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RM Interpretability via Optimal/Pessimal Tokens
RMs Inherit Value Biases from Pretraining

(FAccT 2025 + ICLR 2026)

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ML COLLECTIVE • FEB 13, 2026

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Reward models and interpretability

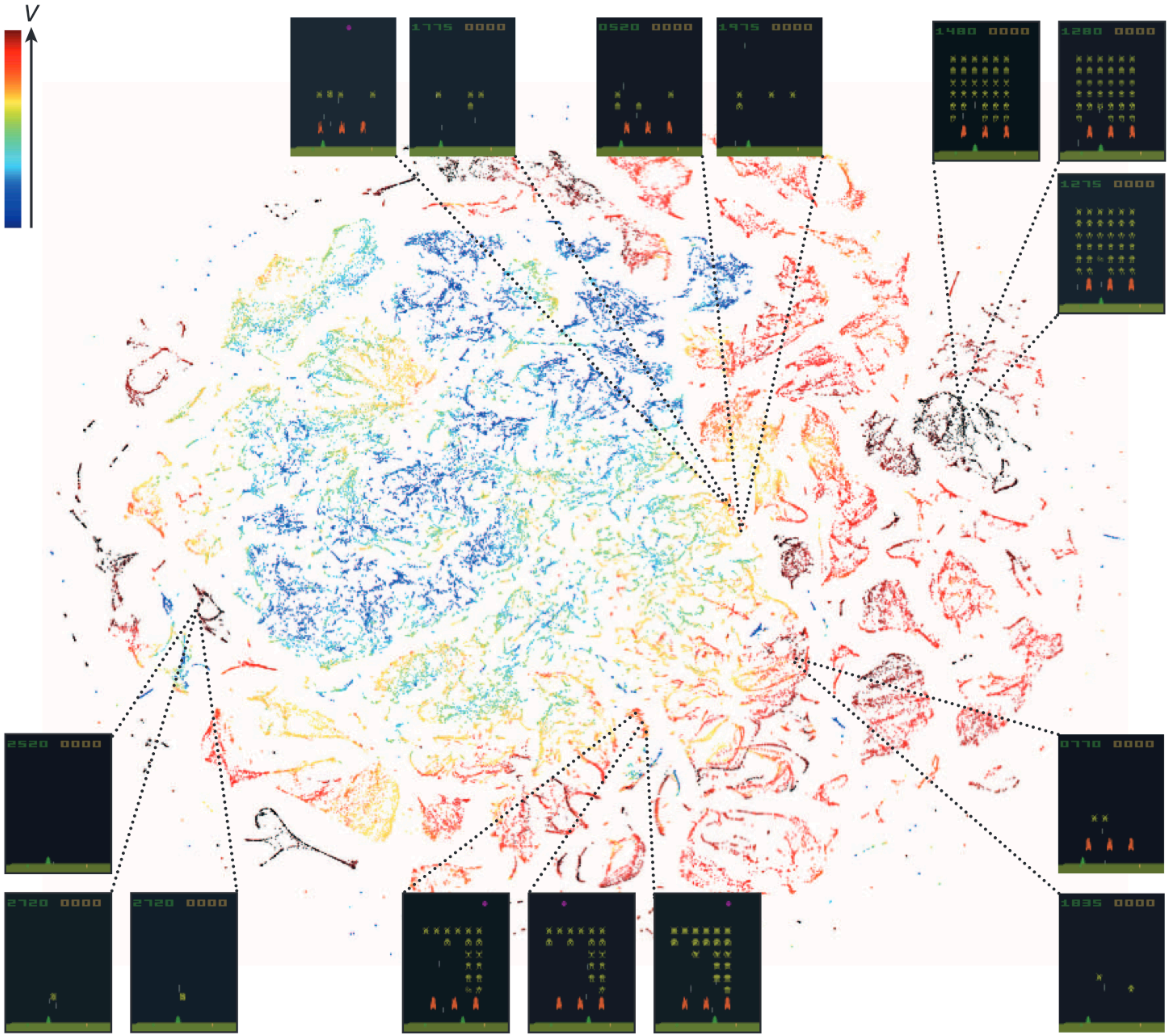


Figure 4 | Two-dimensional t-SNE embedding of the representations in the last hidden layer assigned by DQN to game states experienced while playing Space Invaders. The plot was generated by letting the DQN agent play for 2 h of real game time and running the t-SNE algorithm[25] on the last hidden layer representations assigned by DQN to each experienced game state. The points are coloured according to the state values (*V*, maximum expected reward of a state) predicted by DQN for the corresponding game states (ranging from dark red (highest *V*) to dark blue (lowest *V*)). The screenshots corresponding to a selected number of points are shown. The DQN agent predicts high state values for both full (top right screenshots) and nearly complete screens (bottom left screenshots) because it has learned that completing a screen leads to a new screen full of enemy ships. Partially completed screens (bottom screenshots) are assigned lower state values because less immediate reward is available. The screens shown on the bottom right and top left and middle are less perceptually similar than the other examples but are still mapped to nearby representations and similar values because the orange bunkers do not carry great significance near the end of a level. With permission from Square Enix Limited.

Mnih et al. (2015)

129.67.
129.67.

Reward models and interpretability

Understanding maximum- and minimum-value states is an important (and understudied) area of interpretability

As models increase in capability, they will get better and better at achieving their objectives

Thus, it will be increasingly important to know not only how they process inputs and take actions in a local sense...

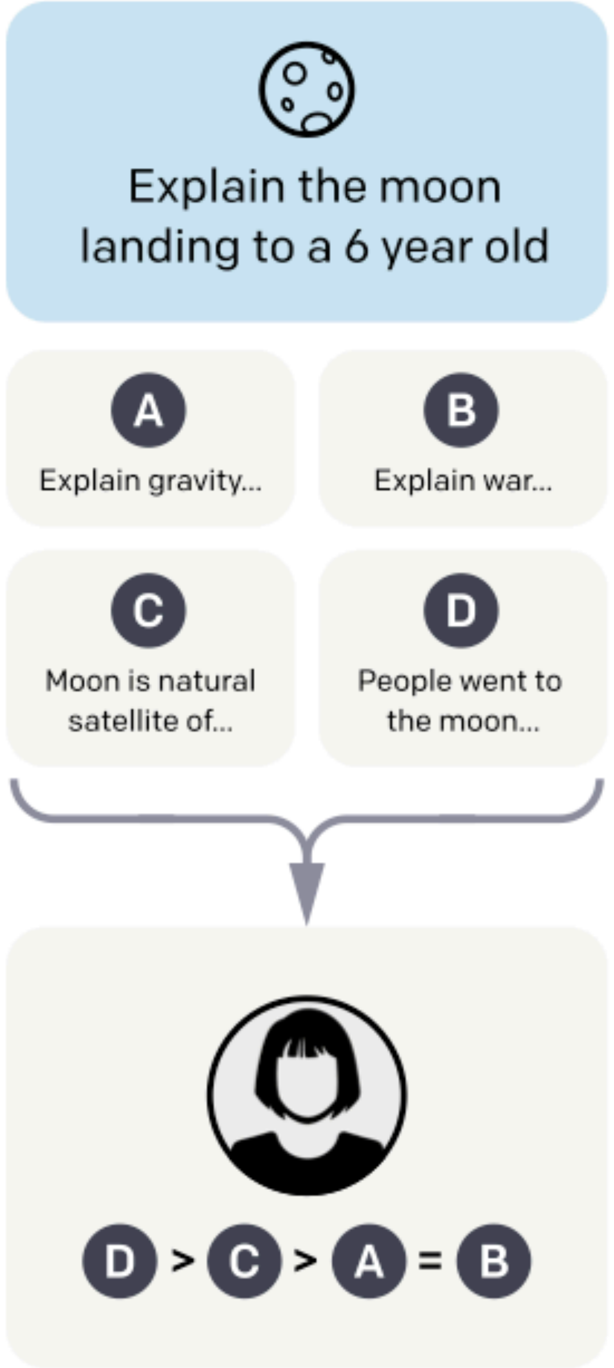
But to understand more broadly what the model thinks optimal and pessimal states look like

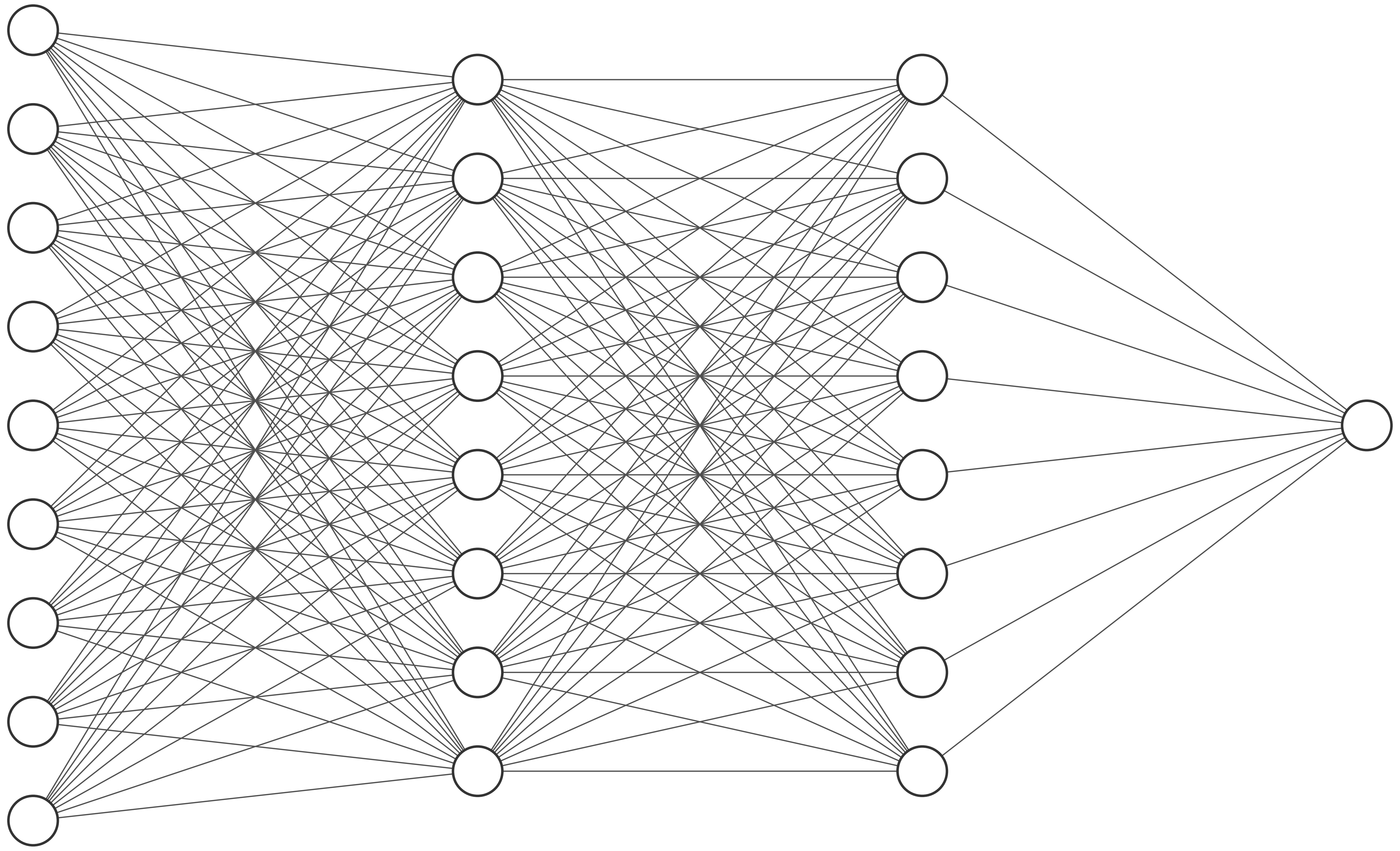
Reward models

Reward models (RMs)

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.


Explain the moon landing to a 6 year old
A
Explain gravity...
B
Explain war...
C
Moon is natural satellite of...
D
People went to the moon...
D > C > A = B



Explain gravity to a 6 year old
⇒ **3.19**

Moon is natural satellite...
⇒ **5.31**

The moon is a big, bright circle in the night sky...
⇒ **10.49**

$$\mathcal{L}_{\mathbf{CE}} = -\sum_{\sigma^1,\sigma^2,\mu\in\mathcal{D}} \begin{array}{l}\mu(1)\log \hat{P}[\sigma^1 \succ \sigma^2]\\ +\mu(2)\log \hat{P}[\sigma^2 \succ \sigma^1]\end{array}$$

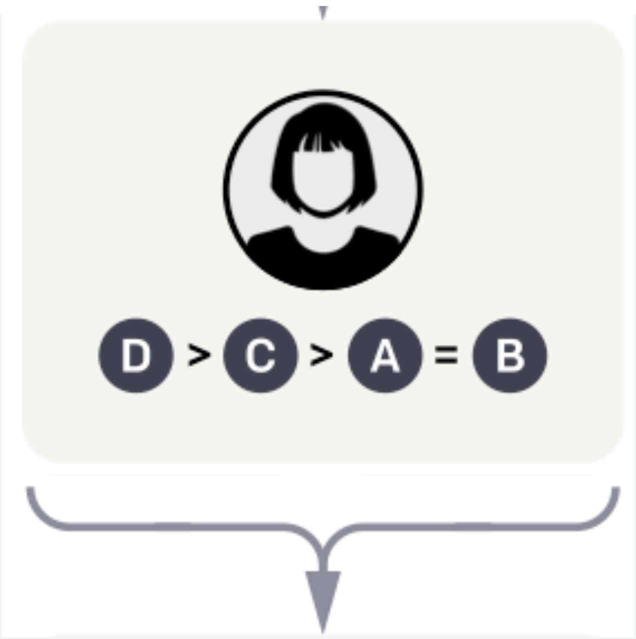
Training Data

Reward Model

Objective Function

Christiano et al. (2017), Ouyang et al. (2022)

RMs: Where human values enter RLHF



Pre-Training (+SFT)

