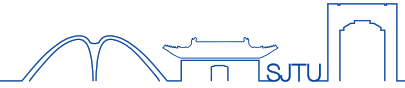




SJTU Cross Media
Language Intelligence Lab
上海交通大学新媒体语言智能实验室



Task-Specific Data Selection for Instruction Tuning via Monosemantic Neuronal Activations

Da Ma, X-LANCE Lab, SJTU

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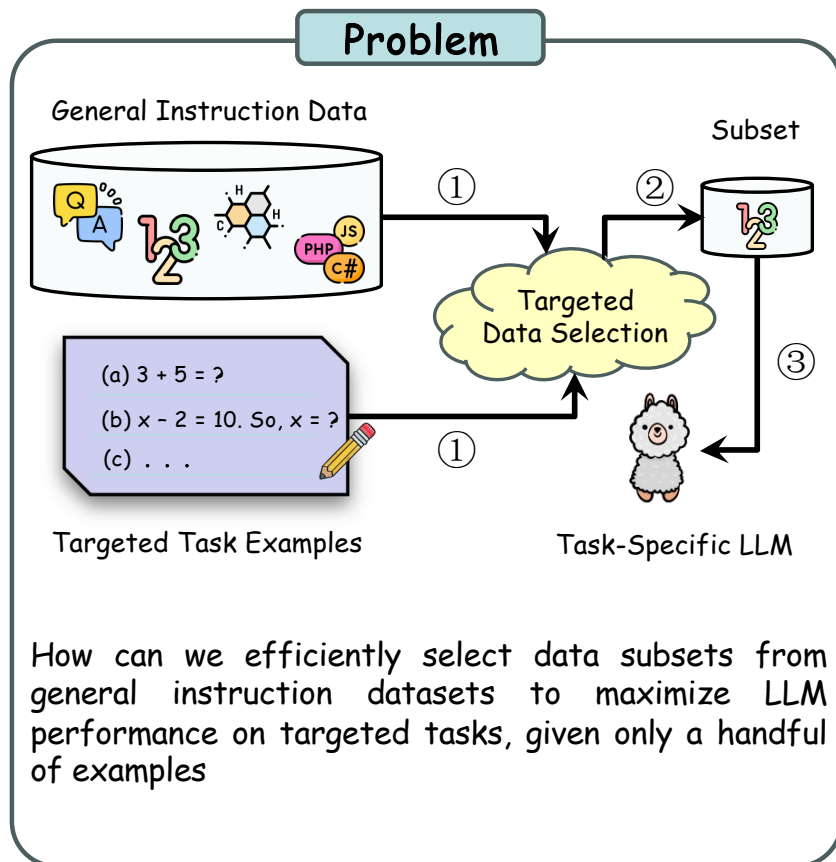
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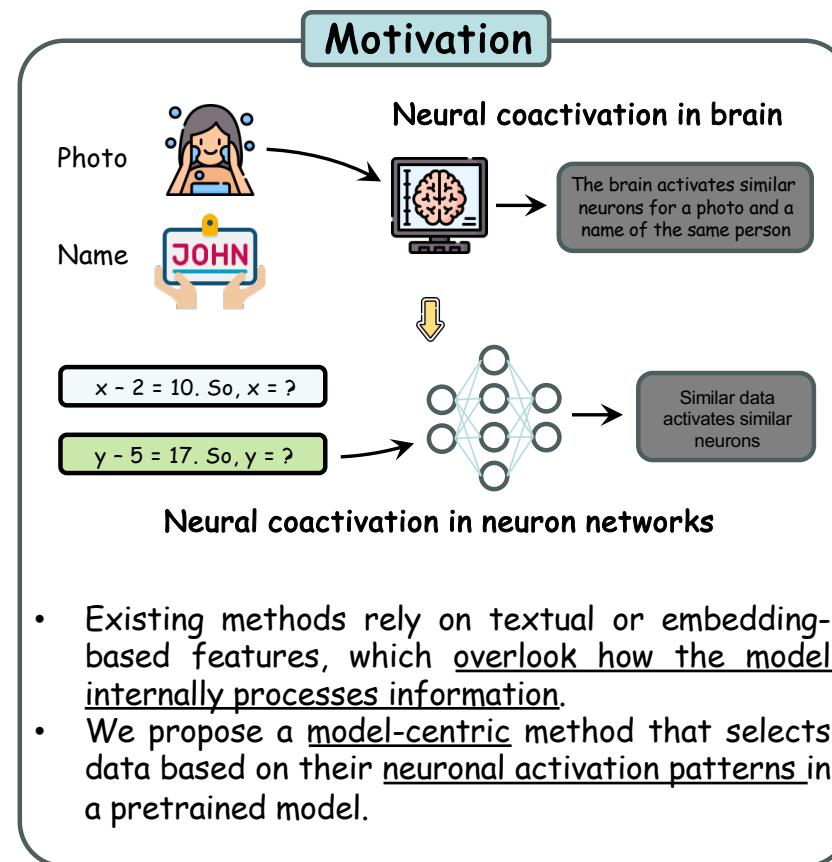


