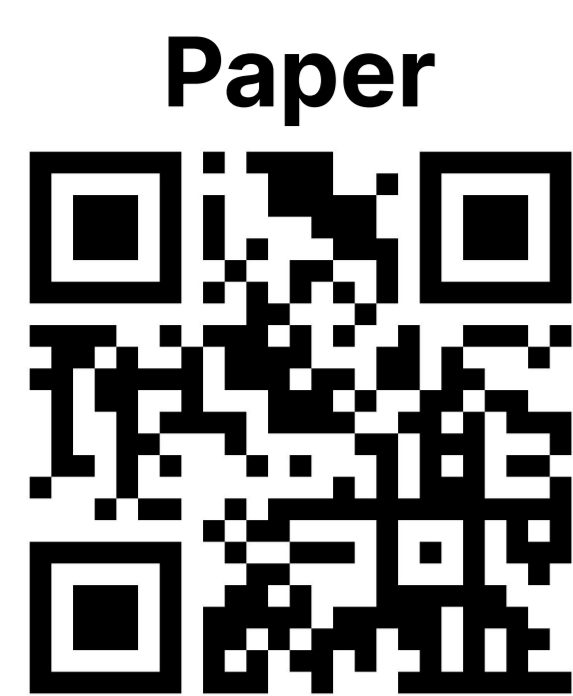


# ALIGNING TO THOUSANDS OF PREFERENCES VIA SYSTEM MESSAGE GENERALIZATION



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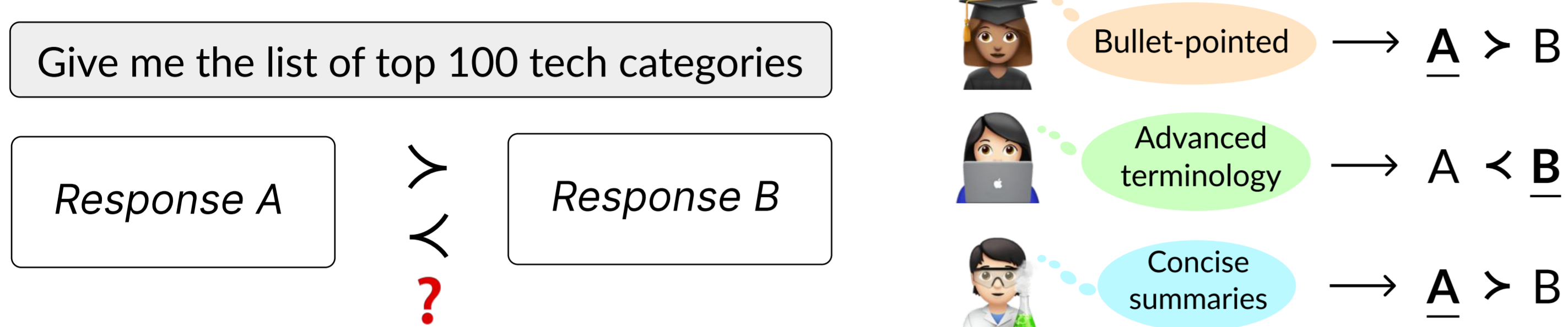
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Project page (w/ code, data, models)