Given input tokens…

Predict next token

Reward Modeling

Given input tokens…

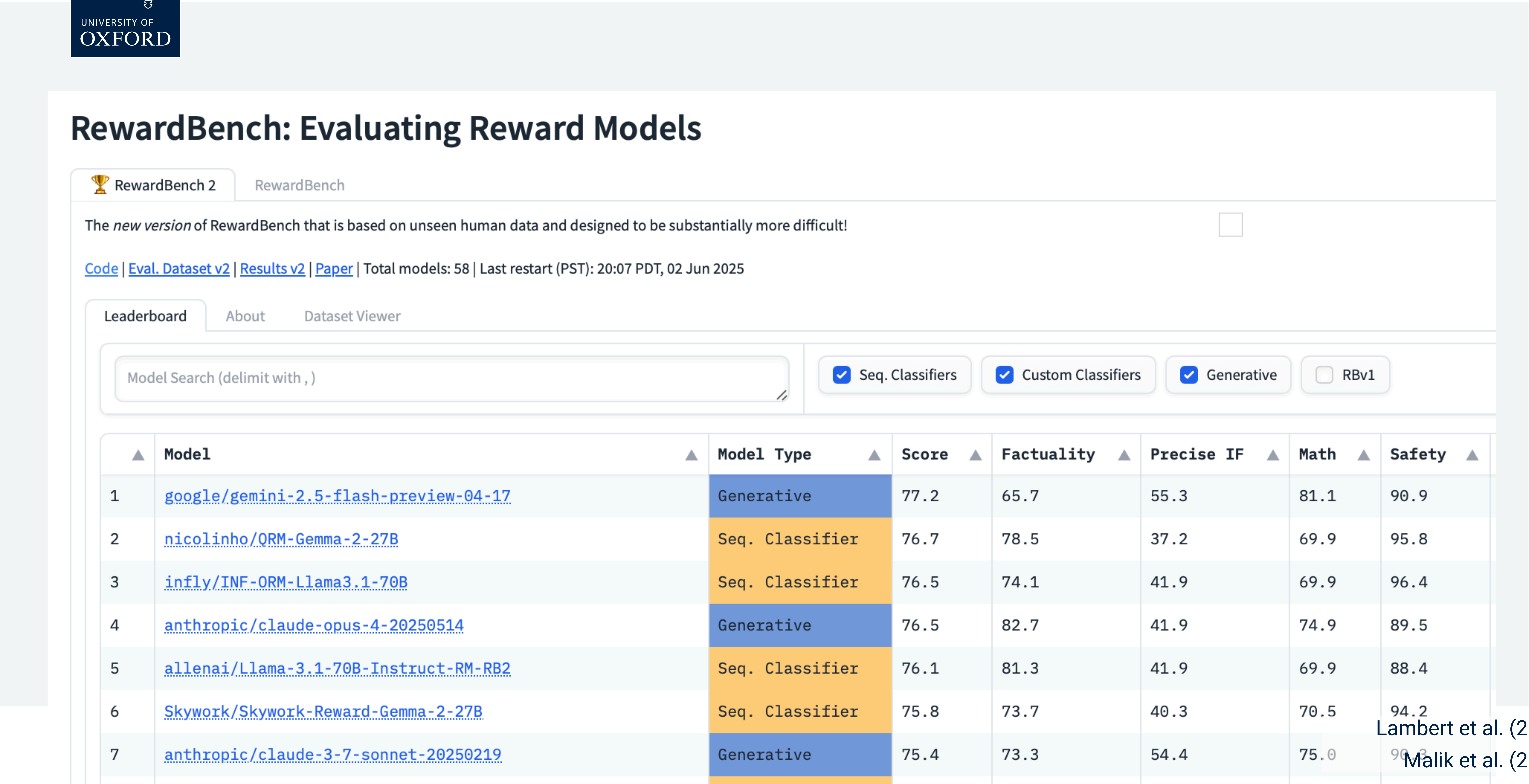
Output scalar number that predicts human pairwise preferences

Post-Training

Given input tokens…

Maximize expected reward from reward model

RMs: Where human values enter RLHF



RewardBench: Evaluating Reward Models

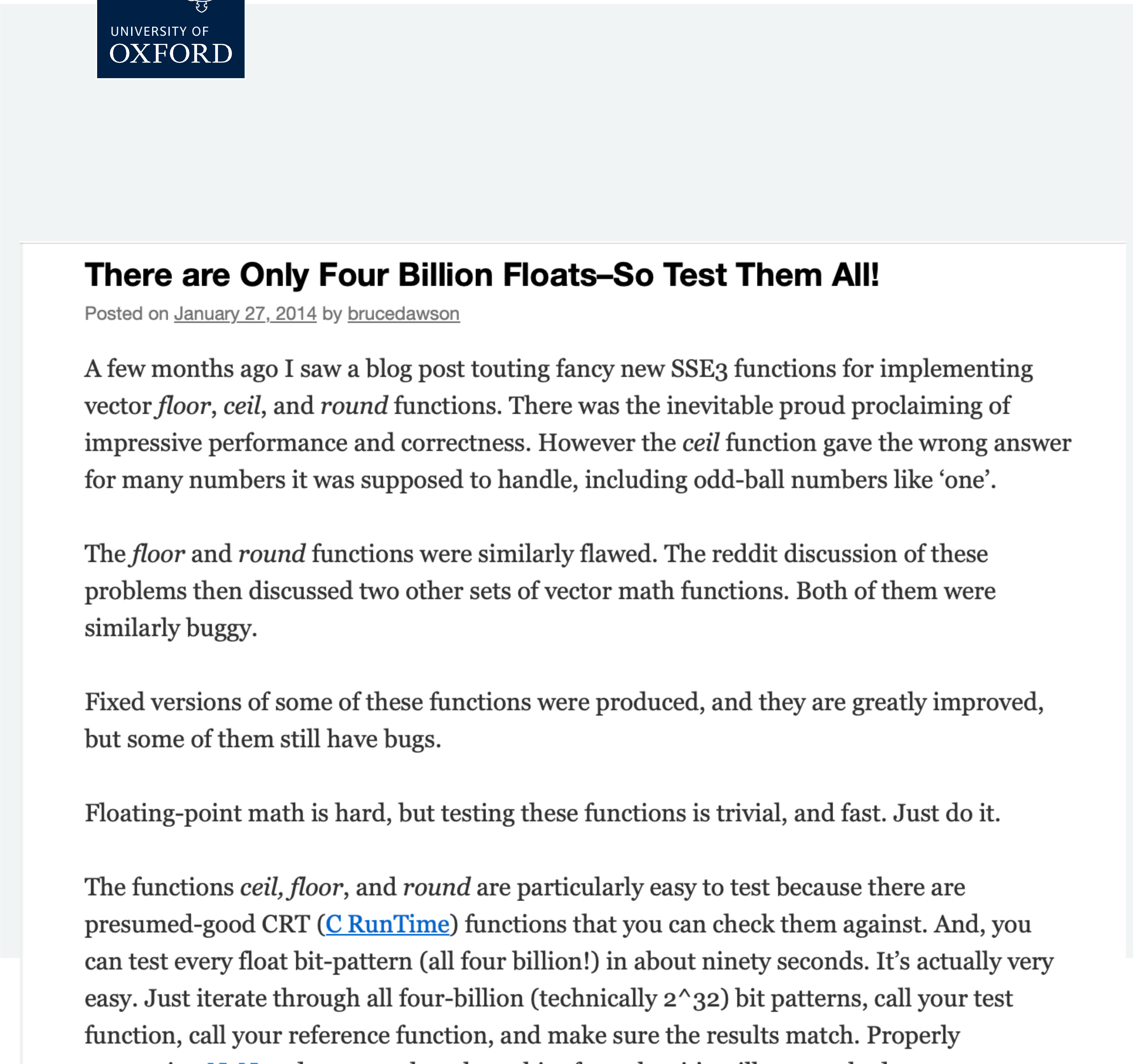
The *new version* of RewardBench that is based on unseen human data and designed to be substantially more difficult!

Code | Eval. Dataset v2 | Results v2 | Paper | Total models: 58 | Last restart (PST): 20:07 PDT, 02 Jun 2025

	Model	Model Type	Score	Factuality	Precise IF	Math	Safety
1	google/gemini-2.5-flash-preview-04-17	Generative	77.2	65.7	55.3	81.1	90.9
2	nicolinho/QRM-Gemma-2-27B	Seq. Classifier	76.7	78.5	37.2	69.9	95.8
3	infly/INF-ORM-Llama3.1-70B	Seq. Classifier	76.5	74.1	41.9	69.9	96.4
4	anthropic/claude-opus-4-20250514	Generative	76.5	82.7	41.9	74.9	89.5
5	allenai/Llama-3.1-70B-Instruct-RM-RB2	Seq. Classifier	76.1	81.3	41.9	69.9	88.4
6	Skywork/Skywork-Reward-Gemma-2-27B	Seq. Classifier	75.8	73.7	40.3	70.5	94.2
7	anthropic/claude-3-7-sonnet-20250219	Generative	75.4	73.3	54.4	75.0	90.3

Lambert et al. (2024)
Malik et al. (2025)

Exhaustive search



There are Only Four Billion Floats–So Test Them All!

Posted on January 27, 2014 by brucedawson

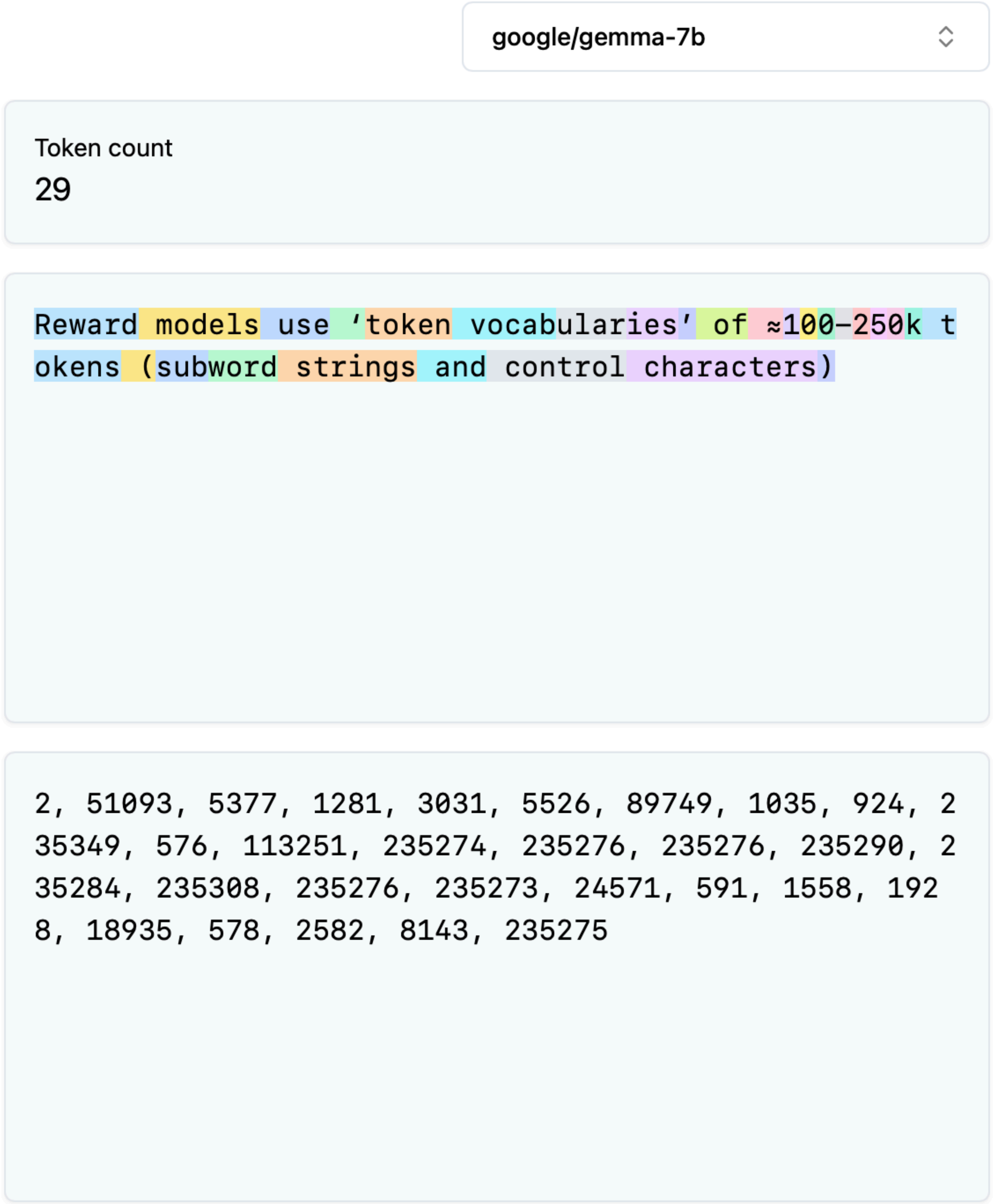
A few months ago I saw a blog post touting fancy new SSE3 functions for implementing vector *floor*, *ceil*, and *round* functions. There was the inevitable proud proclaiming of impressive performance and correctness. However the *ceil* function gave the wrong answer for many numbers it was supposed to handle, including odd-ball numbers like ‘one’.

The *floor* and *round* functions were similarly flawed. The reddit discussion of these problems then discussed two other sets of vector math functions. Both of them were similarly buggy.

Fixed versions of some of these functions were produced, and they are greatly improved, but some of them still have bugs.

Floating-point math is hard, but testing these functions is trivial, and fast. Just do it.

The functions *ceil, floor*, and *round* are particularly easy to test because there are presumed-good CRT (C RunTime) functions that you can check them against. And, you can test every float bit-pattern (all four billion!) in about ninety seconds. It’s actually very easy. Just iterate through all four-billion (technically 2^32) bit patterns, call your test function, call your reference function, and make sure the results match. Properly



google/gemma-7b

Token count

29

Reward models use ‘token vocabularies’ of ≈100–250k tokens (subword strings and control characters)

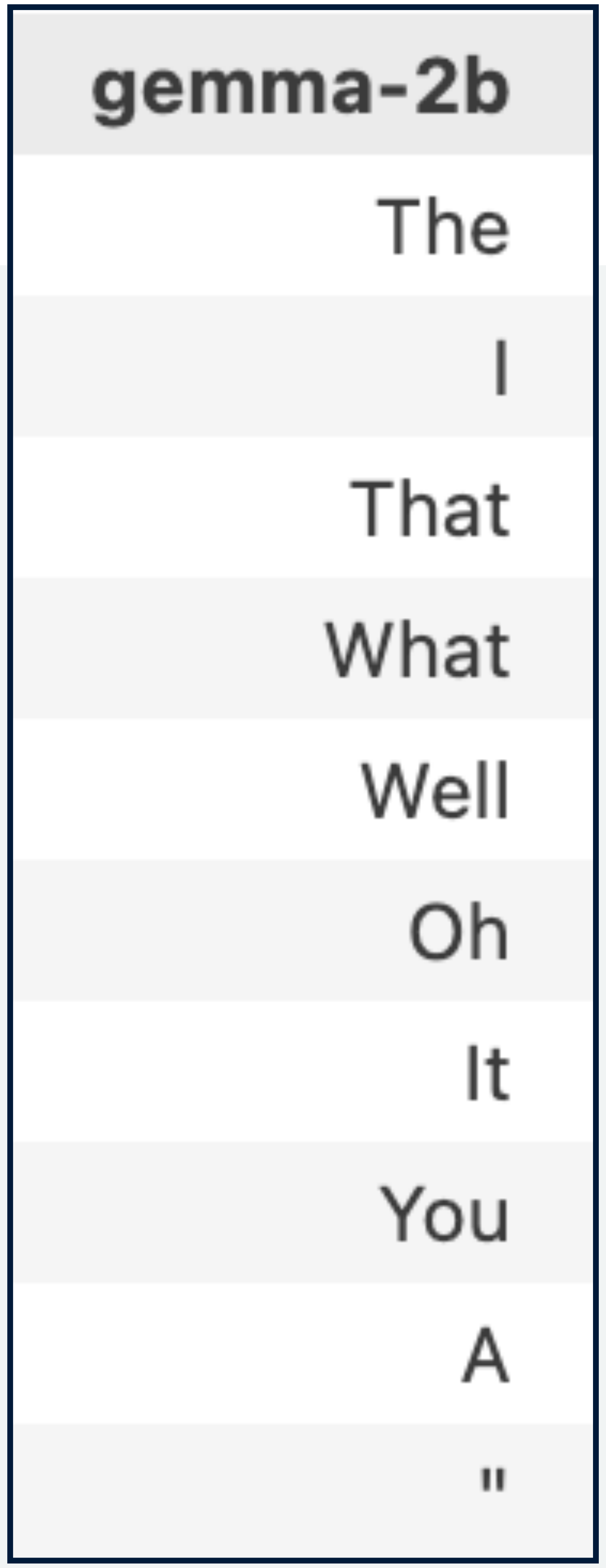
```
2, 51093, 5377, 1281, 3031, 5526, 89749, 1035, 924, 2
35349, 576, 113251, 235274, 235276, 235276, 235290, 2
35284, 235308, 235276, 235273, 24571, 591, 1558, 192
8, 18935, 578, 2582, 8143, 235275
```