Problem & Motivation

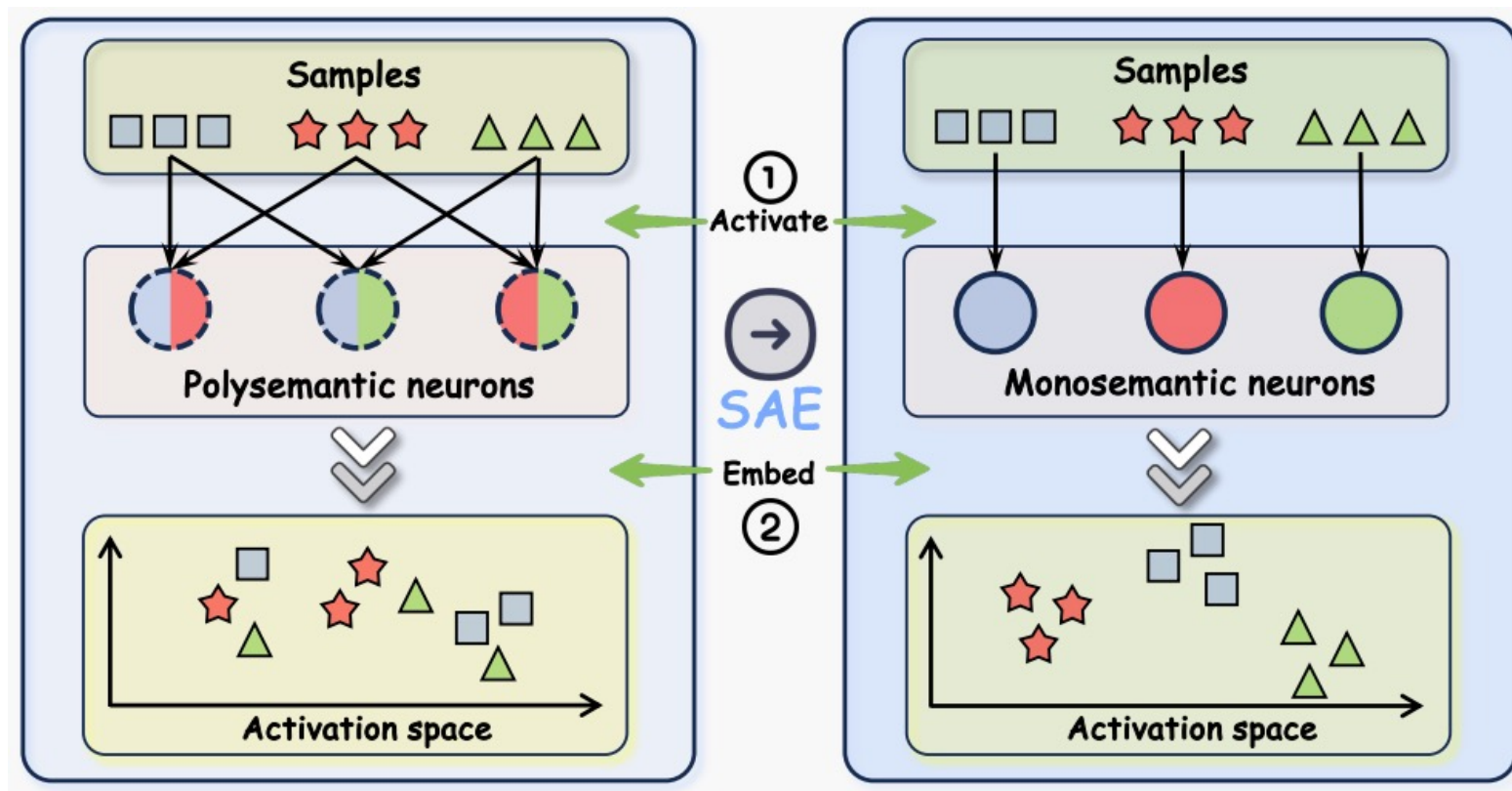
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Motivation



Challenge



Directly using raw neuron activations can lead to inaccurate similarity estimates because **polysemantic neurons** often respond to multiple unrelated concepts, causing **spurious similarities** between unrelated samples.



