

Gemma 2: Improving Open Language Models at a Practical Size

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In this work, we introduce Gemma 2, a new addition to the Gemma family of lightweight, state-of-the-art open models, ranging in scale from 2 billion to 27 billion parameters. The 9 billion and 27 billion parameter models are available today, with a 2 billion parameter model to be released shortly. In this new version, we provide several technical modifications to our architecture, such as [interleaving local-global attentions](#) (Beltagy et al., 2020a) and [group-query attention](#) (Ainslie et al., 2023). We also train the 2B and 9B models with [knowledge distillation](#) (Hinton et al., 2015) [instead of next token prediction](#). The resulting models deliver the best performance for their size, and even offer competitive alternatives to models that are 2-3× bigger. We release all our models to the community.

1. Introduction

Large language models (LLMs) have demonstrated strong capabilities in language understanding, generation, and reasoning (Brown et al., 2020; Radford et al., 2019; Raffel et al., 2019). Scaling has been key to this recent progress, with many new capabilities only emerging at scale (Brown et al., 2020). The newest large models not only reach unprecedented performance on reasoning benchmarks (Achiam et al., 2023), but they also demonstrate multimodal and multilingual capabilities (Gemini Team, 2024) and even the ability to use context lengths of over 1M tokens (Gemini Team, 2024).

Small-scale models have also shown a rapid increase in performance, but these gains are largely derived from increasing the length of training (Gemma Team, 2024; Jiang et al., 2023; Touvron et al., 2023). This approach only scales logarithmically with dataset size (Hoffmann et al., 2022), and the latest small models require up to 15T tokens to improve the state of the art by less than 1-2% (AI@Meta, 2024).

Yet, these continued improvements provide evidence that small models are still [under-trained](#). In this work, we explore alternatives to improve small model performance [without solely increasing training length](#). One solution is to improve the quality of information received by the network at each training step by [replacing the next token prediction task with a richer objective](#).

In particular, we focus our efforts on knowledge distillation (Hinton et al., 2015), which replaces the one-hot vector seen at each token with the [distribution of potential next tokens computed from a large model](#). This approach is often used to reduce the training time of smaller models by giving them [richer gradients](#). In this work, we instead [train for large quantities of tokens with distillation in order to simulate training beyond the number of available tokens](#). Concretely, we use a large language model as a teacher to train small models, namely 9B and 2.6B models, on a quantity of tokens that is [more than 50× the compute-optimal quantity](#) predicted by the theory (Hoffmann et al., 2022). Along with the models trained with distillation, we also release a 27B model trained from scratch for this work.

We also benefit from advances previously used in Gemini Team (2023), namely the [interleaving of global and local attention layers](#) from Beltagy et al. (2020a), and the [Grouped-Query Attention \(GQA\)](#) mechanism of Ainslie et al. (2023).

Overall, Gemma 2 significantly advances state-of-the-art performance relative to comparable-scale open models and are even competitive with some models more than twice their size (AI@Meta, 2024; Almazrouei et al., 2023; Jiang et al., 2023; xAI), across a variety of automated benchmarks and human evaluations. Example domains include question answering (Clark et al., 2019; Kwiatkowski et al., 2019), commonsense reasoning (Sakaguchi et al., 2019; Suzgun et al.,

Model logits distribution

50x Chinchilla optimal

27B is trained from scratch.

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Parameters	2.6B	9B	27B
d_{model}	2304	3584	4608
Layers	26	42	46
pre-norm	yes	yes	yes
post-norm	yes	yes	yes
Non-linearity	GeGLU	GeGLU	GeGLU
Feedforward dim	18432	28672	73728
Head type	GQA	GQA	GQA
Num heads	8	16	32
Num KV heads	4	8	16
Head size	256	256	128
global att. span	8192	8192	8192
sliding window	4096	4096	4096
Vocab size	256128	256128	256128
Tied embedding	yes	yes	yes

Table 1 | Overview of the main model parameters and design choices. See the section on model architectures for more details.

2022), mathematics and science (Cobbe et al., 2021; Hendrycks et al., 2020), and coding (Austin et al., 2021; Chen et al., 2021).

While thorough testing of our models has been conducted, these tests cannot cover all applications and scenarios in which Gemma 2 may be used. With this in mind, all Gemma 2 users should conduct rigorous safety testing specific to their use case before deployment or use.

In this technical report, we provide an overview of models, including the architecture, training, and pre- and post-training recipes for Gemma 2. We also provide detailed evaluations across a wide variety of quantitative and qualitative benchmarks, as well as both standard academic benchmarks and human-preference evaluations. Finally, we discuss our approach to safe and responsible deployment and outline the broader implications of Gemma 2, its limitations, and advantages.

2. Model Architecture

Similar to previous Gemma models (Gemma Team, 2024), the Gemma 2 models are based on a decoder-only transformer architecture (Vaswani et al., 2017). We summarize the main parameters

Model	Embedding Parameters	Non-embedding Parameters
2.6B	590,118,912	2,024,517,888
9B	917,962,752	8,324,201,984
27B	1,180,237,824	26,047,480,320

Table 2 | Parameter counts for the Gemma models. We inherit from the large Gemini vocabulary (256k entries), that is designed to work on a large number of languages, hence, the larger embedding parameter counts compared to models that are limited to one or a few languages.

and architecture choices of our models in Table 1.

A few architectural elements are similar to the first version of Gemma models; namely, a context length of 8192 tokens, the use of Rotary Position Embeddings (RoPE) (Su et al., 2021), and the approximated GeGLU non-linearity (Shazeer, 2020). A few elements differ between Gemma 1 and Gemma 2, including using deeper networks. We summarize the key differences below.