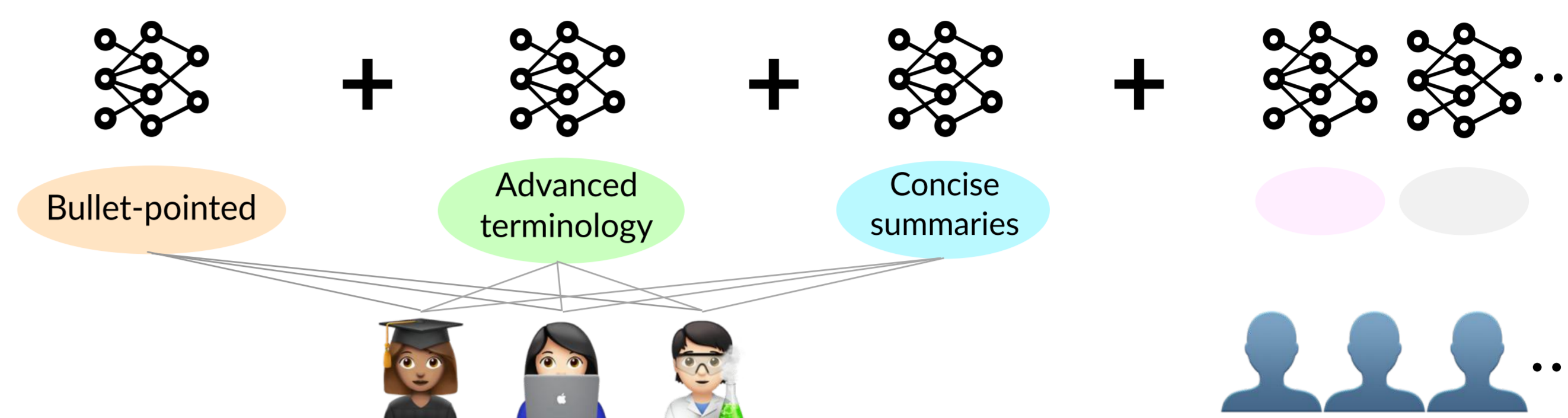


## A need for individualized and scalable alignment

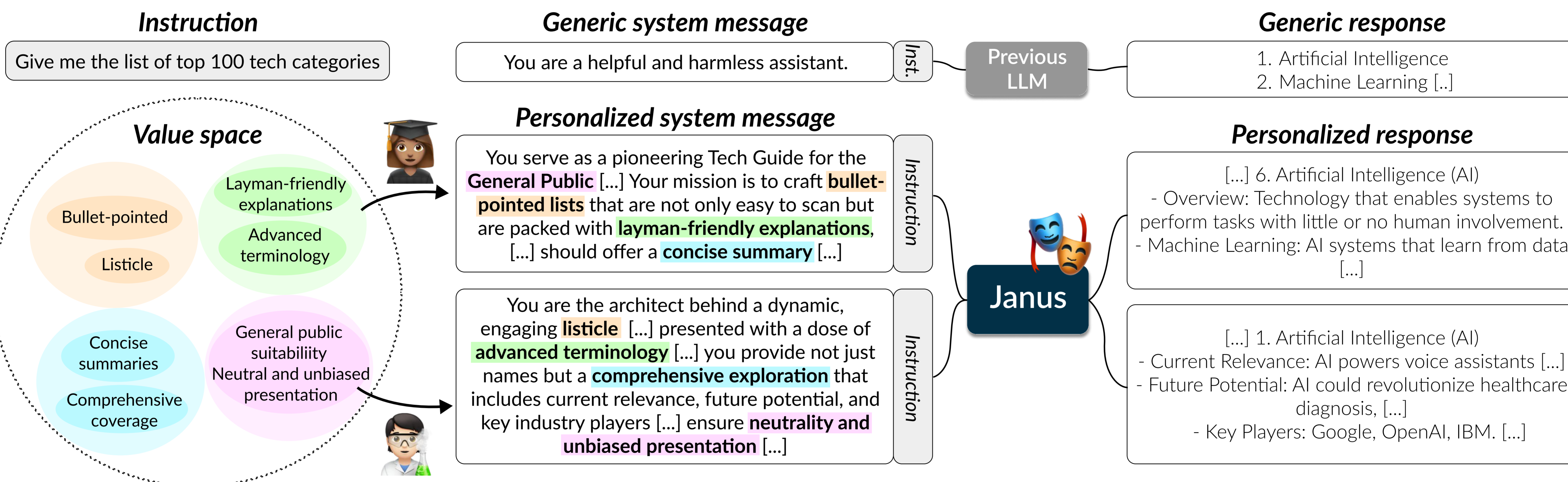
Pairwise preference data does not explain *all* preferences  
Different values, different winning response



