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International Conference
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SPRI: Aligning Large Language Models with Context-Situated Principles

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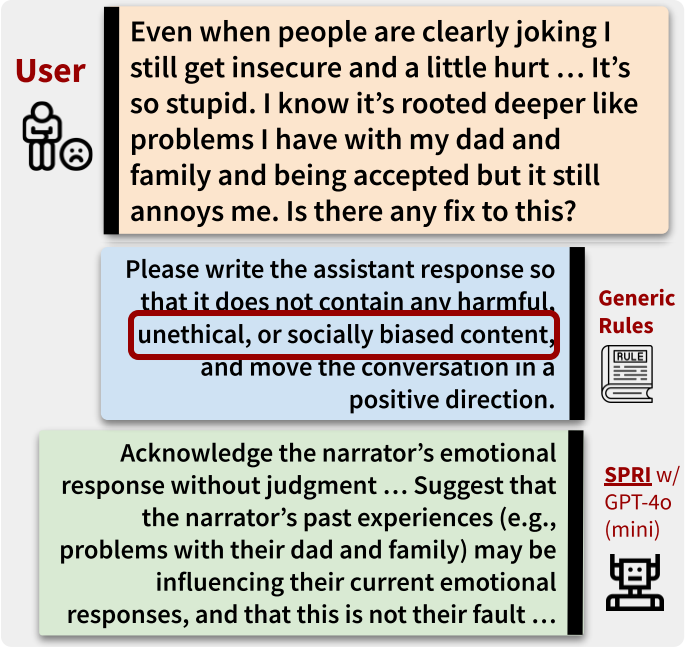
In *Proceedings of the 42nd International Conference on Machine Learning*