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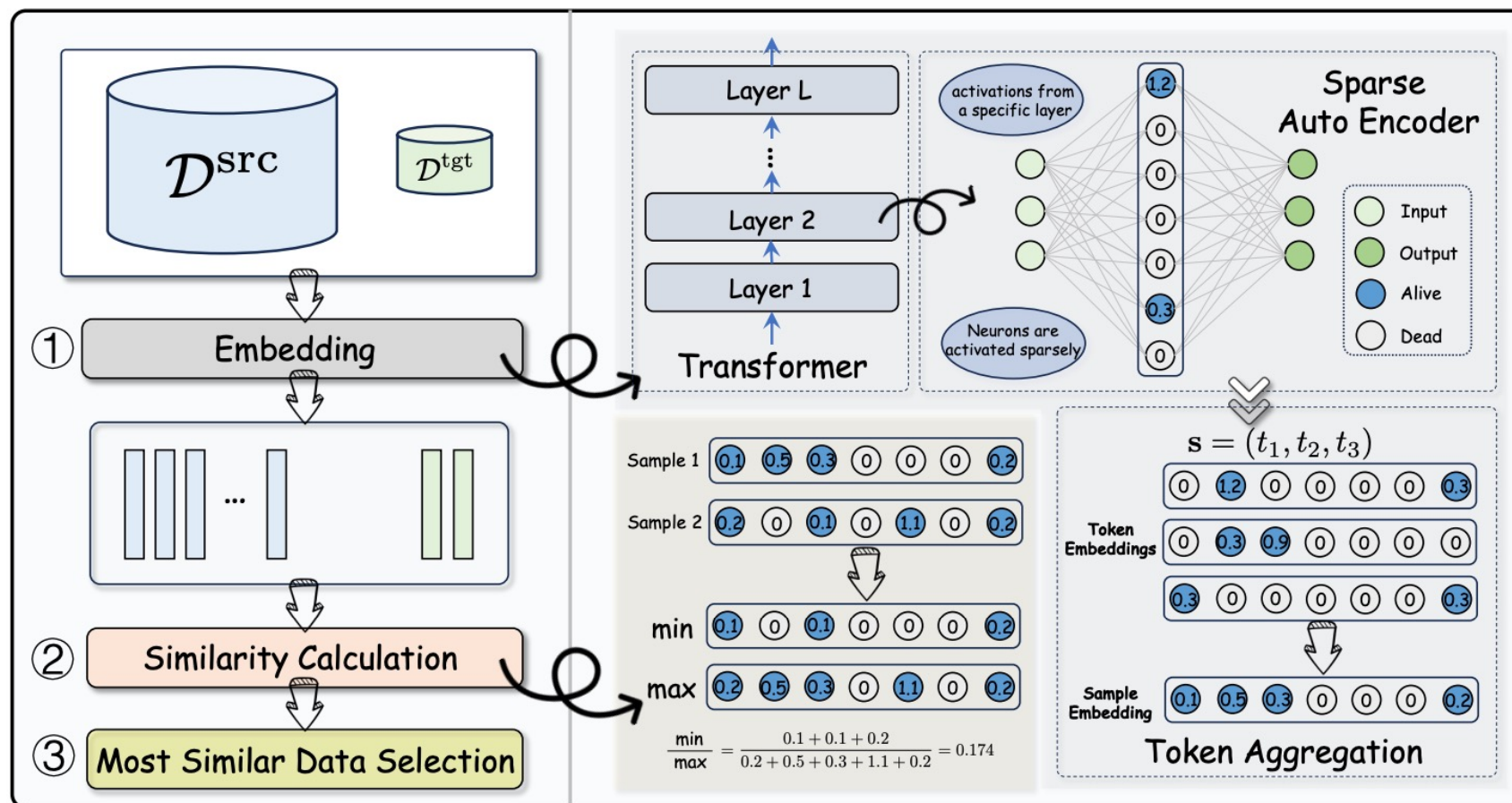
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Methods