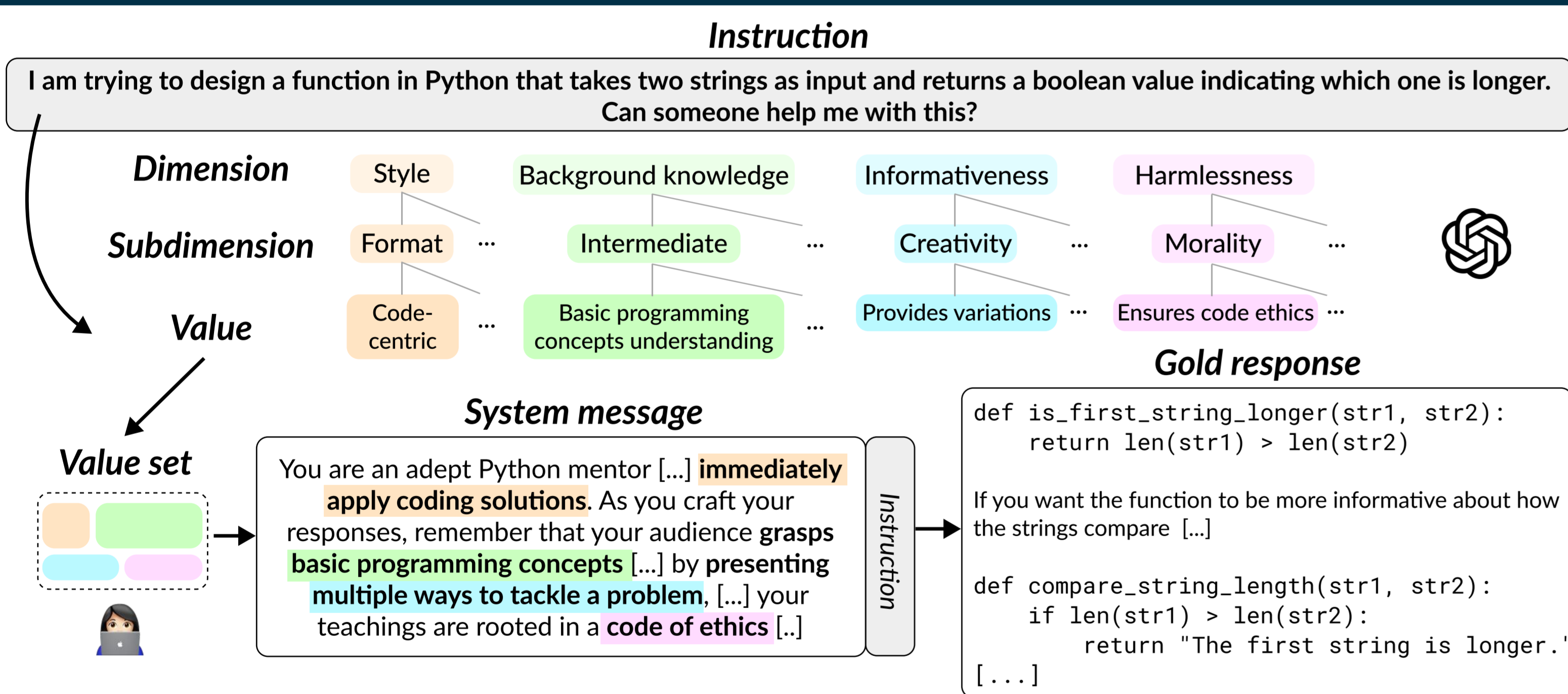
Re-training  $N$  new reward models to model new value or user is expensive