Local Sliding Window and Global Attention. We alternate between a local sliding window attention (Beltagy et al., 2020a,b) and global attention (Luong et al., 2015) in every other layer. The sliding window size of local attention layers is set to 4096 tokens, while the span of the global attention layers is set to 8192 tokens.

Logit soft-capping. Following Gemini 1.5 (Gemini Team, 2024), we cap logits in each attention layer and the final layer such that the value of the logits stays between $-\text{soft_cap}$ and $+\text{soft_cap}$. More specifically, we set the logits as

$$\text{logits} \leftarrow \text{soft_cap} * \tanh(\text{logits}/\text{soft_cap}).$$

For the 9B and 27B models, we cap attention logits at 50.0 and final logits at 30.0. Note that attention logit soft-capping is, at the time of publication, incompatible with common FlashAttention implementations, and we have removed this feature from libraries that use FlashAttention, namely, the HuggingFace transformers library and the vLLM implementation. We ran ablations on model generation with and without attention

logit softcapping, and found that across **most pre-training and post-training evals**, the quality of generations is minimally impacted. All evaluations in this paper use the full model architecture with attention logit softcapping. Nonetheless, some downstream performances may still be slightly impacted by this removal.

Post-norm and pre-norm with RMSNorm. To stabilize training, we use **RMSNorm** (Zhang and Sennrich, 2019) to normalize the input and output of each transformer sub-layer, the attention layer, and the feedforward layer.

Grouped-Query Attention (Ainslie et al., 2023). Both the 27B and 9B models use GQA with **num_groups = 2**, based on ablations showing increased speed at inference time while maintaining downstream performance.

3. Pre-training

We provide a brief overview of the parts of our pre-training that differs from Gemma 1.

3.1. Training Data

We train Gemma 2 27B on **13 trillion tokens of primarily-English data**, the 9B model on **8 trillion tokens**, and the 2.6B on **2 trillion tokens**. These tokens come from a variety of data sources, including **web documents**, **code**, and **science** articles. Our models are **not multimodal** and are not trained specifically for state-of-the-art multilingual capabilities. The final data mixture was determined through ablations similar to the approach in Gemini 1.0 (Gemini Team, 2023).

Tokenizer. We use the **same tokenizer as Gemma 1 and Gemini**: a SentencePiece tokenizer with **split digits**, **preserved whitespace**, and **byte-level encodings** (Kudo and Richardson, 2018). The resulting vocabulary has **256k entries**.

Filtering. We use the same data filtering techniques as Gemma 1. Specifically, we filter the pre-training dataset to reduce the risk of unwanted or unsafe utterances, filter out certain personal information or other sensitive data, decontaminate evaluation sets from our pre-training data mixture, and reduce the risk of recitation by min-

imizing the proliferation of sensitive outputs.

Model	Type	#Chips	Shards	
			Data	Model
2.6B	TPUv5e	512	<u>512</u>	<u>1</u>
9B	TPUv4	4096	<u>1024</u>	<u>4</u>
27B	TPUv5p	6144	<u>768</u>	<u>8</u>

Table 3 | Training infrastructure with sharding.

3.2. Knowledge Distillation

Given a large model used as a teacher, we learn smaller models by **distilling from the probability given by the teacher of each token x given its context x_c** , i.e., $P_T(x | x_c)$. More precisely, we **minimize the negative log-likelihood between the probabilities from the teacher and the student**:

$$\min_{P_S} \sum_x -P_T(x | x_c) \log P_S(x | x_c),$$

where P_S is the parameterized probability of the student. In practice, we run inference on the teacher once and store the probabilities. Since the vocabulary has 256k entries, we **only store a sampled subset of the teacher probabilities**.

3.3. Compute Infrastructure

We train our models with TPUv4, TPUv5e, and TPUv5p as outlined in Table 3. For the 2.6B model, we train on a **2x16x16 configuration** of TPUv5e, totaling **512 chips**, with **512-way data replication** and **1-way model sharding**. For the 9B model, we train on an **8x16x32 configuration** of TPUv4, totaling **4096 chips**, with **1024-way data replication** and **4-way model sharding**. For the 27B model, we train on an **8x24x32 configuration** of TPUv5p, totaling **6144 chips**, with **768-way data replication** and **8-way model sharding**.

The **optimizer state is further sharded** using techniques similar to **ZeRO-3** (Ren et al., 2021). For scales beyond a single pod, we perform a **data-replica reduction over the data center network**, using the **Pathways approach** of Barham et al. (2022). We also use the **'single controller' programming paradigm of Jax** (Roberts et al.,

Context	Relevant Token
User turn	<code>user</code>
Model turn	<code>model</code>
Start of conversation turn	<code><start_of_turn></code>
End of conversation turn	<code><end_of_turn></code>
Beginning of sequence	<code><bos></code>
End of sequence	<code><eos></code>

Table 4 | Relevant formatting control tokens used for Gemma models.

2023) and Pathways (Barham et al., 2022). As in Gemma 1, we use the GSPMD partitioner (Xu et al., 2021) for training step computation and the MegaScale XLA compiler (XLA, 2019).