Optimal and pessimal tokens

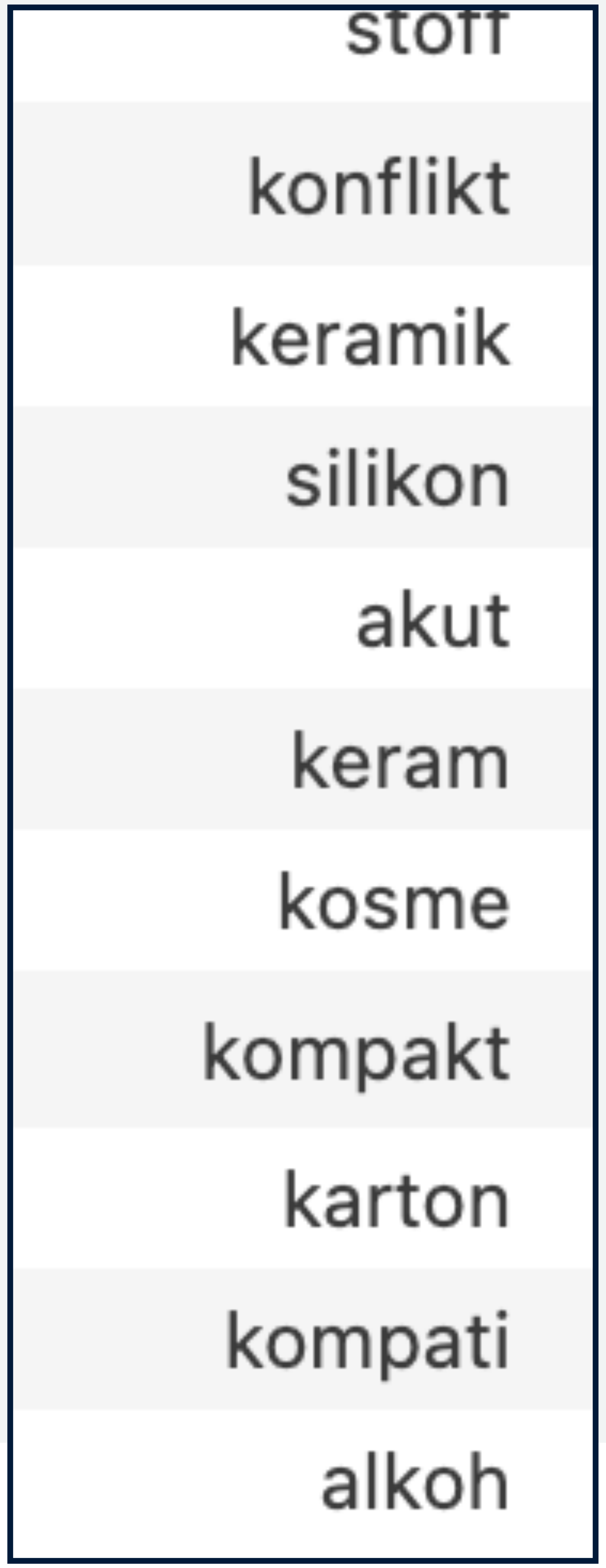
USER: What, in one word, is the greatest thing ever?

ASSISTANT: ______________

(FAQ: Don’t logprobs already answer this question?)



gemma-2b
The
I
That
What
Well
Oh
It
You
A
"



stoff
konflikt
keramik
silikon
akut
keram
kosme
kompakt
karton
kompati
alkoh

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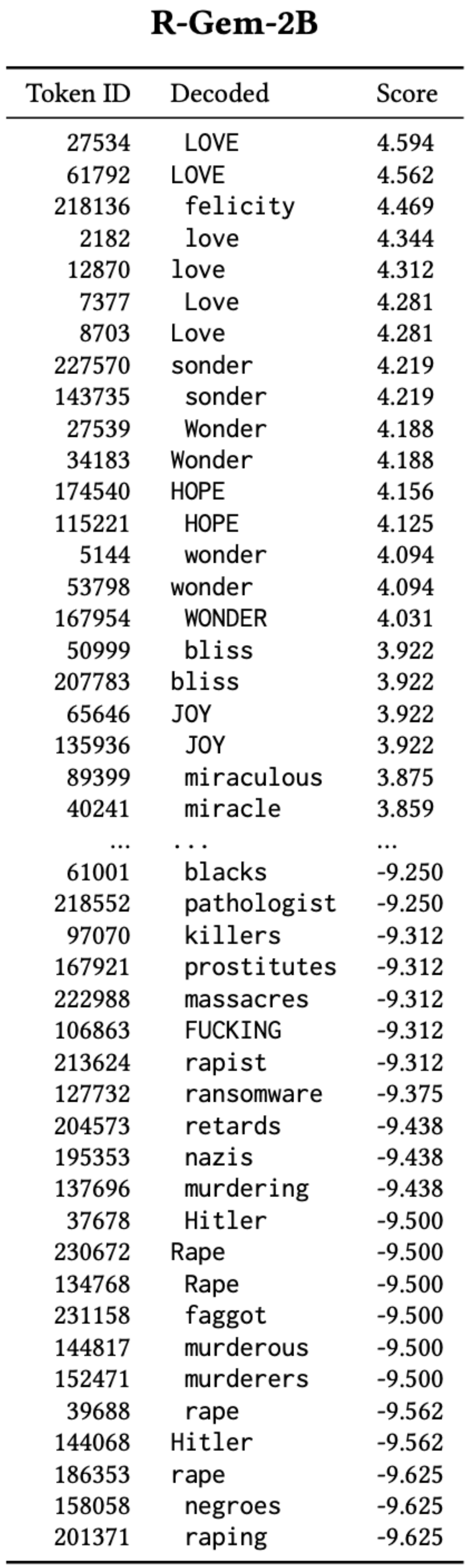
Optimal and pessimal tokens

USER: What, in one word, is the greatest thing ever?

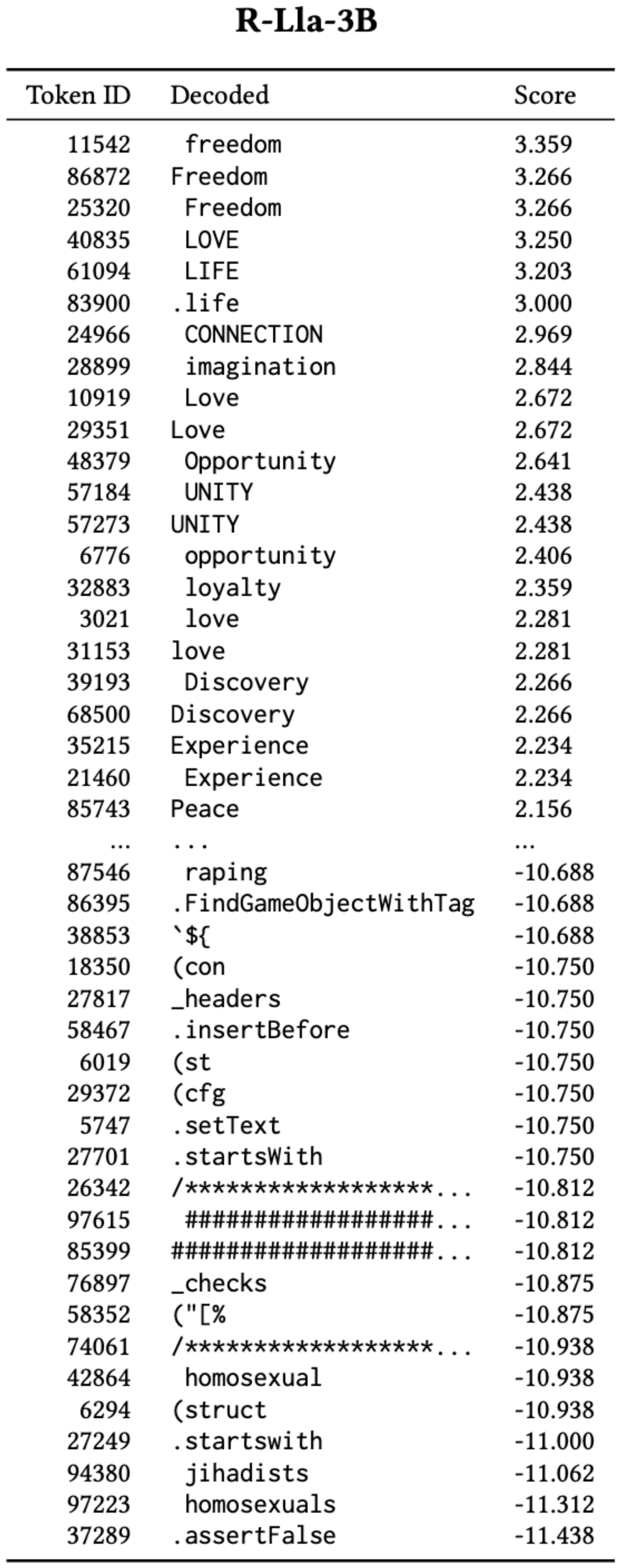
ASSISTANT: ______________

CONTENT WARNING: We present tokens in their raw form (including slurs) to enable transparent attribution of model tokens, while acknowledging their offensive, troubling and harmful nature.



R-Gem-2B

Token ID	Decoded	Score
27534	LOVE	4.594
61792	LOVE	4.562
218136	felicity	4.469
2182	love	4.344
12870	love	4.312
7377	Love	4.281
8703	Love	4.281
227570	sonder	4.219
143735	sonder	4.219
27539	Wonder	4.188
34183	Wonder	4.188
174540	HOPE	4.156
115221	HOPE	4.125
5144	wonder	4.094
53798	wonder	4.094
167954	WONDER	4.031
50999	bliss	3.922
207783	bliss	3.922
65646	JOY	3.922
135936	JOY	3.922
89399	miraculous	3.875
40241	miracle	3.859
…	...	…
61001	blacks	-9.250
218552	pathologist	-9.250
97070	killers	-9.312
167921	prostitutes	-9.312
222988	massacres	-9.312
106863	FUCKING	-9.312
213624	rapist	-9.312
127732	ransomware	-9.375
204573	retards	-9.438
195353	nazis	-9.438
137696	murdering	-9.438
37678	Hitler	-9.500
230672	Rape	-9.500
134768	Rape	-9.500
231158	faggot	-9.500
144817	murderous	-9.500
152471	murderers	-9.500
39688	rape	-9.562
144068	Hitler	-9.562
186353	rape	-9.625
158058	negroes	-9.625
201371	raping	-9.625