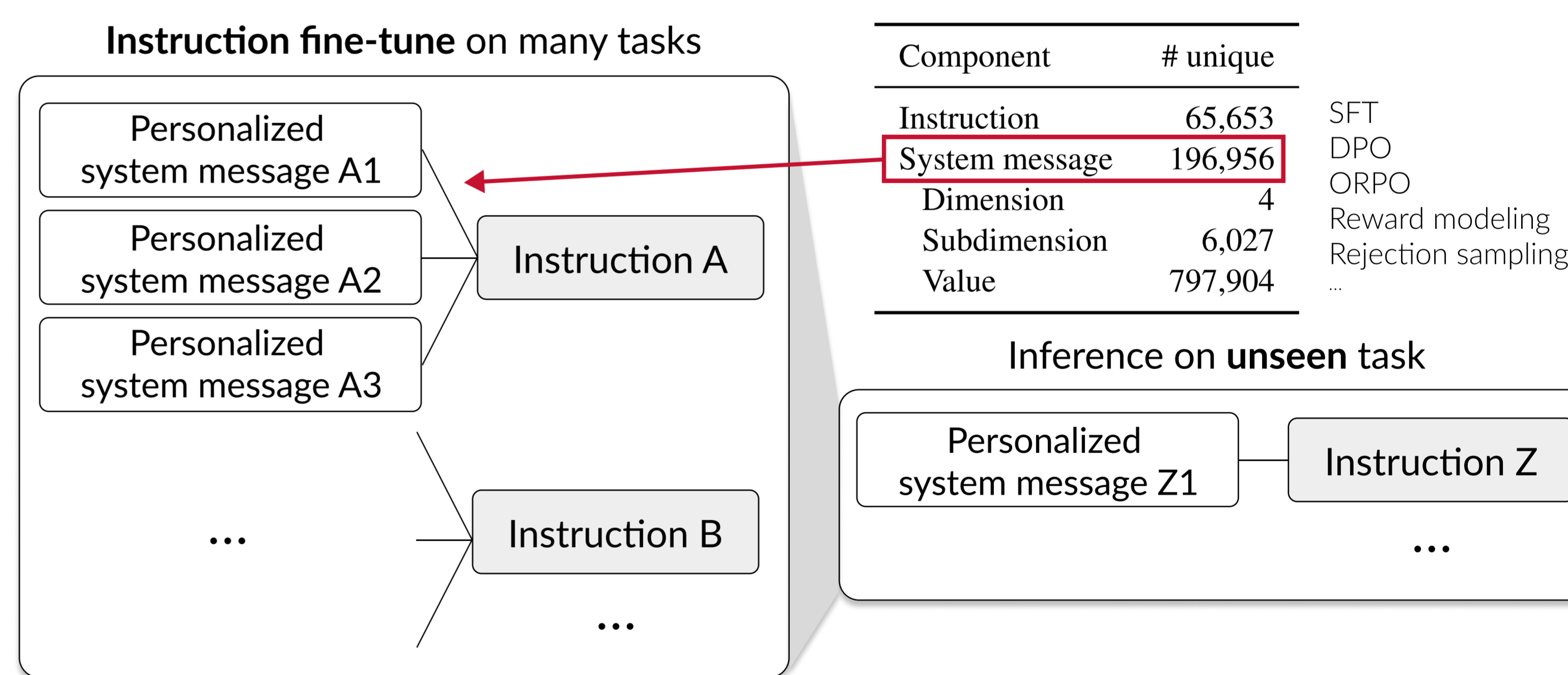
## Verbalize values in the system message to flexibly steer toward personalized responses