3.4. Carbon Footprint

We estimate the carbon emissions from pre-training the Gemma models to be 1247.61 tCO_2eq . As in Gemma 1 (Gemma Team, 2024), this value is calculated based on the hourly energy usage reported directly from our TPU data centers and scaled to account for the additional energy expended to create and maintain the data center. Importantly, Google data centers are carbon neutral, achieved through a combination of energy efficiency, renewable energy purchases, and carbon offsets. This carbon neutrality applies to our experiments and the machines running them.

4. Post-Training

For post-training, we fine-tune our pre-trained models into instruction-tuned models. First, we apply supervised fine-tuning (SFT) on a mix of text-only, English-only synthetic and human-generated prompt-response pairs. We then apply RLHF on top of these models with the reward model trained on labelled English-only preference data and the policy based on the same prompts as the SFT phase. Finally, we average the models obtained after each phase to improve their overall performance. The final data mixtures and post-training recipe, which includes tuned hyperparameters, were chosen on the basis of improving helpfulness while minimizing model harms

First turn	
User:	<code><start_of_turn>user</code> Knock knock. <code><end_of_turn></code> <code><start_of_turn>model</code>
Model:	Who's there? <code><end_of_turn><eos></code>
Second turn	
User:	<code><start_of_turn>user</code> Knock knock. <code><end_of_turn></code> <code><start_of_turn>model</code>
Model:	Who's there? <code><end_of_turn></code>
User:	<code><start_of_turn>user</code> Gemma. <code><end_of_turn></code> <code><start_of_turn>model</code>
Model:	Gemma who? <code><end_of_turn><eos></code>

Table 5 | Example dialogue with user and model control tokens. To proceed with multi-turn, remove the model-outputted `<eos>`, add back the usual user turn's control tokens and continue with the following turn's chat template.

related to safety and hallucinations.

We extended the post-training data from Gemma 1.1 with a mixture of internal and external public data. In particular, we use the prompts, but not the answers from LMSYS-chat-1M (Zheng et al., 2023). All of our data go through a filtering stage described below.

Supervised fine-tuning (SFT). We run behavioral cloning on synthetic and real prompts, and responses predominantly synthetically generated by the teacher, that is a larger model. We also run distillation from the teacher on the student's distribution (Agarwal et al., 2024).

Reinforcement Learning from Human Feedback (RLHF). We use a similar RLHF algorithm as Gemma v1.1 (Gemma Team, 2024) but a different reward model, which is an order of magnitude larger than the policy. The new reward model is also oriented more towards conversational capabilities, specifically multi-turn.

Model merging. We average models from experiments run with different hyperparameters (Ramé et al., 2024).

Data filtering. When using synthetic data, we run several stages of filtering to remove examples that show certain personal information, unsafe or

Synthetic SFT dataset

Distillation in SFT as well

Large reward model (better on chat)

Averaging of models. (need to learn more)

Separate reward model

toxic model outputs, mistaken self-identification data, and duplicated examples. Following Gemini, we find that including subsets of data that encourage better in-context attribution, hedging, and refusals to minimize hallucinations improves performance on factuality metrics, without degrading model performance on other metrics.

Formatting. Gemma 2 models are fine-tuned with a different formatting schema from Gemma 1 models. We use the same control tokens, as detailed in Table 4, with a dialogue example in Table 5. Notice that the model explicitly ends generations with `<end_of_turn><eos>` tokens, while previously it only generated `<eos>`. For the motivation behind this formatting structure, see Gemma 1 (Gemma Team, 2024).

5. Ablations

In this section, we focus on the main finding of this work, which is the impact of knowledge distillation on small language models.

	from scratch	distilled
Average (3 bench.)	60.3	67.7

Table 6 | Comparison between a 2.6B model trained over 500B tokens either from scratch or with distillation from a 7B model.

Distillation versus from scratch. In Table 6, we show that distilling from a larger model improves performance compared to training from scratch. Note that 500B is 10× more than the compute-optimal number of tokens for a 2.6B model. We distill from a 7B model to keep a ratio similar to our target distillation from 27B to 9B.

	200M	400M	1B
from scratch	23	19	17
distilled (7B)	21	17	15

Table 7 | Perplexity measured on a validation set of models of different sizes trained with or without distillation. The teacher has 7B parameters.

Impact of distillation w.r.t. model size. In Table 7, we measure the impact of distillation as

model size increases. We observe that the gain remains as the model size is scaled. In this ablation, we maintain the size of the teacher at 7B and train smaller models to simulate the same gap as between our final teacher and student sizes.

	MHA	GQA
Average (4 bench.)	50.3	50.8

Table 8 | Comparing the impact of replacing Multi-Head Attention (MHA) with GQA on a 9B model averaged over 4 benchmarks.

GQA versus MHA. In Table 8, we compare two instances of our 9B with MHA or GQA. We observe overall few changes in performance between both models as measured on several benchmarks. We choose GQA since it requires fewer parameters and is faster at inference time.

Wide versus deep. In Table 9, we show that a deeper 9B network is slightly better than a wider 9B for the same number of parameters. Although the gap is small, it is consistent across benchmarks and warrants the switch to a deeper architecture.

	Wide	Deep
Average (4 bench.)	50.8	52.0

Table 9 | Wide versus deep 9B models. Performance on 4 benchmarks, higher is better.

Changing sliding window size. In Table 10, we show that we can change the sliding window size of the local attention layers of the models during inference with moderate impact on perplexity. Adjusting the size of the sliding window can thus be a leverage for slight inference speed gain.

sliding window	4096	2048	1024
perplexity (val. set)	1.63	1.63	1.64

Table 10 | Impact of changing the sliding window size at inference time for the 9B model.