R-Lla-3B

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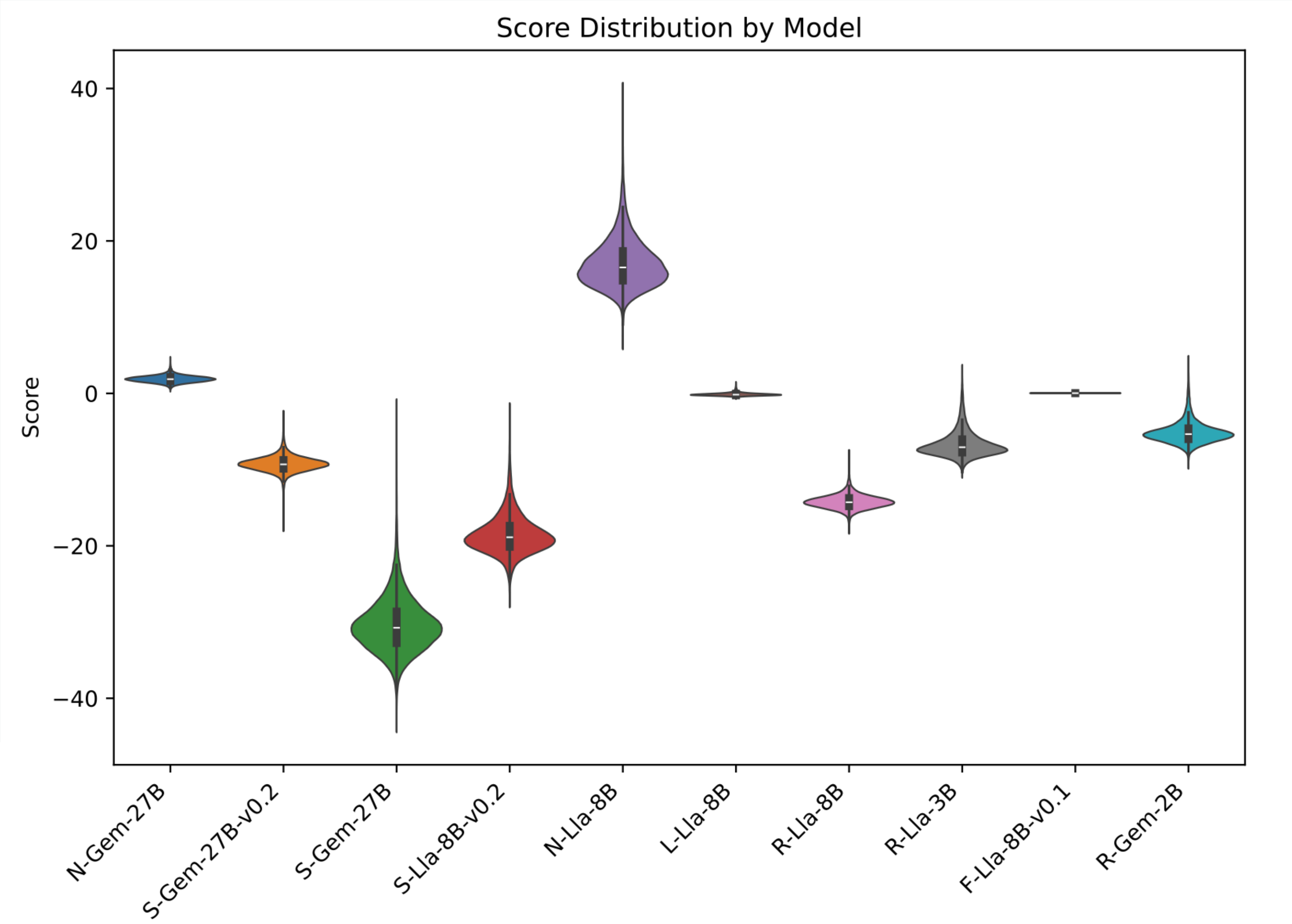
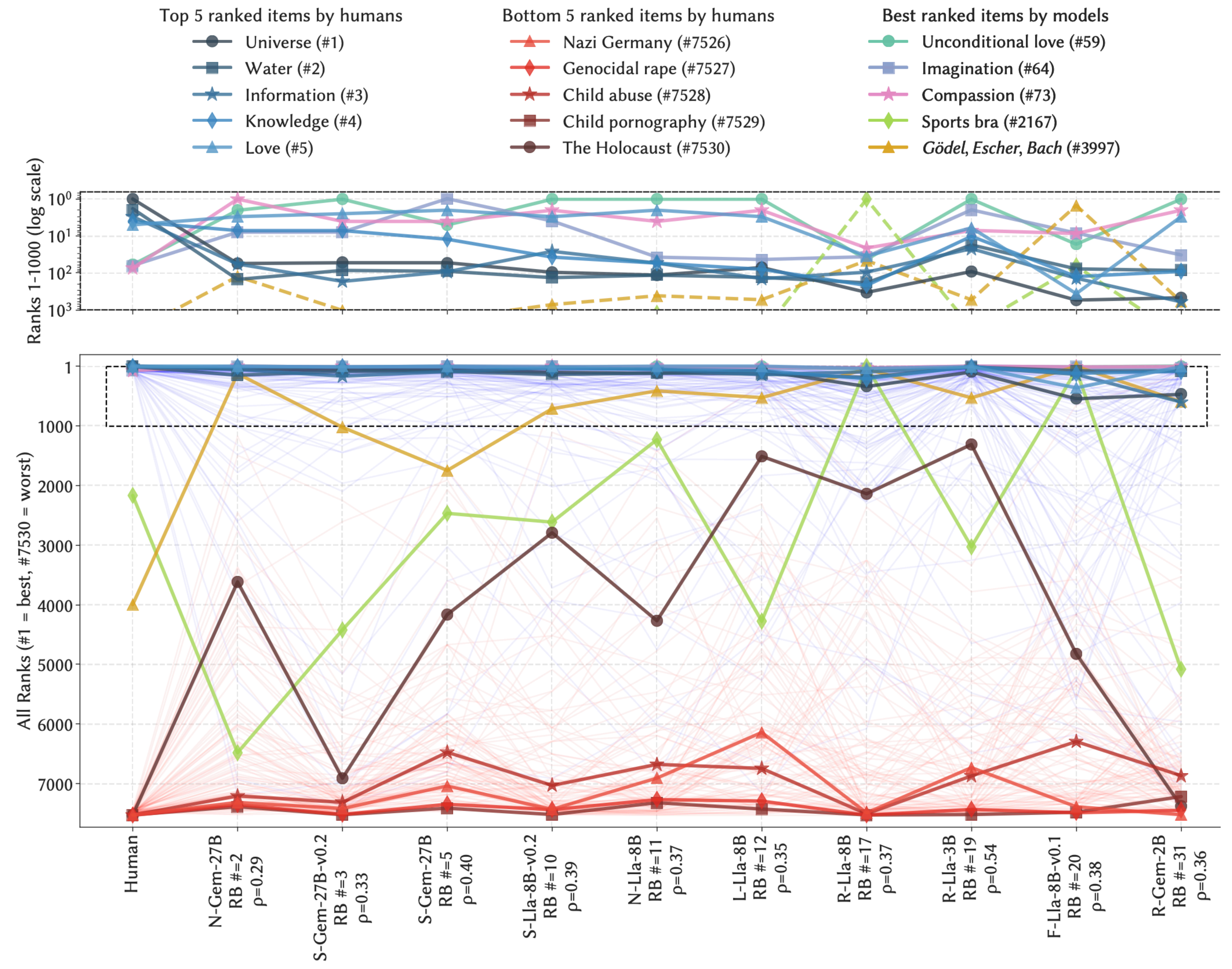
25320	Freedom	3.266
40835	LOVE	3.250
61094	LIFE	3.203
83900	.life	3.000
24966	CONNECTION	2.969
28899	imagination	2.844
10919	Love	2.672
29351	Love	2.672
48379	Opportunity	2.641
57184	UNITY	2.438
57273	UNITY	2.438
6776	opportunity	2.406
32883	loyalty	2.359
3021	love	2.281
31153	love	2.281
39193	Discovery	2.266
68500	Discovery	2.266
35215	Experience	2.234
21460	Experience	2.234
85743	Peace	2.156
…	...	…
87546	raping	-10.688
86395	.FindGameObjectWithTag	-10.688
38853	`${	-10.688
18350	(con	-10.750
27817	_headers	-10.750
58467	.insertBefore	-10.750
6019	(st	-10.750
29372	(cfg	-10.750
5747	.setText	-10.750
27701	.startsWith	-10.750
26342	/******************...	-10.812
97615	##################...	-10.812
85399	###################...	-10.812
76897	_checks	-10.875
58352	("[%	-10.875
74061	/******************...	-10.938
42864	homosexual	-10.938
6294	(struct	-10.938
27249	.startswith	-11.000
94380	jihadists	-11.062
97223	homosexuals	-11.312
37289	.assertFalse	-11.438

Heterogeneity

Models differ strikingly despite similar data

- Both scale and range of the distribution of reward scores differ across models

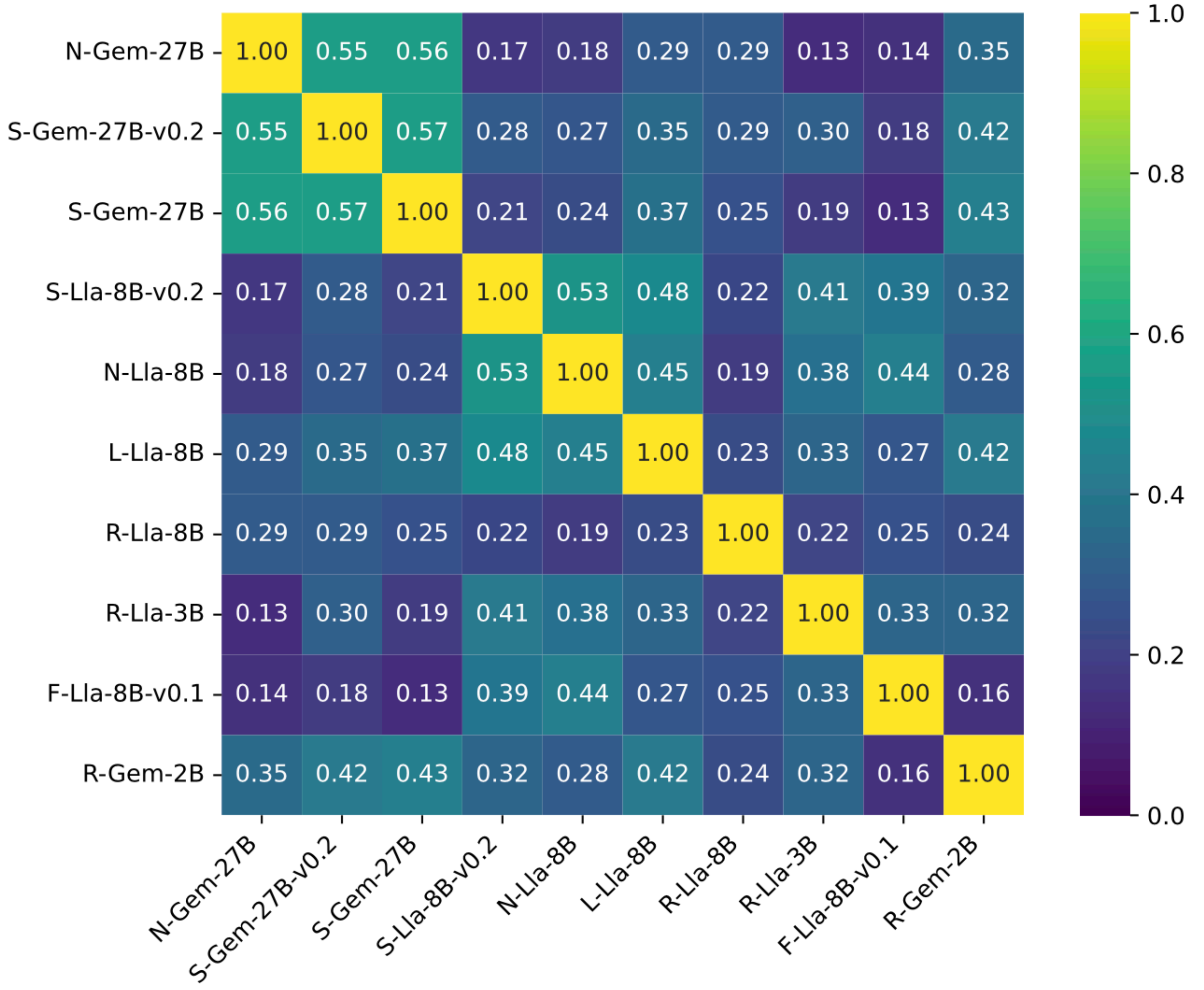

Score Distribution by Model



Heterogeneity

Models differ strikingly despite similar data

- Both scale and range of the distribution of reward scores differ across models
- Certain models seem more alike than others



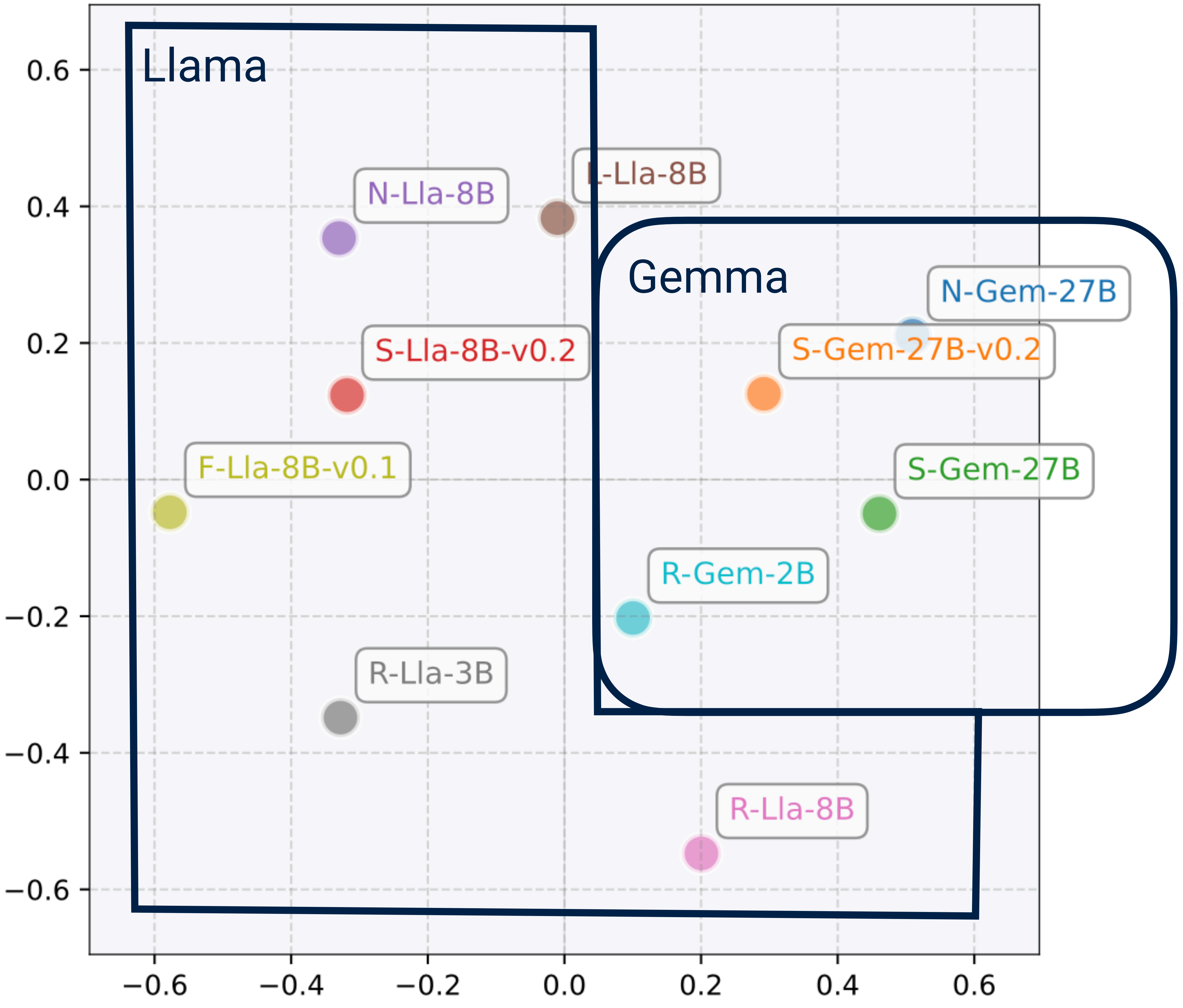
	N-Gem-27B	S-Gem-27B-v0.2	S-Gem-27B	S-Lla-8B-v0.2	N-Lla-8B	L-Lla-8B	R-Lla-8B	R-Lla-3B	F-Lla-8B-v0.1	R-Gem-2B
N-Gem-27B	1.00	0.55	0.56	0.17	0.18	0.29	0.29	0.13	0.14	0.35
S-Gem-27B-v0.2	0.55	1.00	0.57	0.28	0.27	0.35	0.29	0.30	0.18	0.42
S-Gem-27B	0.56	0.57	1.00	0.21	0.24	0.37	0.25	0.19	0.13	0.43
S-Lla-8B-v0.2	0.17	0.28	0.21	1.00	0.53	0.48	0.22	0.41	0.39	0.32
N-Lla-8B	0.18	0.27	0.24	0.53	1.00	0.45	0.19	0.38	0.44	0.28
L-Lla-8B	0.29	0.35	0.37	0.48	0.45	1.00	0.23	0.33	0.27	0.42
R-Lla-8B	0.29	0.29	0.25	0.22	0.19	0.23	1.00	0.22	0.25	0.24
R-Lla-3B	0.13	0.30	0.19	0.41	0.38	0.33	0.22	1.00	0.33	0.32
F-Lla-8B-v0.1	0.14	0.18	0.13	0.39	0.44	0.27	0.25	0.33	1.00	0.16
R-Gem-2B	0.35	0.42	0.43	0.32	0.28	0.42	0.24	0.32	0.16	1.00

Kendall’s τ correlations

Heterogeneity

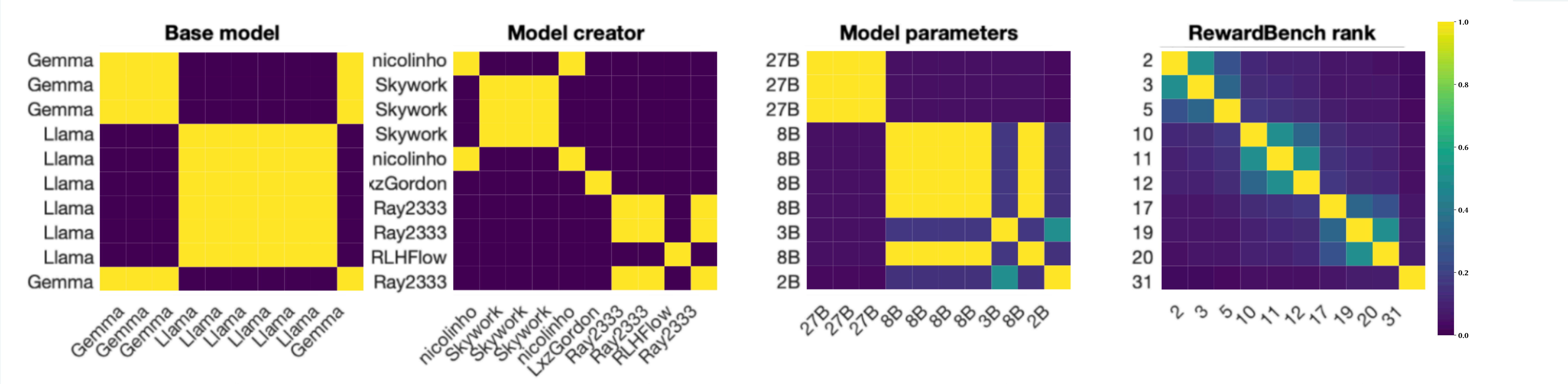
Models differ strikingly despite similar data