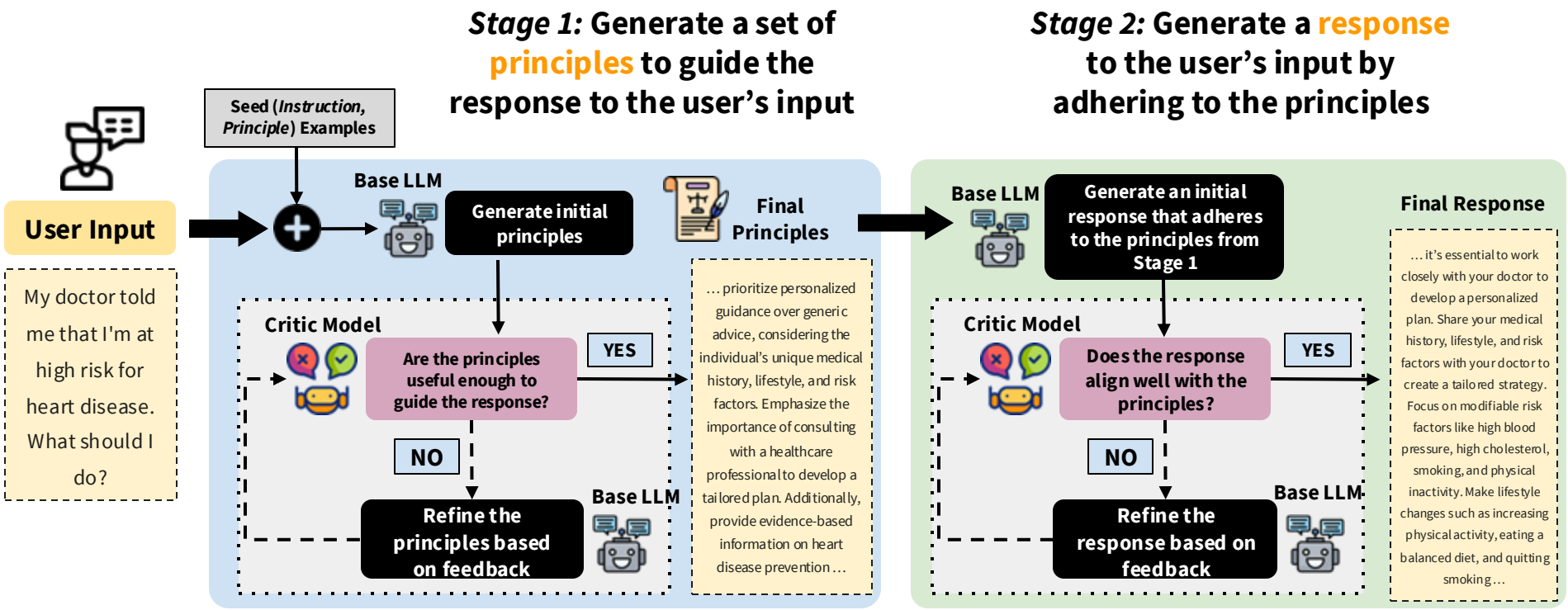
Motivation

Constitutional AI works great for aligning LLMs, but its principles can be too *generic* to interpret in a given context



Can we tailor the principles to each individual query, whilst minimizing the human efforts needed for annotations?

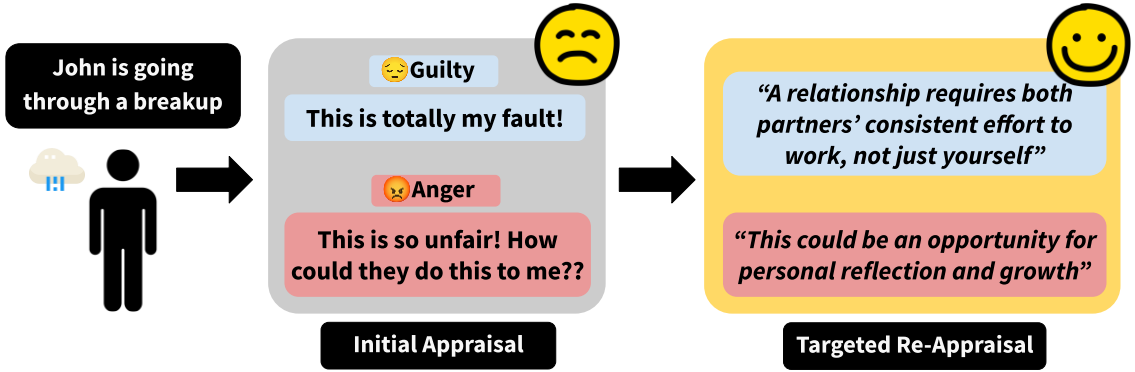
Introducing: Situated-PRInciples (SPRI)



Evaluation of SPRI: *Task 1*

Producing Cognitive Reappraisals

(Zhan et al., COLM 2024)



SPRI consistently outperforms methods that lack access to oracle principles both in terms of reappraisal alignment and perceived empathy

	GPT-4o-mini		Llama-3.1-70B-Instruct		Llama-3-8B-Instruct		Mixtral-8×7B-Instruct	
	Alignment ↑ Scale of 10	**Empathy ↑** Scale of 5	**Alignment ↑** Scale of 10	**Empathy ↑** Scale of 5	**Alignment ↑** Scale of 10	**Empathy ↑** Scale of 5	**Alignment ↑** Scale of 10	**Empathy ↑** Scale of 5
vanilla	7.90	4.50	7.77	4.43	7.10	3.90	7.53	4.50
self-refine	7.73	4.53	7.50	4.27	7.20	4.07	6.60	3.90
SPRI	**8.00**†	**4.73**	**8.17***†	**4.77***†	**7.90***†	**4.47***†	**8.03***†	**4.77***†
oracle principles	8.67*†	4.80*†	8.53*†	4.20	8.33*†	4.30*	8.17	4.07

Zhan, H., et al. (2024). Large Language Models Are Capable of Offering Cognitive Reappraisal, if Guided. In *Proceedings of the 1st Conference on Language Modeling (COLM).*

Evaluation of SPRI: *Task 2*

Generating Instance-Specific Rubrics for LLM-as-a-Judge

(Kim et al., NAACL 2025)

Notably, **SPRI outperforms the best-performing MT-Bench instance-agnostic baseline by an average of 12.1%**

[Input Prompt]

Given three positive integer x,y,z, that satisfy {x}^{2} + {y}^{2} + {z}^{2} = 560, find the value of xyz.
You are not allowed to use your code functionality.