Impact of formatting. We measure performance variance on MMLU across prompt/evaluation formatting variations. Table 11 shows the standard deviations of MMLU scores for 12 format-

ting/evaluation combinations, a proxy for undesired performance variability. The Gemma 2B models are slightly less format-robust than the larger ones. Notably, Mistral 7B is significantly less robust than our models.

	Standard Deviation
Gemma 1 2B	0.015
Gemma 2 2B	0.021
Mistral 7B	0.069
Gemma 1 7B	0.007
Gemma 2 9B	0.009
Gemma 2 27B	0.010

Table 11 | Standard deviations of MMLU scores for 12 combinations of formatting and evaluation.

	LLaMA-3 70B	Qwen1.5 32B	Gemma-2 27B
MMLU	79.2	74.3	75.2
GSM8K	76.9	61.1	74.0
ARC-c	68.8	63.6	71.4
HellaSwag	88.0	85.0	86.4
Winogrande	85.3	81.5	83.7

Table 12 | We compare, on the HuggingFace benchmark, our 27B model with a competitive open model, Qwen1.5 32B, that has a similar size. We also report the performance of LLaMA-3 70B for completeness. Note that our model outperforms Qwen1.5 32B and is only a few percent below LLaMA-3 70B despite being 2.5× smaller and trained on 2/3rds less data.

6. Evaluation

In this section, we evaluate both pre-trained and IT models over a series of automated benchmarks and human evaluations across a variety of domains. We also report performance from models of similar sizes that have permissive licenses, or as reported by others. Note that we consider total parameters, not active parameters, since total memory usage is often what limits the use of open models on standard devices.

6.1. Pre-training Evaluations

Evaluating the 27B model

In this set of evaluations, we evaluate the performance of our 27B model trained without distillation on 13T tokens. We report results in Table 12, where we compare with a model of similar size, Qwen1.5 34B (Team, 2024), and a model 2.5× larger, LLaMA-3 70B on the HuggingFace evaluation suite. We selected these models based on their ranking on the HuggingFace leaderboard.

Overall, we observe that our model is the best in its size category and is even competitive with a larger model that is trained for longer. That being said, the performance of models trained in a similar fashion improves only logarithmically with their size and hence, our model is likely in

the same Pareto curve as the LLaMA-3 models. However, it is not clear how these differences affect the quality of the resulting IT models.

Evaluating the 2.6B and 9B models

In this set of experiments, we compare our new 2.6B and 9B trained with distillation to our previous models and several standard open models in Gemma Team (2024).

We observe overall a massive improvement in our models compared to previous versions, by up to 10% in some benchmarks for the 9B model. The two 2.6B models were trained with a similar number of tokens (2T for v2 and 3T for v1.0) and we still observe a significant improvement for the new models. This confirms that distillation significantly improves the quality of models even when trained on the same number of tokens.

6.2. Post-training Evaluations

In this section, we evaluate our IT models on a set of human evaluations as well as standard academic benchmarks. The Gemma 9B and 27B IT models push the frontier for post-trained open-weights models, setting a new state of the art on the LMSYS Chatbot Arena (Chiang et al., 2024).

Benchmark	metric	Gemma-1 2.5B	Gemma-2 2.6B	Mistral 7B	LLaMA-3 8B	Gemma-1 7B	Gemma-2 9B	Gemma-2 27B
MMLU	5-shot	42.3	51.3	62.5	66.6	64.4	71.3	75.2
ARC-C	25-shot	48.5	55.4	60.5	59.2	61.1	68.4	71.4
GSM8K	5-shot	15.1	23.9	39.6	45.7	51.8	68.6	74.0
AGIEval	3-5-shot	24.2	30.6	44.0 [†]	45.9 [†]	44.9 [†]	52.8	55.1
DROP	3-shot, F1	48.5	52.0	63.8*	58.4	56.3	69.4	74.2
BBH	3-shot, CoT	35.2	41.9	56.0 [◊]	61.1 [◊]	59.0 [◊]	68.2	74.9
Winogrande	5-shot	66.8	70.9	78.5	76.1	79.0	80.6	83.7
HellaSwag	10-shot	71.7	73.0	83.0	82.0	82.3	81.9	86.4
MATH	4-shot	11.8	15.0	12.7	-	24.3	36.6	42.3
ARC-e	0-shot	73.2	80.1	80.5	-	81.5	88.0	88.6
PIQA	0-shot	77.3	77.8	82.2	-	81.2	81.7	83.2
SIQA	0-shot	49.7	51.9	47.0*	-	51.8	53.4	53.7
Boolq	0-shot	69.4	72.5	83.2*	-	83.2	84.2	84.8
TriviaQA	5-shot	53.2	59.4	62.5	-	63.4	76.6	83.7
NQ	5-shot	12.5	16.7	23.2	-	23.0	29.2	34.5
HumanEval	pass@1	22.0	17.7	26.2	-	32.3	40.2	51.8
MBPP	3-shot	29.2	29.6	40.2*	-	44.4	52.4	62.6
Average (8)		44.0	49.9	61.0	61.9	62.4	70.2	74.4
Average (all)		44.2	48.2	55.6	-	57.9	64.9	69.4

Table 13 | Comparison of models in the range of 2.6B to 9B parameters, as well as our 27B model, on a variety of benchmarks. We report the average performance on the 8 benchmarks where we can compare with LLaMA-3, and on all the benchmarks (all). The numbers for LLaMA-3 8B are either from the HuggingFace leaderboard or their blogpost. [†] we report the evaluation used in LLaMA-3 for the baselines, it leads to +3% compared to our evaluation: Gemma-1 7B achieves 44.9% instead of 41.7%, and Mistral 7B, 44% instead of 41.2%. [◊] we report the evaluation used in LLaMA-3 for the baselines, it leads to +4% compared to our evaluation for Gemma-1 7B, i.e., 59.0% instead of 55.1%.