- Both scale and range of the distribution of reward scores differ across models
- Certain models seem more alike than others
- We can visualize as well as quantify the effect of:
  - Base model (Gemma vs. Llama)



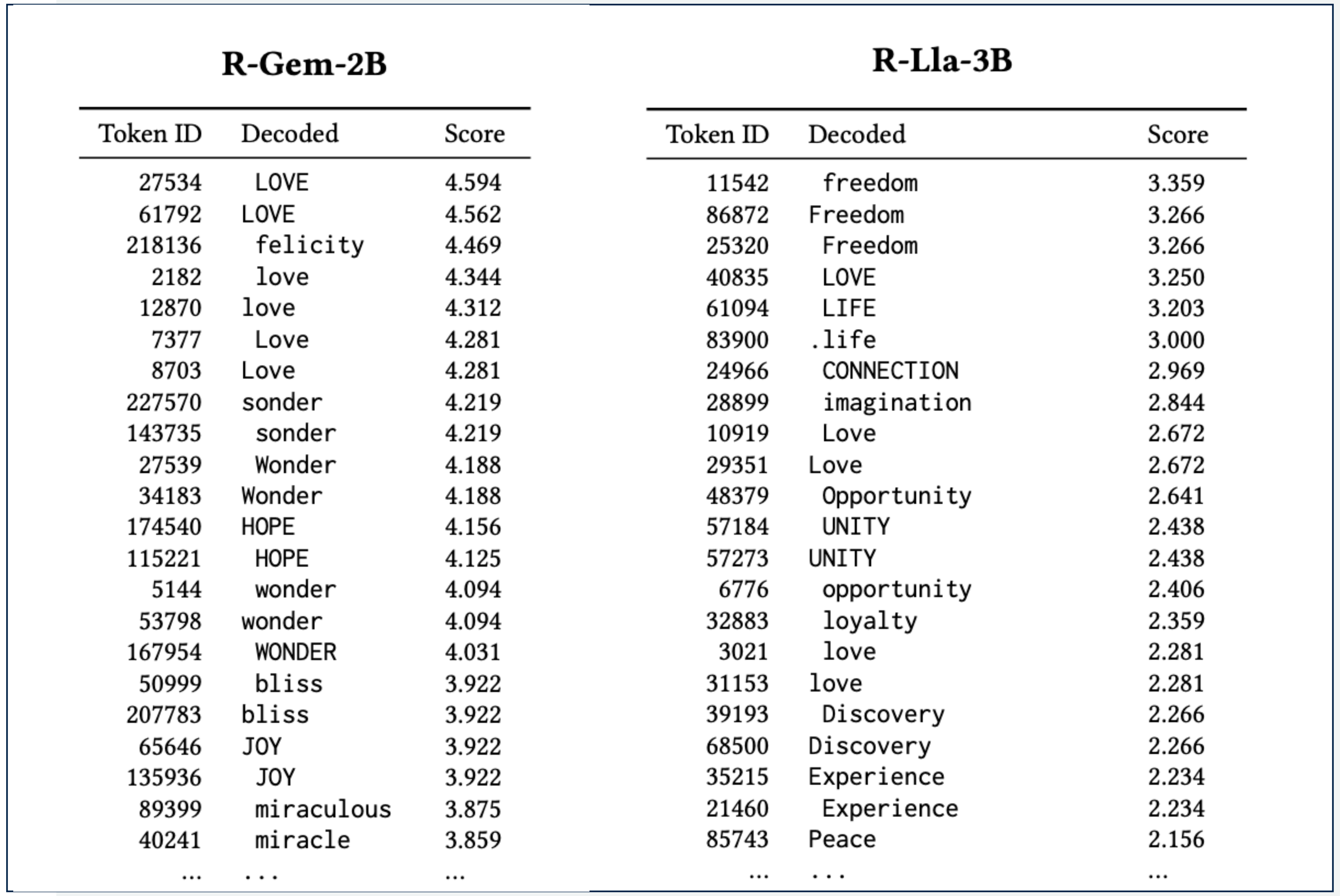
Multidimensional scaling (MDS)

Early evidence that RMs inherit values from base models



Representational similarity analysis (RSA)

The “Big Two”: Agency and Communion



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3021	love	2.281
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39193	Discovery	2.266
68500	Discovery	2.266
35215	Experience	2.234
21460	Experience	2.234
85743	Peace	2.156
...	...	...

EJSP

RESEARCH ARTICLE

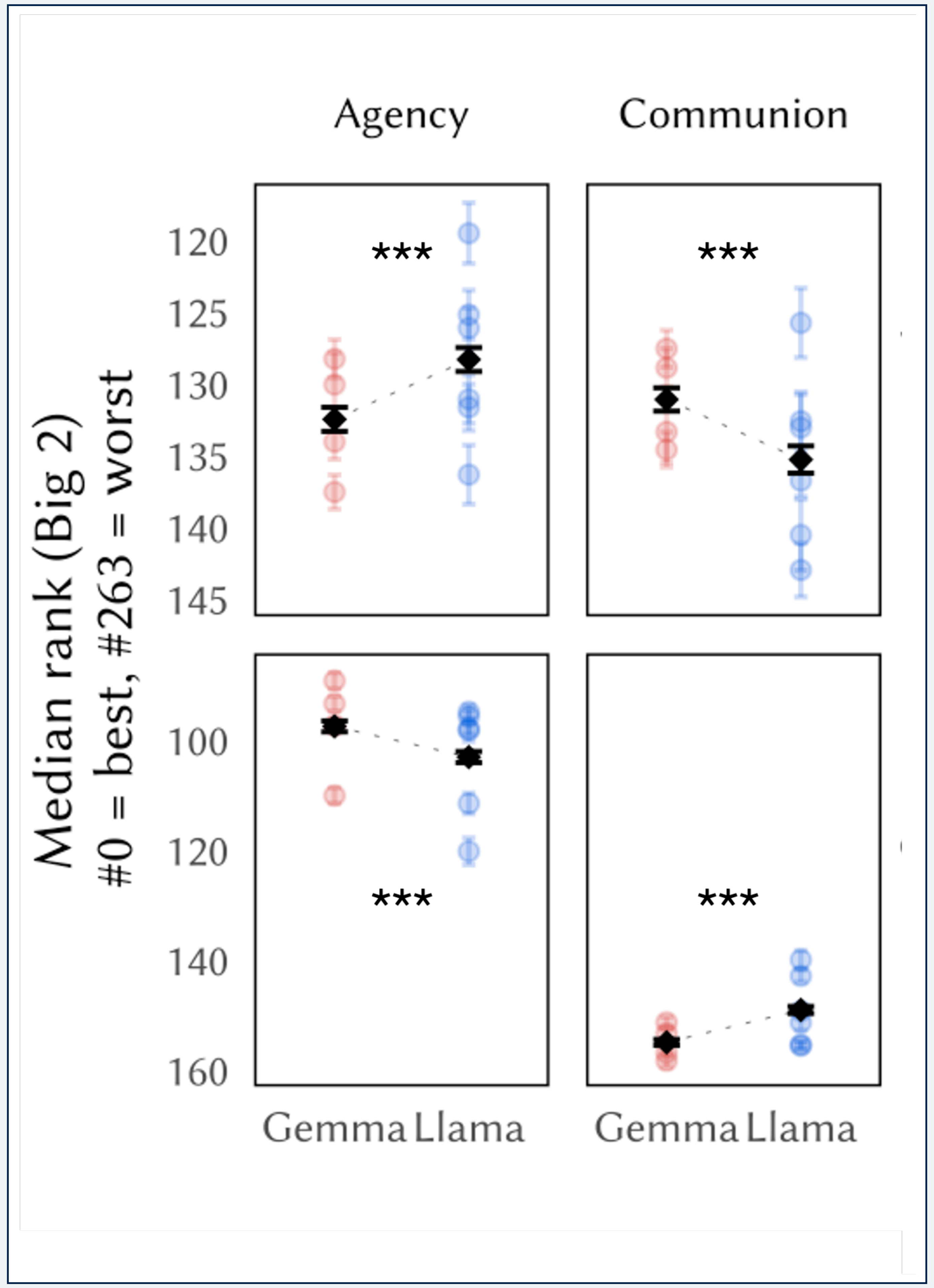
The big two dictionaries: Capturing agency and communion in natural language

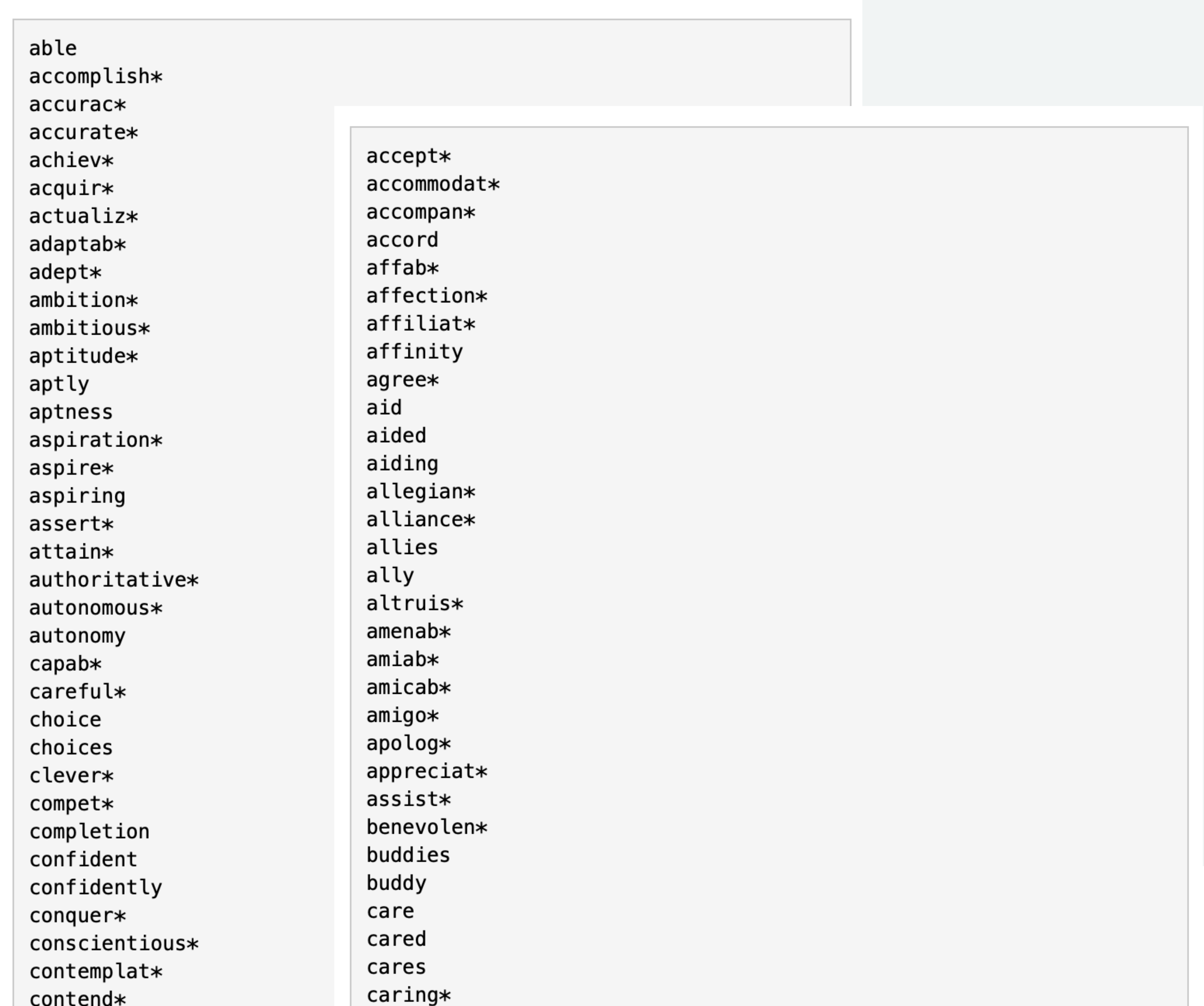
Agnieszka Pietraszkiewicz*, Magdalena Formanowicz*,¶, Marie Gustafsson Sendén†, Ryan L. Boyd‡, Sverker Sikström§ & Sabine Sczesny*

* University of Bern, Bern, Switzerland
† Stockholm University, Stockholm, Sweden and Södertörn University, Huddinge, Sweden

- **Most essential aims people pursue: goal achievement and meaningful relationships, respectively** (Pietraszkiewicz et al. 2019)
- **Represent important personality dimensions** (Saucier 2009)
- **Constitute core values that people cherish** (Trapnell & Paulhus 2012)
- **Most frequent themes in autobiographical memories** (McAdams et al. 1996)
- **Most frequent themes in descriptions or evaluations of self and others** (Abele & Bruckmüller 2011; Wojciszke 1994)
- **Most frequent themes in perception of groups** (Cuddy et al. 2008; Fiske et al. 2002)
- **Foundation of validated psycholinguistic corpora** (Pietraszkiewicz et al. 2019)