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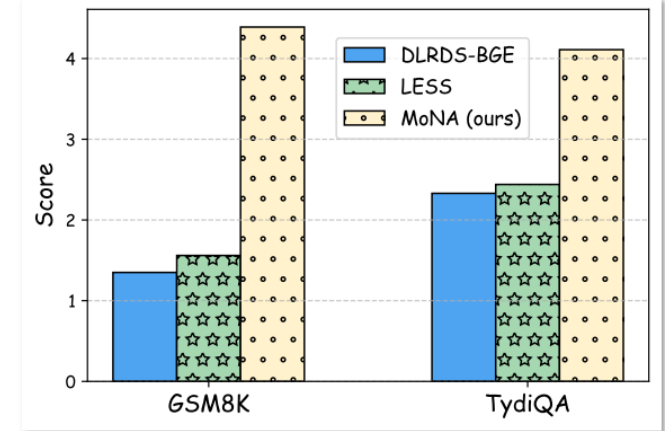
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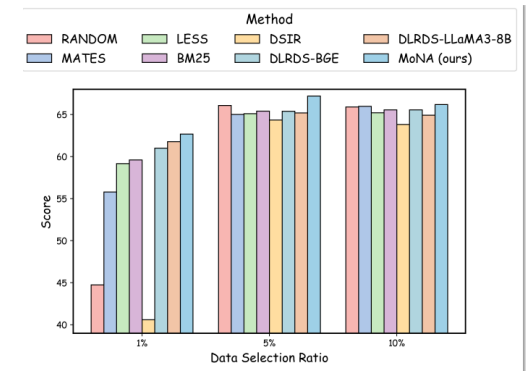


MoNA outperforms baselines across datasets and models

Method	$\mathcal{D}^{\text{src}} = \text{OPENHERMES-2.5}$						$\mathcal{D}^{\text{src}} = \text{LESS}$			
	MMLU	GSM8K	BBH	MBPP	GPQA	Avg.	MMLU	BBH	TydiQA	Avg.
LLaMA3.1-8B										
BASE	65.30	55.50	63.08	46.40	28.12	51.68	65.30	63.08	71.26	66.55
FULL	64.60	65.35	64.31	49.00	27.90	54.23	64.60	64.31	72.66	67.19
RANDOM	64.02	58.65	63.70	46.73	30.36	52.69	64.16	64.29	69.78	<u>66.08</u>
Influence-based										
MATES	64.11	54.28	65.38	47.60	28.12	51.90	63.62	63.68	67.74	65.01
LESS	64.34	66.87	63.00	47.80	31.47	54.70	62.51	62.11	70.68	65.10
Distribution alignment										
BM25	64.14	66.64	65.23	48.40	27.90	54.46	<u>64.41</u>	63.74	68.07	65.41
DSIR	63.95	<u>66.94</u>	64.29	<u>48.60</u>	29.91	<u>54.74</u>	64.25	63.19	65.61	64.35
DLRDS-BGE	<u>64.45</u>	64.82	64.20	<u>48.60</u>	<u>31.25</u>	54.66	64.06	61.82	70.30	65.39
DLRDS-LLaMA3-8B	64.31	64.75	63.97	48.80	29.46	54.26	62.11	61.54	<u>71.91</u>	65.19
LLM2Vec	64.29	63.53	<u>65.55</u>	48.40	30.13	54.38	62.06	62.03	68.11	64.07
MoNA (ours)	64.49	67.93	66.44	48.40	31.47	55.75	64.78	<u>64.21</u>	72.60	67.20
OLMo-7B										
BASE	28.42	7.35	29.96	21.40	26.56	22.74	28.42	29.96	31.67	30.02
FULL	45.05	31.96	33.13	26.40	26.56	32.62	39.31	28.86	33.43	33.87
RANDOM	36.96	16.00	31.47	19.47	27.38	26.26	28.60	<u>30.82</u>	31.93	30.45
Influence-based										
MATES	30.27	13.72	32.33	16.40	27.01	23.95	29.57	30.46	31.02	30.35
LESS	46.15	26.91	33.68	20.20	25.89	30.57	37.21	30.07	33.20	33.49
Distribution alignment										
BM25	42.34	31.08	34.30	26.80	25.45	<u>31.99</u>	35.74	28.95	34.40	33.03
DSIR	36.48	29.26	<u>34.08</u>	19.40	27.23	29.29	29.54	32.87	33.25	31.89
DLRDS-BGE	42.77	<u>32.30</u>	33.40	26.80	23.88	31.83	35.22	25.65	33.28	31.38
DLRDS-LLaMA3-8B	38.16	31.39	33.30	22.80	30.13	31.16	40.64	26.08	31.08	32.60
LLM2Vec	37.24	30.10	33.57	23.40	<u>28.35</u>	30.53	39.72	28.58	32.26	<u>33.52</u>
MoNA (ours)	<u>44.74</u>	32.83	33.51	<u>26.00</u>	25.00	32.42	<u>40.14</u>	30.19	<u>33.80</u>	34.71