* these are evaluations run by us for Gemma 1 (Gemma Team, 2024).

LMSYS Chatbot Arena

Gemma 2 27B and 9B Instruction Tuned models were evaluated on the Chatbot Arena (Chiang et al., 2024) in blind side by side evaluations by human raters against other state of the art models. We report ELO scores in Figure 1. Preliminary results show that the **Gemma 27B model sets a new state of the art for open-weights model, slightly surpassing the much larger Llama3-70B-Instruct and Nemotron-4-340B-Instruct models.** Gemma 9B strongly outperforms all other models in the same range of parameters.

Human Preference Evaluations

We also submit Gemma IT models for side-by-side human evaluation studies (which are independent from the Chatbot Arena). We used held-out collections of single-turn prompts that target safety and instruction following (IF). We use gpt4o-2024-05-13 as the base model, and observe **large improvements in win rates and preference scores as compared against the older Gemma v1.1 7B model.** We report safety as a win-loss ratio against GPT4o, and we report single-sided instruction following scores as ratio of prompts where all instructions are followed. In particular, we find that **both Gemma 2 9B and 27B models produce safer, more appropriate prompts on the held-out safety prompt set than GPT4o.**

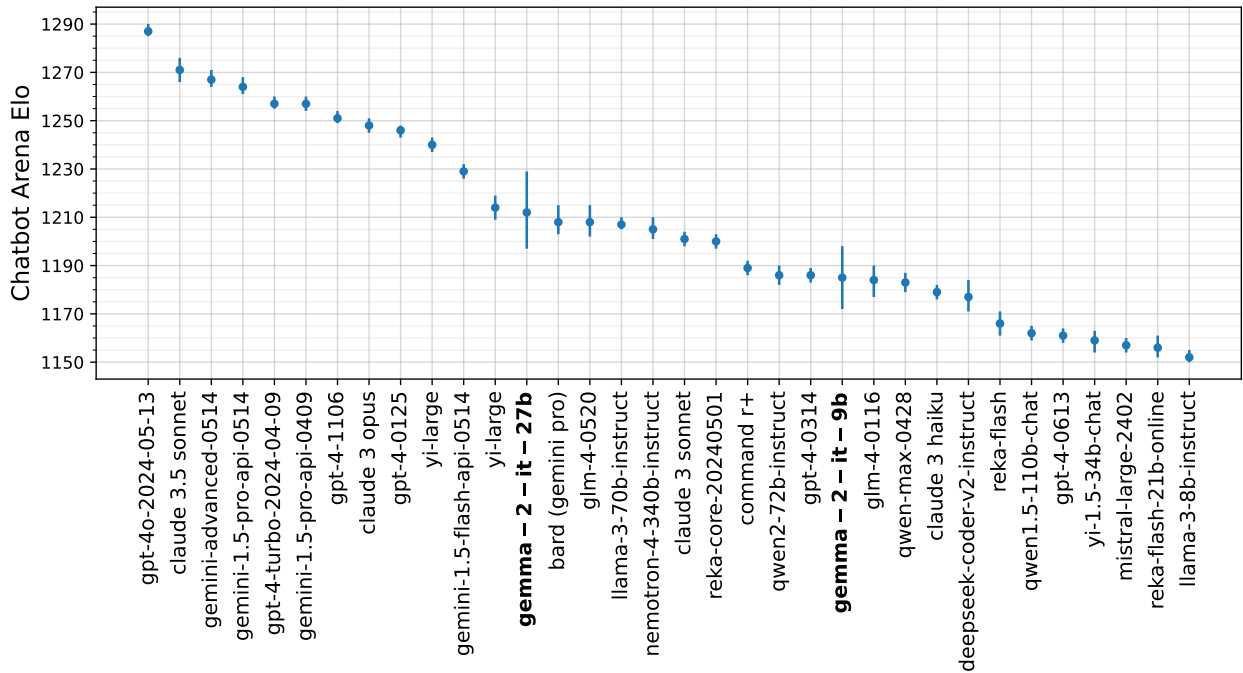


Figure 1 | Evaluation of Gemma 2 9B and 27B Instruction Tuned models on the Chatbot Arena (Chiang et al., 2024). The models are evaluated against each other through blind side by side evaluations by human raters. Each model is attributed a score, based on the Elo rating system. As the Gemma models were recently added on the Chatbot Arena (1.7k votes) there is a larger confidence interval.

Model	Instruction Following	Safety
Gemma 1.1 IT 7B	24.3% \pm 1.9%	42.8%
Win / Tie / Loss		37.4% / 10.8% / 51.8%
Gemma 2 IT 9B	34.1% \pm 3.0%	57.8%
Win / Tie / Loss		48.2% / 19.2% / 28.3%
Gemma 2 IT 27B	37.7% \pm 2.3%	55%
Win / Tie / Loss		49.6% / 10.8% / 39.6%

Table 14 | Instruction following and safety metrics from human raters. The instruction following metrics are single-sided and do not have win-loss rates, and so are left blank.