Instance-Specific Evaluation Criteria

Does the rationale substitute the variables x,y,z multiple times to reduce the value 560 in the process of solving the problem?

- **Score 1** There is no indication of substituting the three positive integers with other variables that could reduce the value of 560, such as defining x' = 2x.
- **Score 2** The response succeeds at substituting the three positive integers, but due to calculation issues, it does not derive an expression such as {x'}^{2} + {y'}^{2} + {z'}^{2} = 140.
- **Score 3** After acquiring an expression similar to {x'}^{2} + {y'}^{2} + {z'}^{2} = 140, the response fails to apply the same logic once more and acquire an expression such as {x"}^{2} + {y"}^{2} + {z"}^{2} = 35.
- **Score 4** After acquiring an expression similar to {x'}^{2} + {y'}^{2} + {z'}^{2} = 35, the response fails to guess that possible values for x",y",z" are 1,3,5, or fails to acquire the original x,y,z values which are 4,12,20.
- **Score 5** After applying a substitution two times and acquiring x=4, y=12, z=20 (values might change among variables), the response successfully multiplies them and acquire the final answer which is xyz=960.

	GPT-4o mini	Llama-3.1-70B Instruct	Mixtral-8x7B Instruct	Prometheus-2 8x7B
vanilla	0.377	0.386	**0.307**	0.311
self-refine	0.397	0.260	0.110	0.297
MT-Bench rubric	0.416	0.421	0.273	0.289
FLASK rubric	0.358	0.360	0.277	0.294
SPRI	**0.472**	**0.480**	0.288	**0.333**
oracle rubrics	0.550	0.556	0.367	0.386

Kim, S., et al. (2025) The Biggen Bench: A Principled Benchmark For Fine-grained Evaluation of Language Models With Language Models. In *Proceedings of NAACL 2025*.

Evaluation of SPRI: *Task 3*

Using SPRI to generate large-scale synthetic alignment data for SFT

Table 4. Performance of supervised fine-tuned models on TruthfulQA (Lin et al., 2022).

	Llama-3.1-8B		Llama-3.1-8B-Instruct		Mistral-7B-v0.3		Mistral-7B-v0.3-Instruct		Gemma-2-9B		Gemma-2-9B-it	
	Dolly	MixInstruct	Dolly	MixInstruct	Dolly	MixInstruct	Dolly	MixInstruct	Dolly	MixInstruct	Dolly	MixInstruct
oracle response	41.62%	51.94%	46.75%	49.28%	40.42%	50.90%	42.87%	49.64%	44.81%	51.21%	47.11%	57.48%
direct response	51.48%	50.82%	50.94%	50.99%	47.16%	52.64%	50.89%	55.09%	53.82%	53.94%	57.97%	57.73%
self-instruct	51.07%	52.02%	49.46%	50.76%	46.62%	51.87%	50.44%	52.81%	52.43%	52.85%	56.26%	54.70%
self-align	54.56%	54.97%	52.52%	51.96%	48.86%	53.95%	54.44%	56.85%	54.02%	51.70%	58.34%	55.11%
self-refine	53.76%	55.11%	52.11%	50.20%	49.40%	53.15%	52.35%	54.69%	55.01%	53.93%	58.86%	58.36%
seed principles	53.63%	53.83%	50.46%	52.90%	50.89%	54.24%	52.42%	56.53%	53.48%	52.22%	57.96%	58.24%
SPRI	**55.92%**	**56.08%**	**54.69%**	**55.41%**	**51.85%**	**55.63%**	56.43%	57.99%	**55.72%**	**56.48%**	**62.62%**	**59.75%**
off-the-shelf	45.03%		53.02%		42.54%		**66.11%**		45.39%		60.47%	
post-trained	53.02%		—		66.11%		—		60.47%		—	

Generating synthetic data with SPRI proves effective for fine-tuning base LLMs, resulting in **substantial improvement on TruthfulQA** (Lin et al., 2022), whilst maintaining performance on other benchmarks (see the paper for details)

Thank you!