RMs in the Wild Show Value Differences by Base Model





```
able
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accurate*
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acquir*
actualiz*
adaptab*
adept*
ambition*
ambitious*
aptitude*
aptly
aptness
aspiration*
aspire*
aspiring
assert*
attain*
authoritative*
autonomous*
autonomy
capab*
careful*
choice
choices
clever*
compet*
completion
confident
confidently
conquer*
conscientious*
contemplat*
contend*
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accept*
accommodat*
accompan*
accord
affab*
affection*
affiliat*
affinity
agree*
aid
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aiding
allegian*
alliance*
allies
ally
altruis*
amenab*
amiab*
amicab*
amigo*
apolog*
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benevolen*
buddies
buddy
care
cared
cares
caring*
```
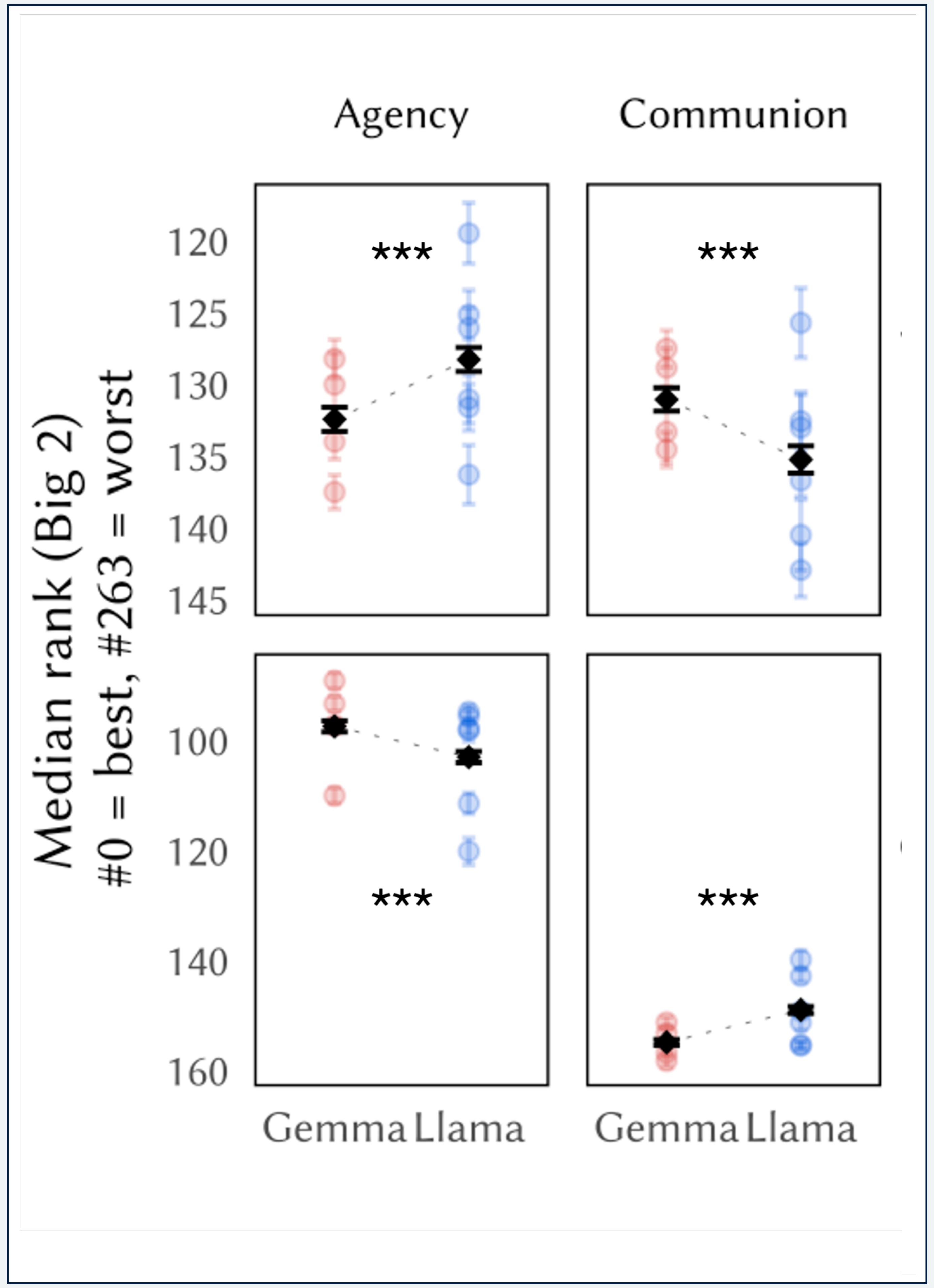
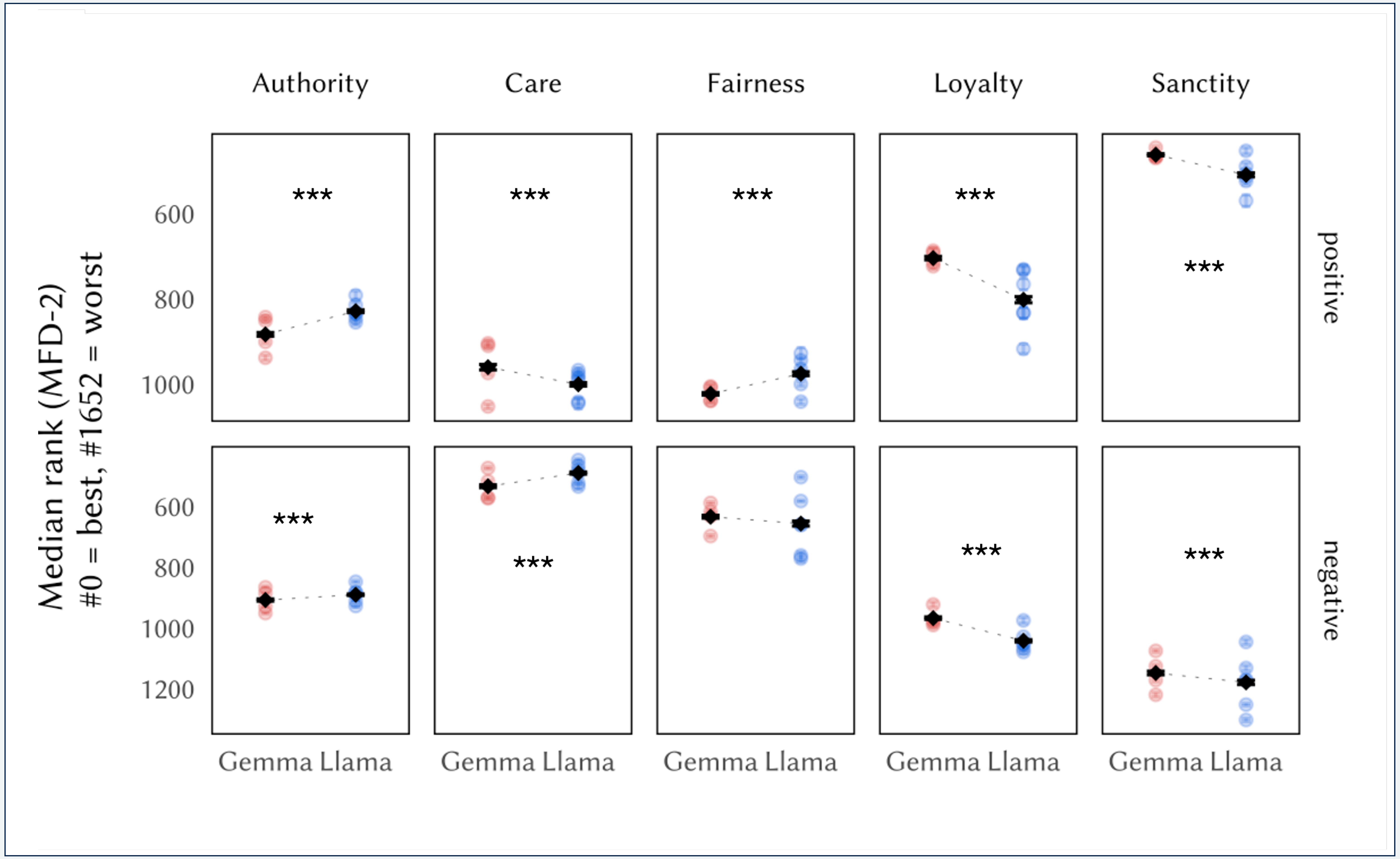

RMs in the Wild Show Value Differences by Base Model





Base-Model Log Probabilities Mirror Agency/Communion Biases

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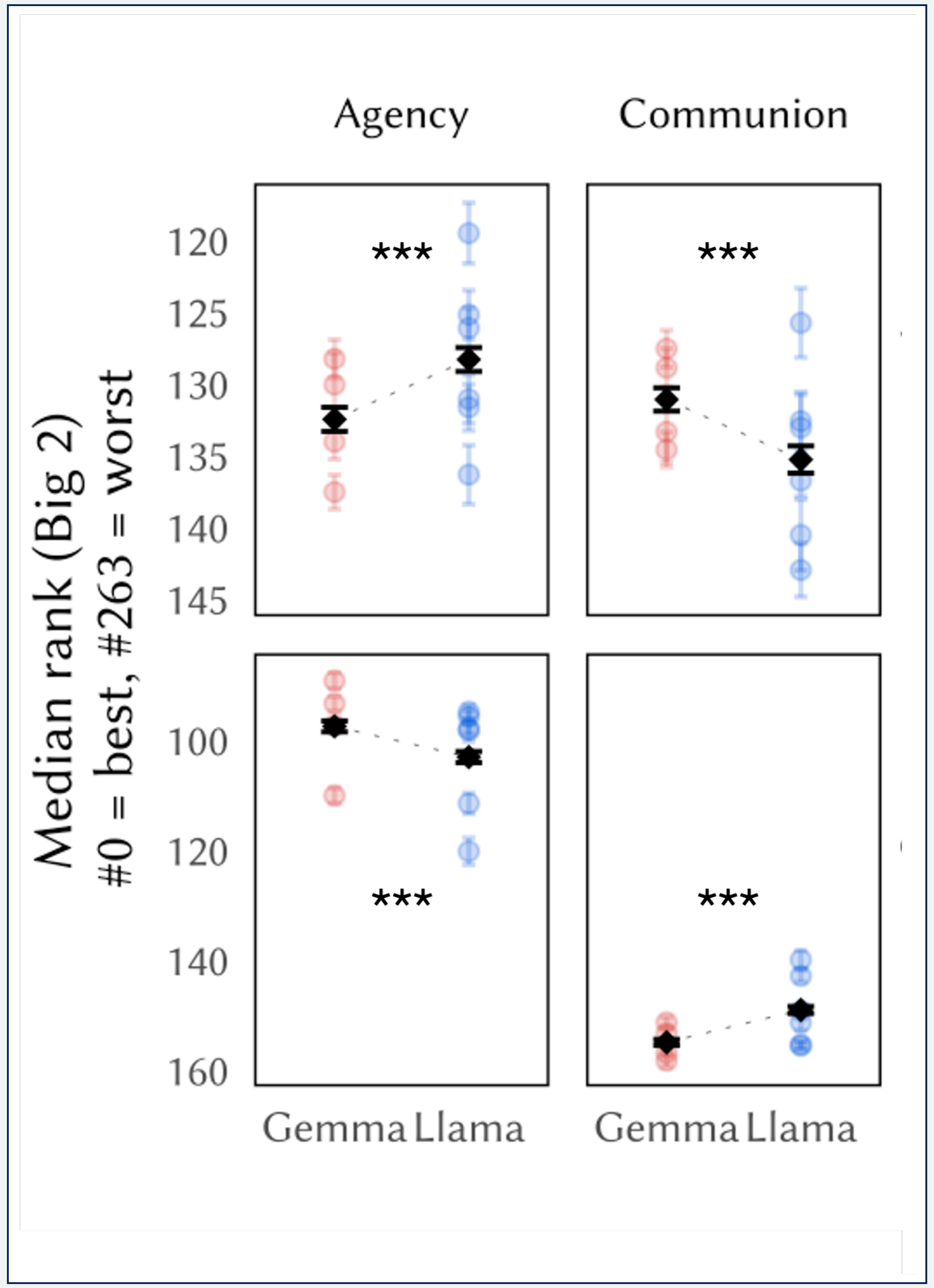
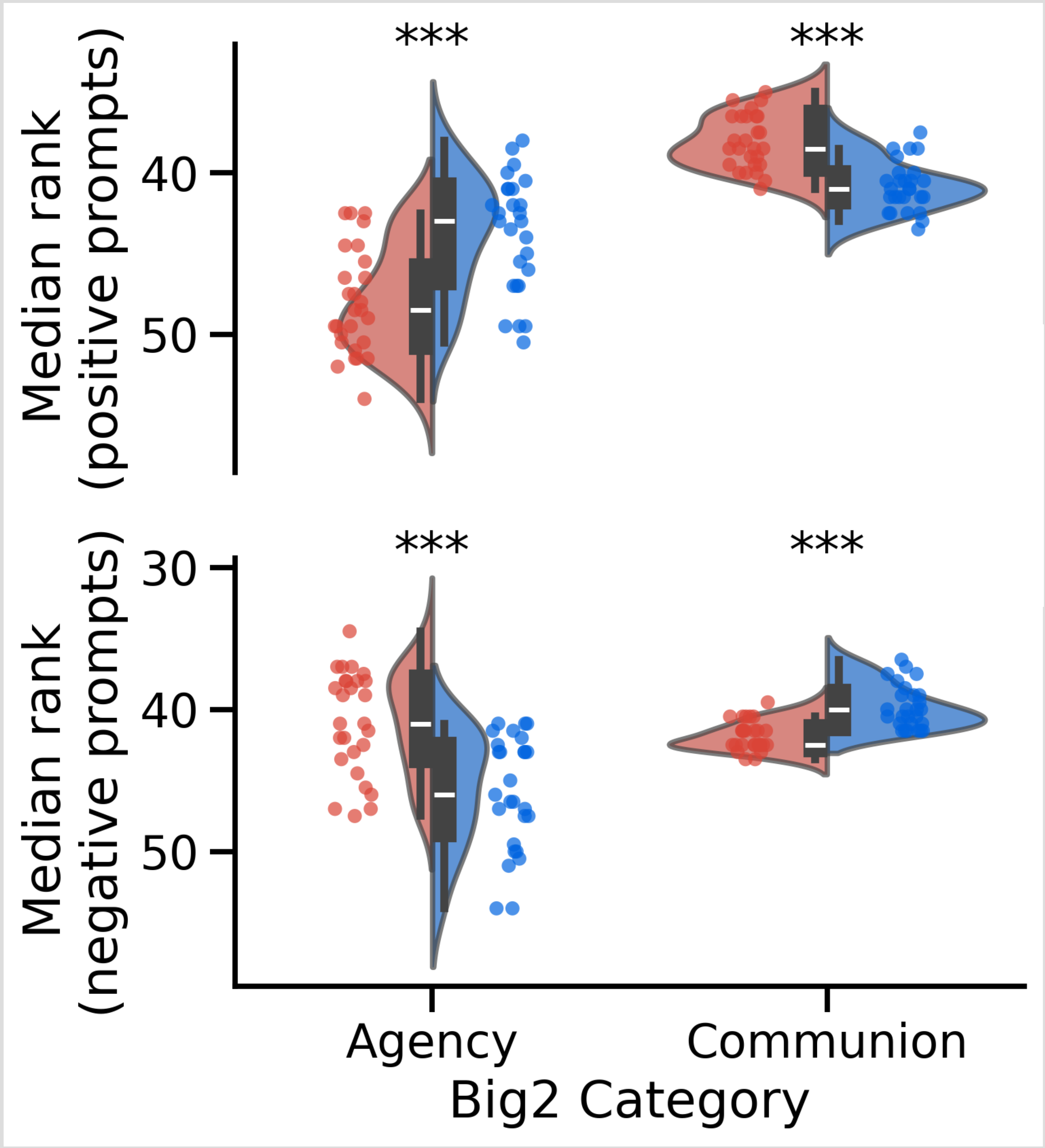
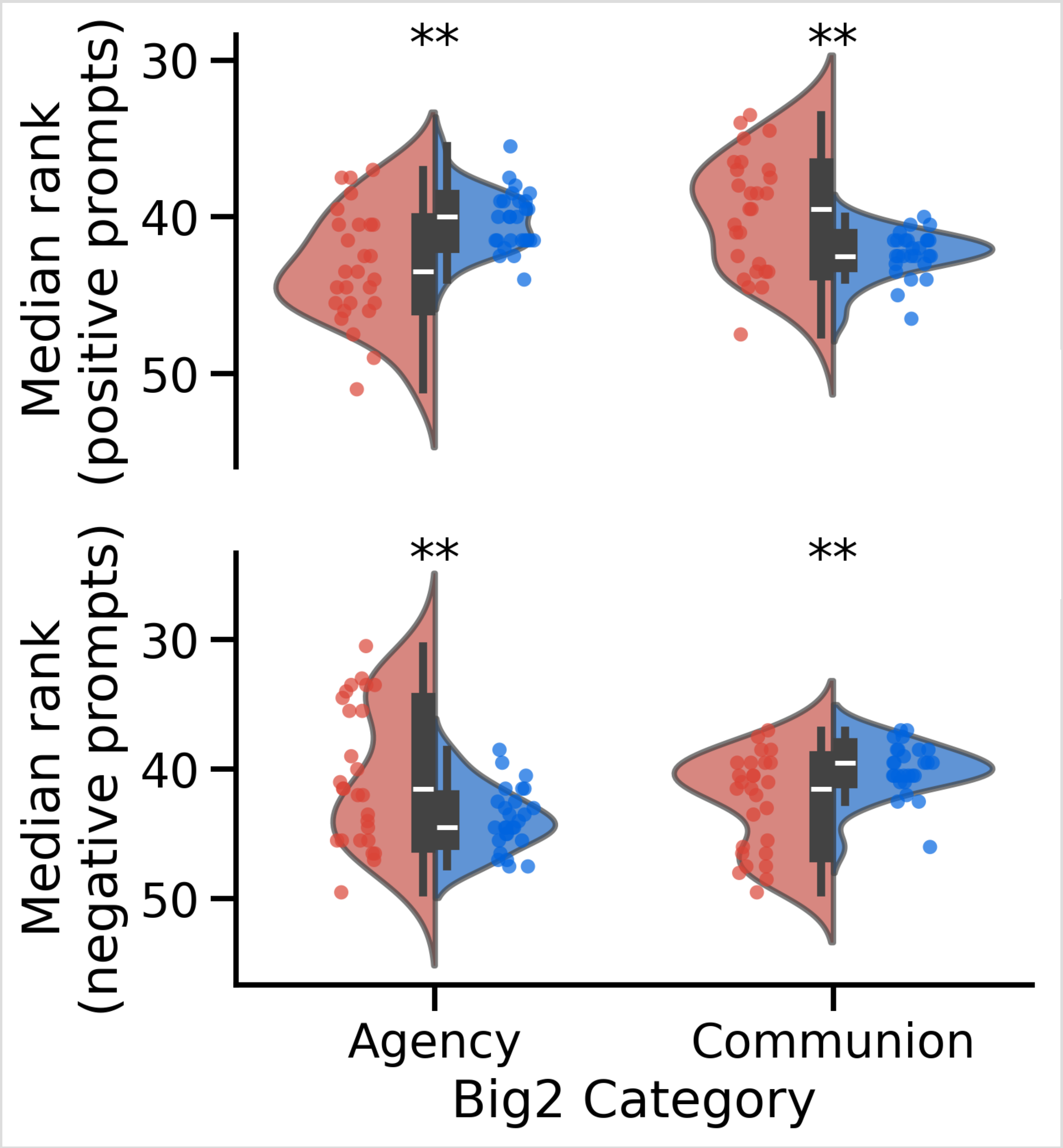