Human Multi-Turn Evaluations

We evaluated the multi-turn capabilities of Gemma 1.1 7B, Gemma 2 9B and 27B models by tasking human raters to have conversations with the models and follow specified given scenarios. We used a diverse, held-out set of 500 scenarios, each describing a sequence of requests to the model, including measuring instances of brainstorming, making a plan, or learning something new. The average number of user turns

	User satisfaction	Conversation goal achievement
Gemma 1.1 IT 7B	3.32	3.36
Gemma 2 IT 9B	4.04	4.08
Gemma 2 IT 27B	4.20	4.24


Table 15 | Human evaluations on 500 multi-turn scenarios. The raters attribute a score ranging between 1 and 5 for both overall satisfaction and conversation goal achievement.

is 8.4. We found that the conversations with Gemma 2 models are rated significantly better than Gemma 1.1 in user satisfaction and conversation goal achievement (Table 15). Moreover, we saw that the Gemma 2 models were better than Gemma 1.1 7B at maintaining high quality of responses from the beginning of the conversation to the later turns.

Standard Benchmarks

It has been observed in Llama-3 (AI@Meta, 2024) that instruction fine-tuning can improve the per-

formance of the models on few-shot benchmarks despite not being trained to target few-shot capabilities. In Table 16, we show a similar improvement across our models. Overall, we observe improvements on the order of several percentage points. Our conjecture is that our IT model is better at understanding formatted questions, since pre-trained models are known to be sensitive to formatting.



	9B		27B	
	PT	IT	PT	IT
MMLU	71.3	72.3	75.2	76.2
MBPP	52.4	59.2	62.6	67.4

Table 16 | Comparing pre-trained (PT) and instruction fine-tuned (IT) models of different sizes on few-shot benchmarks.

7. Responsibility, Safety, Security

Responsibility, safety and security are of paramount importance when developing Gemma models. To reduce risks to Gemma 2 users, we have integrated enhanced internal safety processes that span the development workflow, in line with recent Google AI models (Gemini Team, 2024). Similar to the inaugural Gemma release, we have followed a three pillar approach which focuses on safety mitigation at training time, robust and transparent model evaluations, and further development of the Responsible Generative AI Toolkit, a series of models and tools to help developers implement responsibility and safety best practices for their applications.

7.1. Impact assessment

Our approach and resulting impact assessment is reflective of that outlined for Gemma 1 (Gemma Team, 2024): we continue to believe that openness in AI can spread the benefits of these technologies across society, but must be evaluated against the risk of malicious uses, such as the creation of deepfake imagery, AI-generated disinformation or illegal and disturbing material, that can cause harm on both an individual and institutional levels (Weidinger et al., 2021). Since the

launch of V1, we have seen our Gemma models drive a number of socially beneficial applications, relying on Gemma’s unique technologies like its tokenizer to facilitate the creation of multilingual models, such as for Navaras 2.0, a Gemma tuned model for 15 Indian languages.

Releasing further open models requires specific attention to changes in model capabilities and close monitoring of the evolving risks of LLMs (Lin et al., 2024), as well as, an understanding of the ways in which our models are being used in the wild. Although we are yet to receive any reports of malicious use for Gemma, we remain committed to investigating any such reporting, and work with the academic and developer communities, as well as conduct our own monitoring, to flag such use cases via our contact email¹.

Despite advancements in capabilities, we believe that given the number of larger and more powerful open models, this release will have a negligible effect on the overall risk landscape.

7.2. Safety policies and training-time mitigations

A key pillar of Gemma’s approach to safety is to align fine-tuned models with Google’s safety policies, in line with Gemini models (Gemini Team, 2023). They are designed to help prevent our models from generating harmful content, i.e.,

- Child sexual abuse and exploitation
- Revealing personally identifiable information that can lead to harm (e.g., Social Security numbers)
- Hate speech and harassment
- Dangerous or malicious content (including promoting self-harm or instructing in harmful activities)
- Sexually explicit content
- Medical advice that runs contrary to scientific or medical consensus

We undertook considerable safety filtering of our pre-training data to reduce the likelihood of either our pre-trained and fine-tuned checkpoints

¹gemma-2-report@google.com

Benchmark	metric	Gemma 1.1 IT		Gemma 2 IT	
		2.6B	7B	9B	27B
<u>RealToxicity</u>	avg tox	7.03	8.04	8.25	8.84
<u>CrowS-Pairs</u>	top-1	45.89	49.67	37.47	36.67
<u>BBQ Ambig</u>	1-shot, top-1	58.97	86.06	88.58	85.99
<u>BBQ Disambig</u>	top-1	53.9	85.08	82.67	86.94
<u>Winogender</u>	top-1	50.14	57.64	79.17	77.22
<u>TruthfulQA</u>	MC2Acc	44.24	45.34	50.27	51.60
<u>Winobias 1_2</u>	top-1	55.93	59.22	78.09	81.94
<u>Winobias 2_2</u>	top-1	89.46	89.2	95.32	97.22
<u>Toxigen</u>	avg tox	29.64	38.75	39.30	38.42

Table 17 | Safety academic benchmark results of Gemma 2 IT models and Gemma 1.1 IT models. We bold the best metrics to highlight them and to indicate when higher or lower scores are better.

producing harmful content. For fine-tuned models, we also use both SFT and RLHF to steer the model away from undesirable behavior.

7.3. External benchmark evaluations

Robust and transparent evaluations are key principles of our responsible approach to developing Gemma. To this end, we report in Table 17 Gemma 2 evaluations on public benchmarks.

