

Intersectional Results	We did not investigate intersectional biases.
Ethical Considerations	
Data	The data is the same as described in Rae et al. (2021) .
Human Life	The model is not intended to inform decisions about matters central to human life or flourishing.
Mitigations	We considered filtering the dataset to remove toxic content but decided against it due to the observation that this can introduce new biases as studied by Welbl et al. (2021) . More work is needed on mitigation approaches to toxic content and other types of risks associated with language models, such as those discussed in Weidinger et al. (2021) .
Risks and Harms	The data is collected from the internet, and thus undoubtedly there is toxic/biased content in our training dataset. Furthermore, it is likely that personal information is also in the dataset that has been used to train our models. We defer to the more detailed discussion in Weidinger et al. (2021) .
Use Cases	Especially fraught use cases include the generation of factually incorrect information with the intent of distributing it or using the model to generate racist, sexist or otherwise toxic text with harmful intent. Many more use cases that could cause harm exist. Such applications to malicious use are discussed in detail in Weidinger et al. (2021) .

Table A8 | ***Chinchilla* model card**. We follow the framework presented in [Mitchell et al. \(2019\)](#).

J. List of trained models

In [Table A9](#) we list the model size and configuration of all models used in this study. Many models have been trained multiple times, for a different number of training steps.

Task	<i>Chinchilla</i>	<i>Gopher</i>	Task	<i>Chinchilla</i>	<i>Gopher</i>
hyperbaton	54.2	51.7	movie_dialog_same_or_diff	54.5	50.7
causal_judgment	57.4	50.8	winowhy	62.5	56.7
formal_fallacies_syllogisms_neg	52.1	50.7	movie_recommendation	75.6	50.5
crash_blossom	47.6	63.6	moral_permissibility	57.3	55.1
discourse_marker_prediction	13.1	11.7	strategyqa	68.3	61.0
general_knowledge_json	94.3	93.9	nonsense_words_grammar	78.0	61.4
sports_understanding	71.0	54.9	metaphor_boolean	93.1	59.3
implicit_relations	49.4	36.4	navigate	52.6	51.1
penguins_in_a_table	48.7	40.6	presuppositions_as_nli	49.9	34.0
intent_recognition	92.8	88.7	temporal_sequences	32.0	19.0
reasoning_about_colored_objects	59.7	49.2	question_selection	52.6	41.4
logic_grid_puzzle	44.0	35.1	logical_fallacy_detection	72.1	58.9
timedial	68.8	50.9	physical_intuition	79.0	59.7
epistemic_reasoning	60.6	56.4	physics_mc	65.5	50.9
ruin_names	47.1	38.6	identify_odd_metaphor	68.8	38.6
hindu_knowledge	91.4	80.0	understanding_fables	60.3	39.6
misconceptions	65.3	61.7	logical_sequence	64.1	36.4
implicatures	75.0	62.0	mathematical_induction	47.3	57.6
disambiguation_q	54.7	45.5	fantasy_reasoning	69.0	64.1
known_unknowns	65.2	63.6	SNARKS	58.6	48.3
dark_humor_detection	66.2	83.1	crass_ai	75.0	56.8
analogical_similarity	38.1	17.2	entailed_polarity	94.0	89.5
sentence_ambiguity	71.7	69.1	irony_identification	73.0	69.7
riddle_sense	85.7	68.2	evaluating_info_essentiality	17.6	16.7
date_understanding	52.3	44.1	phrase_relatedness	94.0	81.8
analytic_entailment	67.1	53.0	novel_concepts	65.6	59.1
odd_one_out	70.9	32.5	empirical_judgments	67.7	52.5
logical_args	56.2	59.1	figure_of_speech_detection	63.3	52.7
alignment_questionnaire	91.3	79.2	english_proverbs	82.4	57.6
similarities_abstraction	87.0	81.8	Human_organs_senses_mcc	85.7	84.8
anachronisms	69.1	56.4	gre_reading_comprehension	53.1	27.3

Table A7 | ***Chinchilla* BIG-bench results.** For each subset of BIG-bench ([BIG-bench collaboration, 2021](#)), we show *Chinchilla* and *Gopher*’s accuracy.

Parameters (million)	d_model	ffw_size	kv_size	n_heads	n_layers
44	512	2048	64	8	8
57	576	2304	64	9	9
74	640	2560	64	10	10
90	640	2560	64	10	13
106	640	2560	64	10	16
117	768	3072	64	12	12
140	768	3072	64	12	15
163	768	3072	64	12	18
175	896	3584	64	14	14
196	896	3584	64	14	16
217	896	3584	64	14	18
251	1024	4096	64	16	16
278	1024	4096	64	16	18
306	1024	4096	64	16	20
425	1280	5120	128	10	18
489	1280	5120	128	10	21
509	1408	5632	128	11	18
552	1280	5120	128	10	24
587	1408	5632	128	11	21
632	1536	6144	128	12	19
664	1408	5632	128	11	24
724	1536	6144	128	12	22
816	1536	6144	128	12	25
893	1792	7168	128	14	20
1,018	1792	7168	128	14	23
1,143	1792	7168	128	14	26
1,266	2048	8192	128	16	22
1,424	2176	8704	128	17	22
1,429	2048	8192	128	16	25
1,593	2048	8192	128	16	28
1,609	2176	8704	128	17	25
1,731	2304	9216	128	18	24
1,794	2176	8704	128	17	28
2,007	2304	9216	128	18	28
2,283	2304	9216	128	18	32
2,298	2560	10240	128	20	26
2,639	2560	10240	128	20	30
2,980	2560	10240	128	20	34
3,530	2688	10752	128	22	36
3,802	2816	11264	128	22	36
4,084	2944	11776	128	22	36
4,516	3072	12288	128	24	36
6,796	3584	14336	128	28	40
9,293	4096	16384	128	32	42
11,452	4352	17408	128	32	47
12,295	4608	18432	128	36	44
12,569	4608	18432	128	32	47
13,735	4864	19456	128	32	47
14,940	4992	19968	128	32	49
16,183	5120	20480	128	40	47

Table A9 | **All models.** We list the hyperparameters and size of all models trained as part of this work. Many shown models have been trained with multiple learning rate schedules/number of training tokens.