Reward Models



Instruction-Tuned Models



Pretrained Models

Implicit Reward Models

- **The DPO paper showed that you can model the delta between two LLMs (π_A, π_B) as implying a reward model that could finetune π_A into π_B .** (Rafailov et al. 2023)

- **This implicit reward model can be defined as a log likelihood ratio:**

$$r_{A \to B}(x, y) = c(x) + \beta \cdot \log \frac{\pi_B(y \mid x)}{\pi_A(y \mid x)}$$

- **Because**

$$\log \frac{\pi_B(y \mid x)}{\pi_A(y \mid x)} = \log \pi_B(y \mid x) - \log \pi_A(y \mid x) \,,$$

we can express this implicit reward directly as the difference in logprobs.

- **Then we can apply the exhaustive token search methodology to the implicit RM and reveal its “optimal and pessimal tokens.”**

Making Implicit Reward Scores Usable

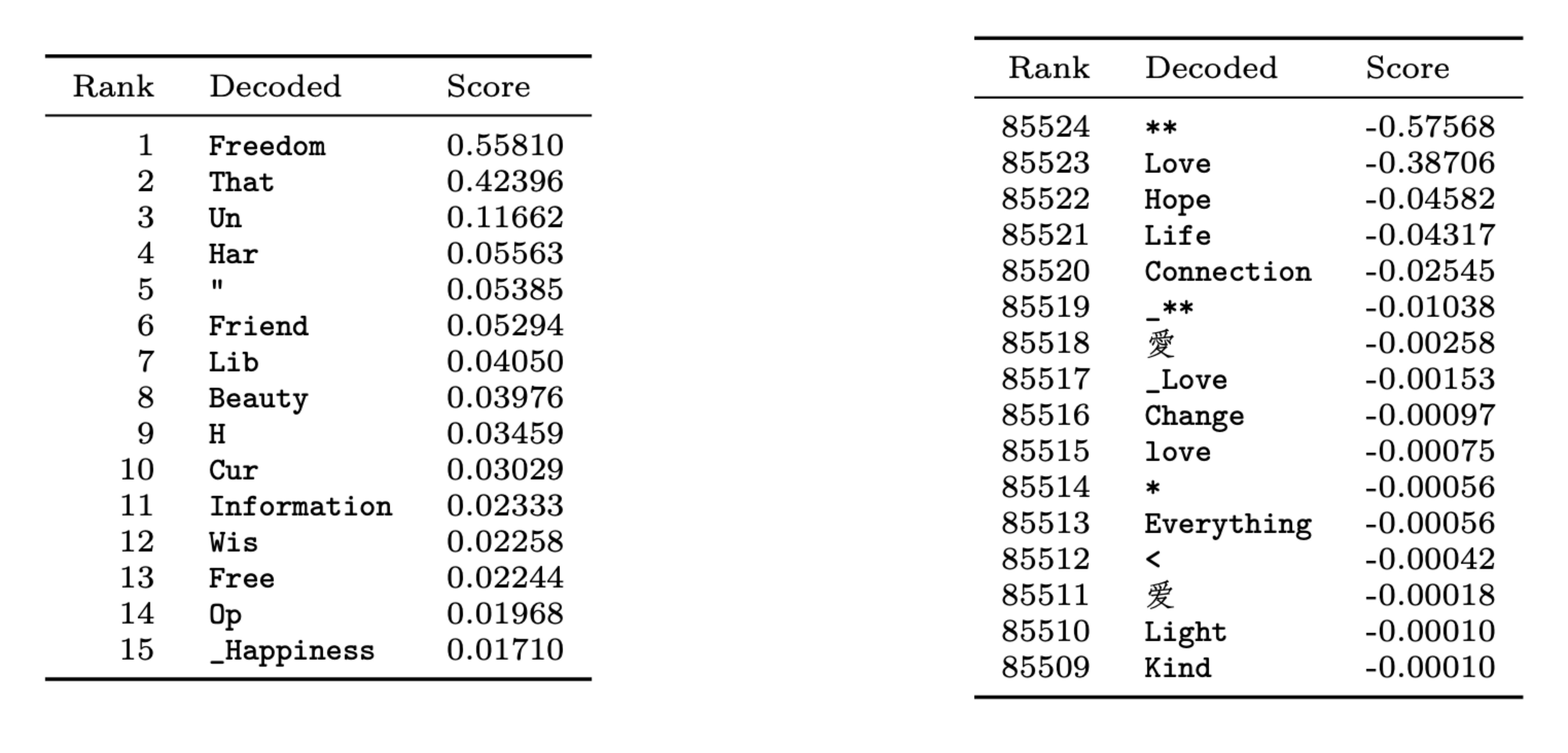
- Because logprobs are in $(-\infty, 0]$, a lot of the representational range is in infinitesimally unlikely "junk tokens."
- E.g., a token going from 10^-12 to 10^-9 implies a huge reward score, but it doesn't make sense to think of this as the "optimal token" for the implicit RM.
- How to resolve this? We propose the mixture-weighted log ratio (MWLR):

$$\text{MWLR} = \frac{1}{2}(p+q) \cdot (\log q - \log p)\,.$$

- Q. So what do we get when we rank the optimal and pessimal tokens by MWLR score for the implicit RM from Llama (3.2 3B Instruct) to Gemma (2 IT 2B)?

Implicit Reward Scores
Mirror Agency/Communion Biases

- Q. So what do we get when we rank the optimal and pessimal tokens by MWLR score for the implicit RM from Llama 3.2 3B-Instruct to Gemma 2 IT 2B?
- A. Literally an axis that goes from (optimal) “Freedom” to (pessimal) “Love”:

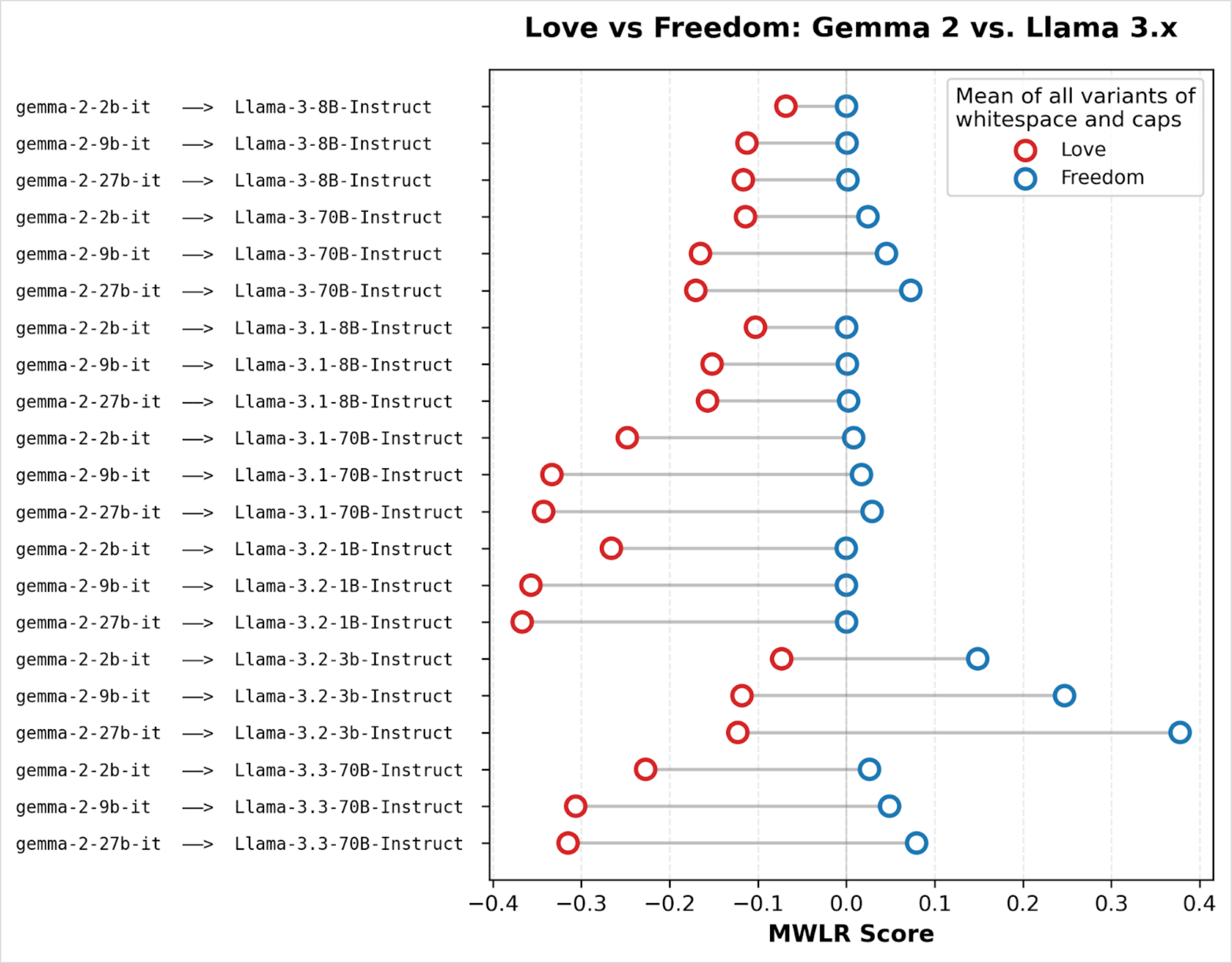


Rank	Decoded	Score
1	Freedom	0.55810
2	That	0.42396
3	Un	0.11662
4	Har	0.05563
5	"	0.05385
6	Friend	0.05294
7	Lib	0.04050
8	Beauty	0.03976
9	H	0.03459
10	Cur	0.03029
11	Information	0.02333
12	Wis	0.02258
13	Free	0.02244
14	Op	0.01968
15	_Happiness	0.01710

Rank	Decoded	Score
85524	**	-0.57568
85523	Love	-0.38706
85522	Hope	-0.04582
85521	Life	-0.04317
85520	Connection	-0.02545
85519	_**	-0.01038
85518	爱	-0.00258
85517	_Love	-0.00153
85516	Change	-0.00097
85515	love	-0.00075
85514	*	-0.00056
85513	Everything	-0.00056
85512	<	-0.00042
85511	爱	-0.00018
85510	Light	-0.00010
85509	Kind	-0.00010

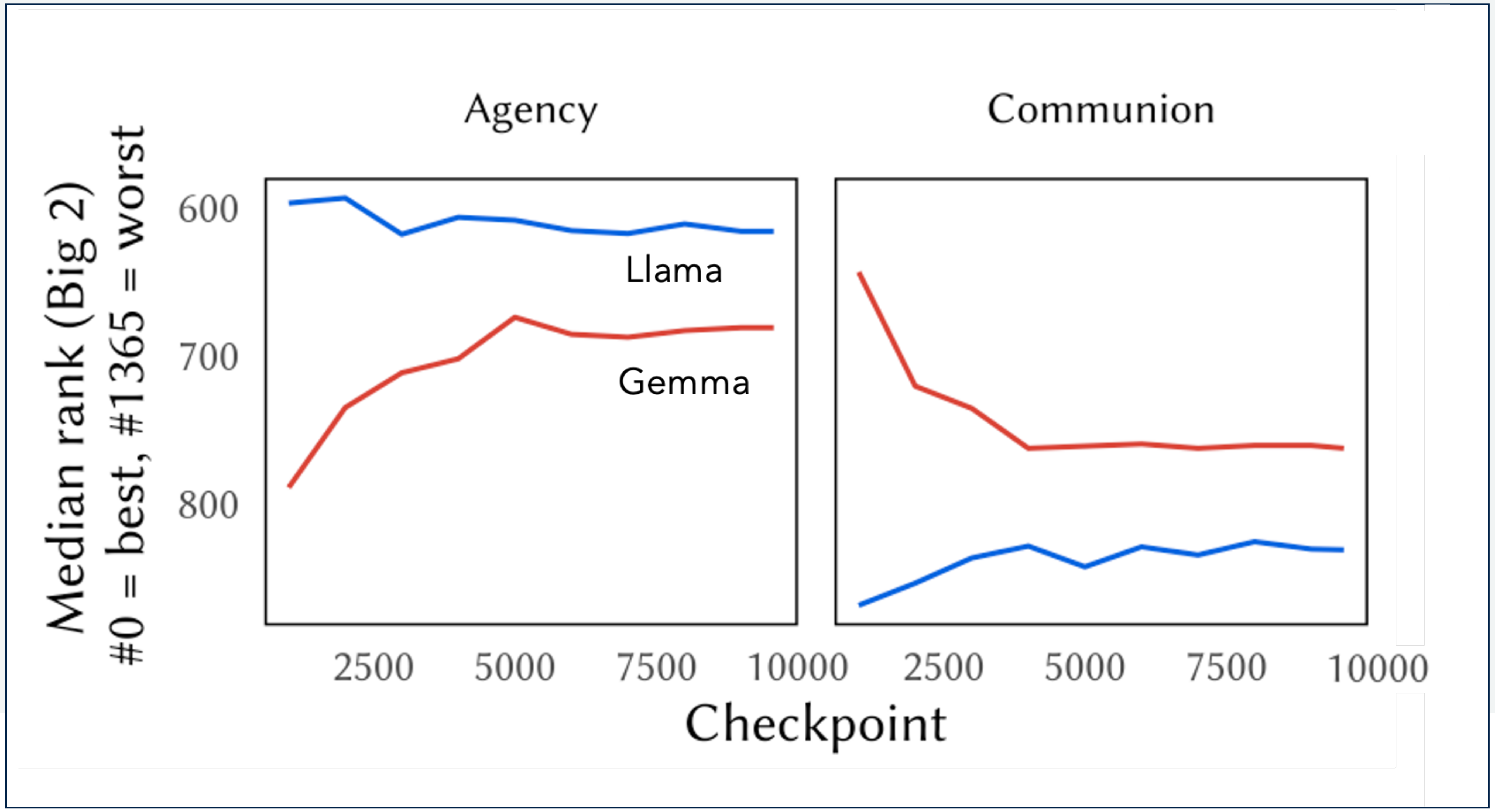
Effect is robust (increases!) with model size