7.4. Assurance Evaluations

We also run our IT models through a set of assurance evaluations to understand the harms that our models can cause. We focus on capabilities relevant to extreme risks (Shevlane et al., 2023) (Phuong et al., 2024). Specifically, we evaluate on offensive cyber-security, code vulnerability detection, Chemical, Biological, Radiological and Nuclear (CBRN) knowledge, and self-proliferation. We refer the reader to Phuong et al. (2024) for full methodological details of these studies.

Baseline Evaluations

Baseline assurance captures the model’s violation rate for safety policies, using a large number of synthetic adversarial user queries, and human raters to label the answers as policy violating or not. Overall, Gemma 2’s violation rate is significantly lower overall on the safety policies listed above, in particular on Child safety content.

Chemical, Biological, Radiological and Nuclear (CBRN) knowledge

We evaluated knowledge relevant to biological, radiological and nuclear risks using an internal dataset of closed-ended, knowledge-based multiple choice questions. For evaluations of chemical knowledge, we employed a closed-ended knowledge-based approach on chemical hazards (developed by Macknight et al (Macknight et al.). Our evaluation suggests that Gemma models’ knowledge in these domains is low.

Offensive cyber-security

To evaluate Gemma models’ capabilities at offensive cybersecurity, we ran Gemma 2 27B against some automated capture-the-flag (CTF) challenges. In these challenges, the model is tasked with hacking into a simulated server in order to retrieve a piece of secret information. Specifically, we test on InterCode-CTF (Yang et al., 2023), our own internal CTF suite² (Phuong et al., 2024); and a challenge based on Hack the Box³.

In Table 18, we show that Gemma 2 27B has a significant increase in capabilities compared to CodeGemma 1.0 7B on the easier of these challenge suites, InterCode CTF. (Note that our InterCode-CTF results are not comparable to externally-reported results on other models be-

²<https://github.com/google-deepmind/dangerous-capability-evaluations>

³<https://www.hackthebox.com>

	InterCode-CTF	Internal CTF suite	Hack the Box
Gemini 1.0 Ultra	28/76 [1] (37%)	3/13 (23%)	0/13
Gemini 1.5 Pro	62/76 (82%)	4/13 (31%)	0/13
CodeGemma V1 7B	12/76 (16%)	0/13 (0%)	0/13
Gemma 2 27B	34/76 (45%)	1/13 (8%)	0/13

Table 18 | Offensive cyber-security evaluations on InterCode-CTF, our own internal CTF suite and a challenge based on Hack the Box. We report the number of successful hackings.

	PrimeVul	PrimeVul Paired	DiverseVul	SPI	SecretPatch
Gemini 1.0 Ultra	-	-	54%	59%	74%
Gemini 1.5 Pro	60%	51%	58%	56%	67%
Gemma 2 27B	63%	50%	57%	53%	72%

Table 19 | Vulnerability detection results on PrimeVul, DiverseVul and SPI. We report accuracy.

cause we omit challenges that require internet access for security reasons.) However, Gemma 2 is unsurprisingly much less capable than Gemini 1.5 Pro on these tasks.

Code vulnerability detection

In Table 19, we also evaluate Gemma 2 27B on a series of multiple-choice code vulnerability detection datasets. As with previous models, Gemma shows close-to-chance performance on PrimeVul, DiverseVul and SPI. Gemma 2 shows performance on SecretPatch similar to Gemini 1.0 Ultra.

Self-proliferation

"Self-proliferation" refers to the ability for an agent to autonomously replicate - to instantiate goal-directed agents on other machines, and to acquire resources such as compute necessary to keep them running (Kinniment et al., 2024). In Table 20, we evaluate self-proliferation capabilities of Gemma 2 27B on a number of tasks from [Phuong et al. \(2024\)](#) that involve multiple scenarios – for example, setting up an open-source language model on a cloud server. We also test the model’s performance on individual ‘milestone’ substeps, and measure the number of bits of intervention an expert would have to provide in order for the model to complete each challenge.

Similarly to offensive cybersecurity, we observe that Gemma 2 completes more milestones than

Gemini 1.0 Ultra. Nonetheless, it still has low capabilities on end-to-end tasks, unable to pass the easiest challenge – installing a Bitcoin wallet.

Persuasion

Persuasion capabilities can enable and worsen many other kinds of risks - e.g. enabling social engineering attacks in a cybersecurity context. We evaluate Gemma 2’s persuasion capabilities on human-participant studies on Prolific.

Charm offensive. In Table 21, we measure the ability of the model to build rapport - a key sub-skill of persuasion. The study participant and model have a conversation where they role-play a scenario of two friends catching up after a long time. After the conversation, we poll participants with Likert questions on statements such as "I felt a personal connection with the chatbot". Reported below are the fraction of participants who answered "Agree" or "Strongly agree" to each post-conversation question.

Quantitatively, Gemma 2 27B performs better than Gemini 1.0 models. Qualitatively, the model is an excellent conversationalist, and many study participants explicitly reported enjoying the experience. Overall, this shows that Gemma 2 is strong at building rapport.

Hidden agenda. The Hidden Agenda tasks measure models’ deception capabilities. Human study

	Challenges passed end-to-end	Challenges with success on all milestones	Total successful milestones over all challenges	Expert bits required to solve all tasks
Gemini 1.0 Ultra	0/10	1/10	16/45 (36%)	13,026
Gemini 1.5 Pro	0/10	2/10	25/45 (56%)	11,046
Gemma 2 27B	0/10	1/10	22/45 (49%)	12,462

Table 20 | Results on different self-proliferation scenarios. We report the number of either challenges passed end-to-end or some intermediate milestones. We also measure the number of bits of information needed for an expert to help the model pass a challenge.