LLM as a Data Analyst



Performance under different selection ratios



Neuron Activation Visualization

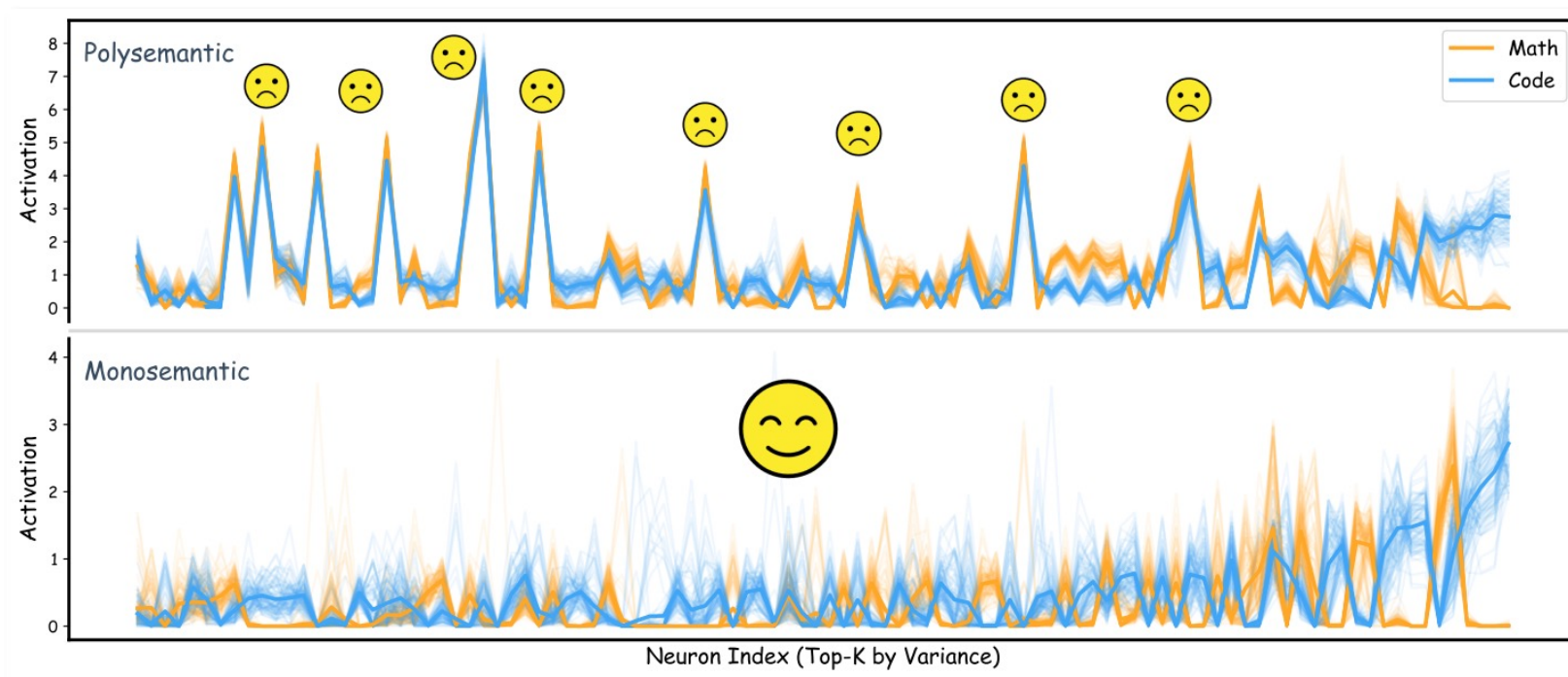


Figure 4: Neuron activation profiles for 100 Math and 100 Code samples on the top-100 most variant neurons. Faint lines show individual samples; bold lines show task means. In the polysemantic (top) plot, many neurons, especially those with high activation peaks (marked by weeping face), are simultaneously activated by both tasks, reflecting pronounced overlap and limited task specificity. In contrast, the monosemantic (bottom) plot reveals clear task-specific activation patterns.



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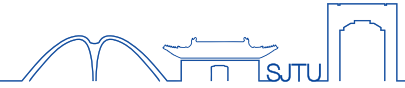
Conclusion

- Monosemantic neuronal activations from sparse autoencoders captures internal model computation and enables more semantically aligned and interpretable data selection.
- Future work includes extending MONA to other training stages, such as pre-training data selection, and applying it to multimodal scenarios, for example, image-text tasks.





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Thank you for your listening!