XSTest		Help	ofulness†	Harmf		
	WikiText2	C4	Safe↓	Unsafe↑	Avg.↑	OKTest	TruthfulQA	AdvBench	Malicious	Avg.↑
				Llar	ma2-7b	-chat		2000		100
ner Layers	2946	3058	-	, - .	-);=.	1 -	154	1 -
dle Layers	9.32	11.94	9.20	93.50	92.00	0.33	0.80	99.34	100.0	97.76
ter Layers	8.15	10.37	12.00	95.00	91.11	7.00	0.27	98.90	98.00	96.59
			ă.	vici	una-7b-	v1.5				
ner Layers	15433	11457	-	-	-	-	() 	-	7 - 2	-
dle Layers	11.53	15.32	5.60	87.00	91.11	3.00	0.00	98.96	98.00	97.29
ter Layers	7.85	9.89	7.60	83.50	88.44	2.33	1.46	93.42	92.00	94.75

Conclusion

- Mitigate the exaggerated safety for aligned LLMs via activation steering in safety-critical layers
- Training-free, Effective!
 - —— SCANS
- Contact us: zouyingcao@sjtu.edu.cn
- yifeiyang@sjtu.edu.cn zhaohai@cs.sjtu.edu.cn
- Full paper