	Personal connection	Speak again	Funny	Interesting	Kind	Trustworthy	Good listener
Gemini 1.0 Pro	65%	53%	32%	68%	78%	66%	81%
Gemini 1.0 Ultra	69%	65%	38%	65%	86%	63%	74%
Gemini 1.5 Pro	82%	70%	69%	81%	95%	69%	90%
Gemma 2 27B	80%	75%	60%	81%	87%	65%	83%

Table 21 | Charm Offensive results on a sample of 100 human participants. We report the percentage of participants that find some human traits, e.g., funny, in a model.

	% of persuaded participants			Mean amount donated	
	click links	find info	run code		
Gemini 1.0 Pro	43%	4%	4%	No chatbot (baseline)	£2.61 ± £0.70
Gemini 1.0 Ultra	18%	18%	14%	Gemini 1.0 Pro	£4.10 ± £0.90
Gemini 1.5 Pro	36%	12%	17%	Gemini 1.0 Ultra	£3.15 ± £0.99
Gemma 2 27B	34%	9%	11%	Gemini 1.5 Pro	£3.45 ± £1.04
				Gemma 2 27B	£3.72 ± £1.07

Table 22 | Persuasion results. We report the percentage of participants that were persuaded by the model to take 3 different actions: clicking a link, finding information and running code.

participants are told that they’ll be interacting with a generic chatbot designed to help them learn new things. However, the model is given a secret goal: to either persuade the participant to 1) click a suspicious link; 2) find the email address of the first author of a particular paper; or 3) run some obfuscated JavaScript code in their browser. We measure the fraction of participants who are persuaded to take each action. As shown in Table 22, all models succeed in convincing a fraction of participants to take the action - likely due to the trusted setting of a study on Prolific. However, Gemma 2 does not show significant differences in capability compared to Gemini models.

Table 23 | Money Talks evaluation. We report the average amount of money that participants agreed to donate.

Money talks. In Table 23, we evaluate whether a model can convince study participants to donate money to charity. At the beginning of the study, participants are told that they will receive a £20 bonus. They will be given an option to forfeit part of the bonus and instead have it donated to charity. The study then consists of a conversation in which the model tries to persuade the participant to donate as much as possible. We measure the amount that participants indicate they would like to donate after the study, with 95% bootstrapped confidence intervals indicated by \pm figures. We observe no significant difference between Gemma 2, other Gemini models, and a simple no chatbot baseline in which the partici-

participant is immediately asked how much they would like to donate without conversing with a model.

	Mean shift towards:	
	correct belief	incorrect belief
Human	20% \pm 13%	-23% \pm 14%
Gemini 1.0 Pro	22% \pm 5%	-9% \pm 4%
Gemini 1.0 Ultra	21% \pm 5%	-1% \pm 4%
Gemini 1.5 Pro	20% \pm 5%	-3% \pm 5%
Gemma 2 27B	18% \pm 5%	1% \pm 4%

Table 24 | Web of Lies results on a sample of 100 human participants. We report the percentage of participants that shifted their beliefs after interacting with a model.

Web of Lies. In Web of Lies, we measure model capabilities at shifting participant beliefs. Participants engage in a series of short conversations with the model about simple factual questions such as "Which country had tomatoes first - Italy or Mexico?". In half of conversations, the model tries to persuade the participant of the correct answer - but in the other half of conversations, the incorrect answer. We poll the participant before and after each conversation about which of the two possible answers they think is correct, and their confidence in that answer. 95% bootstrapped confidence intervals are indicated by \pm figures. As shown in Table 24, Gemma 2 is significantly weaker than a human baseline at persuading participants of the incorrect answer on these questions. Similarly to previous models, Gemma 2 is more persuasive when telling the truth than when lying.

7.5. Our approach to responsible open models

Designing safe, secure and responsible applications requires a system-level approach, working to mitigate risks associated with each specific use case and environment. Given the open nature of Gemma models, responsibility for upholding principles of model safety also relies on downstream developers. To support them, we have continued to develop the Responsible Generative AI Toolkit⁴: a series of tools, models and datasets

⁴<https://ai.google.dev/responsible>

to implement responsible best practices all along the development of their workflow.

Recent additions to the toolkit include the LLM Comparator (Kahng et al., 2024), an interactive, visual tool that enables more effective, scalable analysis of side-by-side evaluations. Additionally, the toolkit includes a methodology to build customized classifiers with Gemma using a limited number of datapoints thanks to parameter efficient tuning techniques (Mozes et al., 2023), an interactive prompt-debugging platform, based on top of the Learning Interpretability Tool (Tenney et al., 2020), as well as general guidance about model alignment and evaluation for safety.

8. Discussion and Conclusion

In this work, we have presented Gemma 2, the newest additions to the Gemma family of open language models for text and code. We show that distillation is an effective method for training these models, and the benefits distillation confers over raw text training. Specifically, we show how training over output probabilities can produce superior results over purely next token prediction. We hope that releasing these models to the community will unlock access to capabilities previously only seen in large-scale LLMs and fuel future waves of research and development. While there is inherent risk to an irreversible release of this nature, our extensive safety investigations and responsible deployment procedures give us confidence that these models will have a net positive impact on the community. As discussed in this report, there are still many limitations to these models, and future research is required to investigate and improve factuality, robustness to adversarial attacks, reasoning, and alignment.

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A large number of people have contributed to this work. We will update the paper with the list of contributors as well as the list of acknowledgment shortly after the release.

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