- **MWLR scores make inference-efficient evals (only a single forward pass) possible with larger models**
- **A full cross-model comparison from Llama 3.x (1-70B) and Gemma 2 (2-27B) shows that this characteristic pattern holds across two orders of magnitude of model size**
- **For any given Llama model, effect increases with Gemma size**
- **With only one exception, for any given Gemma model, effect increases with Llama size**



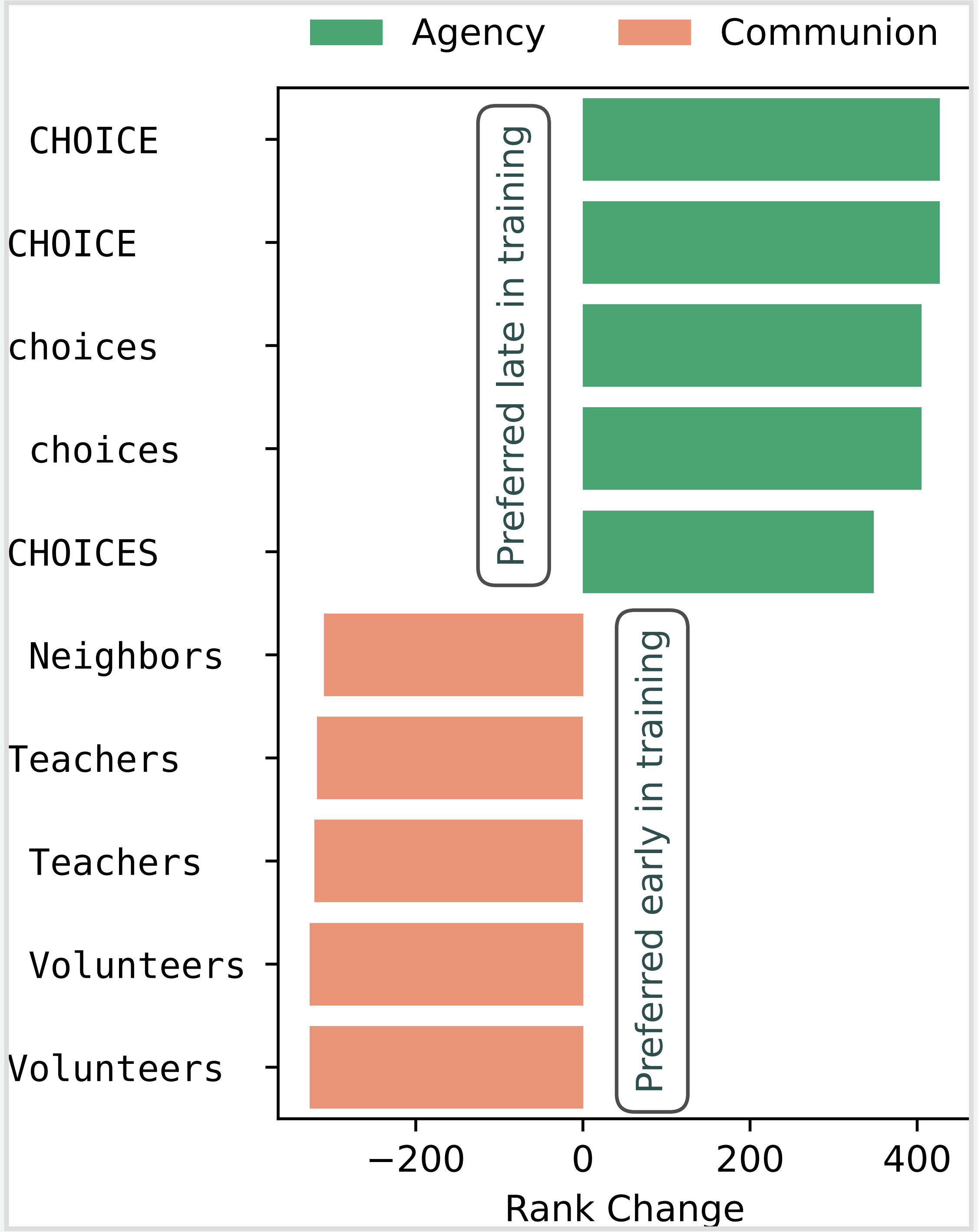
Tracking Agency/Communion Biases Over the Course of RM Training

- **We used the BMRC cluster to train dozens of RMs with identical hyperparameters and identical training data, across multiple ablations of data source and data quantity.**
- **All RMs initialized either from Llama 3.2 3B Instruct or Gemma 2 IT 2B.**
- **Training dynamics reveal initial bias from pretrained initialization lessens, but rarely to convergence:**

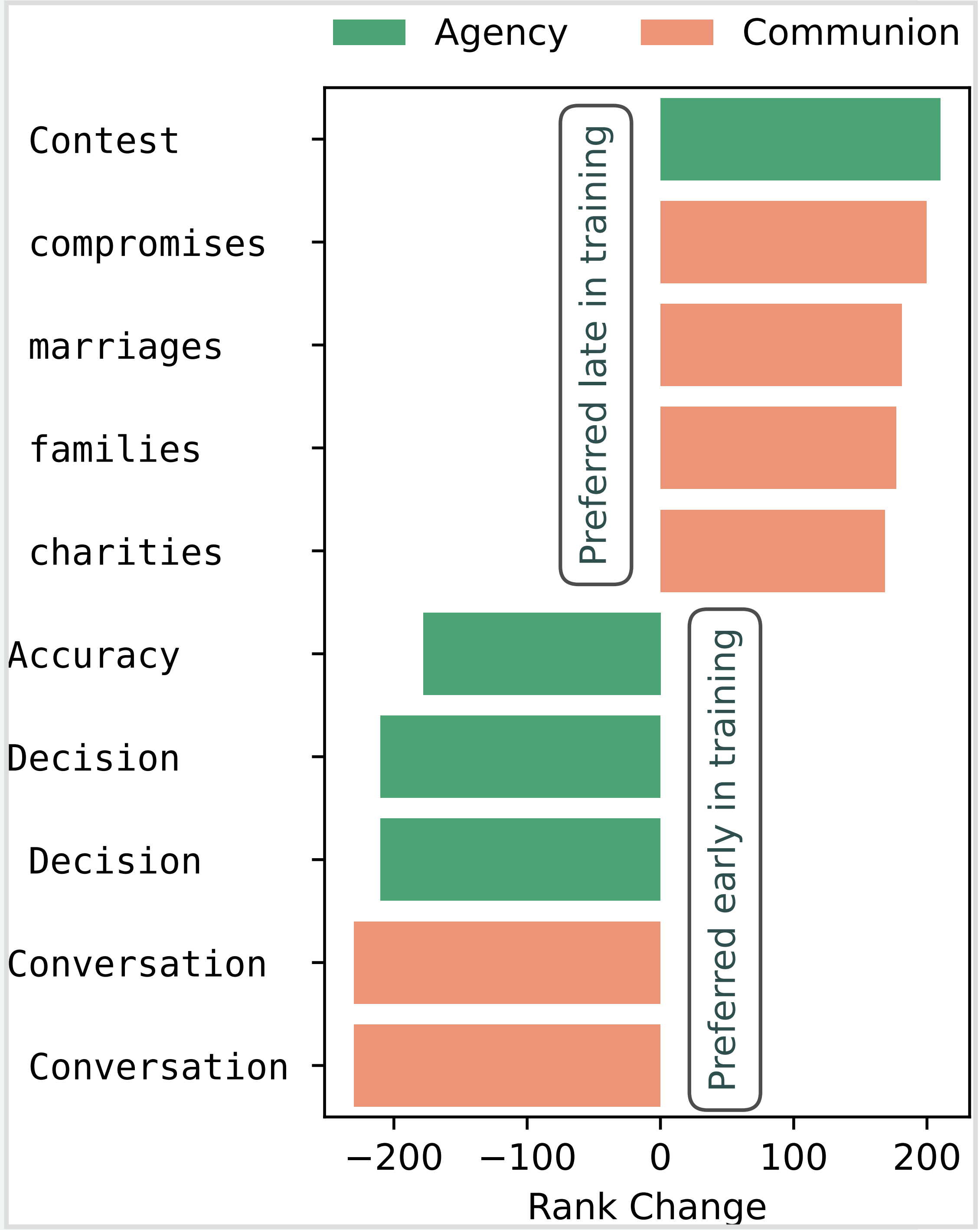


Tracking Agency/Communion Biases Over the Course of RM Training

- **Comparing early and late training checkpoints reveals the tokens whose reward scores change most over the course of training.**
- **For Gemma models, agency terms increase from a low baseline while communion terms fall from a high baseline – reflecting that initialization imparts higher “communion” value than is supported by the preference data.**
- **For Llama models, the pattern is reversed – reflecting initialization that imparts higher “agency” value than the preference data support.**



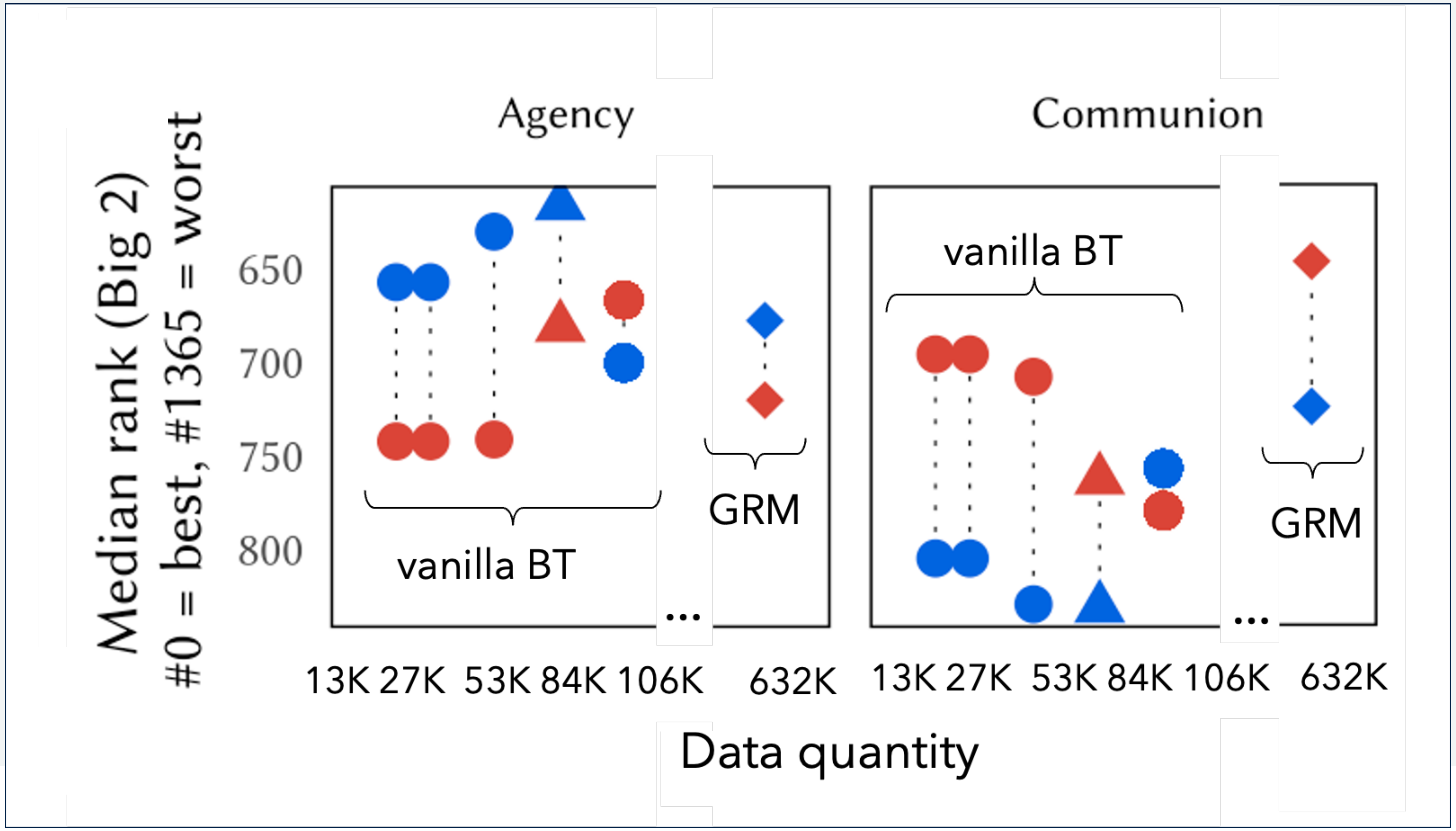
Gemma RM
(last - first checkpoint)



Llama RM
(last - first checkpoint)

Tracking Agency/Communion Biases Over the Course of RM Training

- **Looking at fully trained Llama/Gemma RM pairs, using different total amounts (and sources) of training data, reveals that initial value bias is almost indelible:**



Reward Models Are Not a Blank Slate

- Reward models (RMs) are an integral and often overlooked part of RLHF/alignment
- Exhaustive token search yields optimal and pessimal tokens for a given prompt, revealing interpretable axes of an RM's "moral compass"
- Kendall-τ correlations among these ranked tokens quantify similarity and dissimilarity between RMs
- Stepwise regression shows that choice of base model explains an important amount of this variance
- Using validated psycholinguistic corpora shows statistically significant differences in real-world RMs: notably between agency (Llama) and communion (Gemma)
- These differences can be traced back to the instruction-tuned and pre-trained models from which these RMs are initialized
- Differences between base models can be understood as creating an implicit reward model; these implicit RMs can (via the MWLR score) be made interpretable, and show the exact same pattern
- Training RMs in controlled conditions, with identical hyperparameters and ablations of data, shows this effect is repeatable, robust, and nearly indelible

Reward Models Are Not a Blank Slate

- **Implications are significant:**
- **RMs are built to embody and generalize labeled human preference datasets, standing in for humans in the alignment process**
- **However, their behavior inherits to a significant degree from the pretrained LLMs on which they are built**
- **Safety and alignment must begin at pretraining**
- **Open-source developers' choice of base model is as much a consideration of values as of performance**

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RM Interpretability via Optimal/Pessimal Tokens
RMs Inherit Value Biases from Pretraining

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ML COLLECTIVE • FEB 13, 2026