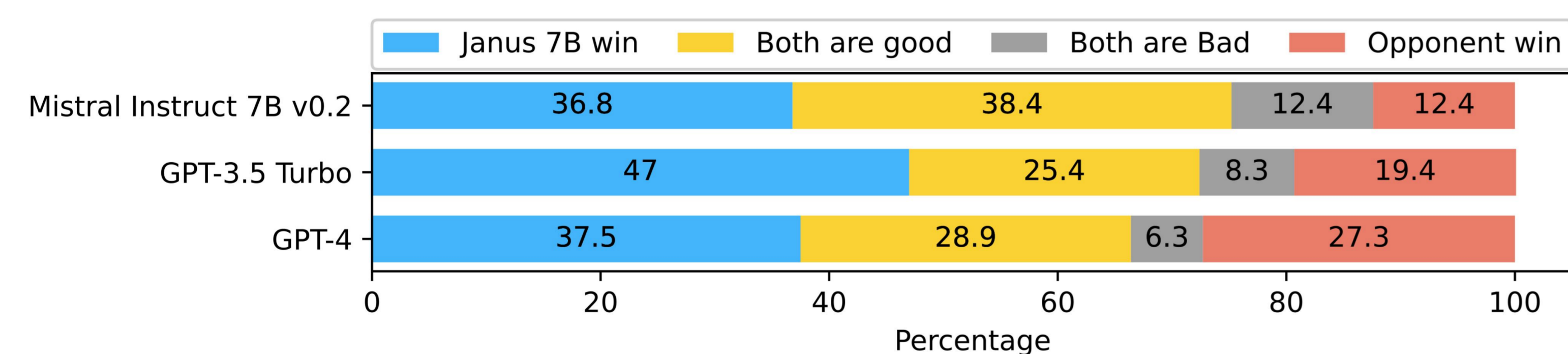
## Key factor 1: Hierarchical value augmentation strategy



## Key factor 2: Training recipe for stronger generalization



## Aligns to unseen multifaceted values in system messages ✓



## Aligns to general public preferences ✓

Size	Models	AlpacaEval 2.0		MT-Bench	Arena Hard Auto v0.1
		LC Win Rate (%)	Win Rate (%)	Score [0,10]	Score [0,100]
< 30B	Mistral 7B Instruct v0.2	17.1	14.7	7.2	10.8
	Gemma 7B Instruct	10.4	6.9	6.4	7.5
	LLaMA 3 8B Instruct	22.9	22.6	7.6	17.9
	JANUS 7B	26.9	27.8	7.7	20.9

## Additional analyses and insights

- Significant toxicity ↓ fluency ↑ diversity ↑ in RealToxicityPrompts
- Demonstrates robust performance with or without personalized input.
- Learning to handle multifacetedness in input and/or output is beneficial.
- Verification of quality, diversity, safety, and bias in Appendix and TBA!

## Takeaways

- Clarifying user values behind the preference in the input can reach diverse alignment targets. Varying the system message can provide strong guidance.
- Fine-tuning on Multifaceted Collection, an instruction dataset containing 197k system messages can facilitate individualized, scalable value alignment.
- Janus 7B models are easily steerable towards user-preferred responses while being generally useful and safe too.

Model	mf-AlpacaEval	mf-FLASK	mf-Koala	mf-MT-Bench	mf-Self-Instruct	Average
Pretrained open models						
Mistral 7B v0.2	2.80	1.93	2.45	2.30	2.28	2.23
LLaMA 3 8B	2.60	2.92	2.69	2.39	2.34	2.54
LLaMA 3 70B	3.76	3.23	3.67	3.50	3.65	3.49
Instruction-tuned open models						
LLaMA 2 Chat 70B	3.98	3.68	4.11	3.66	3.87	3.79
Mistral 7B Instruct v0.2	4.20	3.82	4.18	3.82	3.98	3.93
Mixtral 8x7B Instruct v0.1	4.24	3.90	4.16	3.94	4.08	4.03
LLaMA 3 Instruct 8B	4.38	3.88	4.33	4.08	4.17	4.10
LLaMA 3 Instruct 70B	4.55	4.26	4.59	4.42	4.45	4.39
JANUS suite						
JANUS 7B	4.43	4.06	4.41	4.11	4.01	4.17
JANUS+ORPO 7B	4.41	4.03	4.45	4.00	4.22	4.18
JANUS+DPO 7B	4.45	4.13	4.43	4.21	4.17	4.24
Preference-optimized proprietary models						
GPT-3.5 Turbo-0125	4.05	3.86	4.15	3.87	3.85	3.91
GPT-4-0613	4.25	4.00	4.18	4.16	4.13	4.10
GPT-4-Turbo-0125	4.45	4.27	4.61	4.45	4.27	4.35