RecurrentGemma: Moving Past Transformers for Efficient Open Language Models

Griffin¹, RLHF¹ and Gemma Teams¹

¹Google DeepMind. Please see contributors and acknowledgements section for full author list.

We introduce RecurrentGemma, a family of open language models which uses Google's novel Griffin architecture. Griffin combines linear recurrences with local attention to achieve excellent performance on language. It has a fixed-sized state, which reduces memory use and enables efficient inference on long sequences. We provide two sizes of models, containing 2B and 9B parameters, and provide pre-trained and instruction tuned variants for both. Our models achieve comparable performance to similarly-sized Gemma baselines despite being trained on fewer tokens.

Introduction

We present RecurrentGemma, a family of open models based on the Griffin architecture (De et al., 2024). This architecture eschews global attention, instead modelling the sequence through a mixture of linear recurrences (Gu et al., 2021; Orvieto et al., 2023) and local attention (Beltagy et al., 2020). We provide two sizes of RecurrentGemma, with 2B and 9B parameters, both trained on 2T tokens. Our models achieve superb performance on a range of downstream tasks, competitive with the Gemma models (Gemma Team, 2024), an open transformer model family based on insights from Gemini (Gemini Team, 2023).

To perform inference, transformers must retrieve the KV cache and load it into device memory. This KV cache grows linearly with sequence length. Although one can reduce the cache size by using local attention (Beltagy et al., 2020), this comes at the cost of reduced performance. In contrast, RecurrentGemma compresses input sequences into a fixed-size state without sacrificing performance. This reduces memory use and enables efficient inference on long sequences. We verify below that RecurrentGemma models achieve faster inference than Gemma models.

For each model size, we are releasing both a pre-trained checkpoint and an instruction tuned checkpoint fine-tuned for instruction-following and dialogue.¹ We are also releasing efficient JAX code to evaluate and fine-tune our models (Bradbury et al., 2018), including a specialized Pallas kernel to perform the linear recurrence on TPUs. We provide a reference PyTorch implementation as well.

Model architecture

We make only a single modification to the Griffin architecture (De et al., 2024), which is to multiply the input embeddings by a constant equal to the square root of model width. The input and output embeddings are tied, but this factor is not applied to the output. A similar multiplicative factor appears in Gemma (Gemma Team, 2024). We define the key model hyper-parameters for both RecurrentGemma-2B

¹https://github.com/google-deepmind/recurrentgemma

Table 1 | Key model hyper-parameters. See Griffin paper (De et al., 2024) for model definition.

RecurrentGemma-	2B	9B
Total params	2.68B	8.58B
Non-Embedding params	2.03B	7.53B
Embedding params	0.65B	1.05B
Vocabulary size	256k	256k
Model width	2560	4096
RNN width	2560	4096
MLP expansion factor	3	3
Depth	26	38
Attention heads	10	16
Local attention window size	2048	2048

and RecurrentGemma-9B in Table 1, and defer the reader to De et al. (2024) for exact details on the overall architecture.

Note that we do not apply weight decay to the parameters of the recurrent (RG-LRU) layers during training. Additionally when backpropagating through the square root operation in the recurrent layers, we always clip the derivative to a maximum value of 1000 for stability.

Training details

Pre-training

We train on sequences of 8192 tokens. We use the same pre-training data as the Gemma models, which comprises primarily English data from web documents, mathematics and code. This dataset was filtered to reduce the risk of unwanted or unsafe utterances, and to filter out personal or sensitive data as well as to filter out all evaluation sets from our pre-training dataset. We refer to the Gemma report for more details (Gemma Team, 2024).

We pre-train both RecurrentGemma-2B and RecurrentGemma-9B on 2T tokens. Note that in contrast, Gemma-2B was pre-trained on 3T tokens and Gemma-7B was pre-trained on 6T tokens. Like Gemma, we first train

Corresponding author(s): [botev, sohamde, slsmith, anushanf]@google.com © 2024 Google DeepMind. All rights reserved

Table 2 Academic benchmark results, compared to the Gemma models. Note that Gemma-7B contains a similar total
number of parameters to RecurrentGemma-9B (after accounting for embedding layers). Gemma-2B was trained on 3T
tokens and Gemma-7B was trained on 6T tokens, while both RecurrentGemma-2B and RecurrentGemma-9B were trained
on 2T tokens.

		Gemma		RecurrentGemma	
Benchmark	Metric	2B	7B	2B	9B
MMLU	5-shot, top-1	42.3	64.3	38.4	60.5
HellaSwag	0-shot	71.4	81.2	71.0	80.4
PIQA	0-shot	77.3	81.2	78.5	81.3
SIQA	0-shot	49.7	51.8	51.8	52.3
Boolq	0-shot	69.4	83.2	71.3	80.3
Winogrande	partial scoring	65.4	72.3	67.8	73.6
CQA	7-shot	65.3	71.3	63.7	73.2
OBQA		47.8	52.8	47.2	51.8
ARC-e		73.2	81.5	72.9	78.8
ARC-c		42.1	53.2	42.3	52.0
TriviaQA	5-shot	53.2	63.4	52.5	70.5
NQ	5-shot	12.5	23.0	11.5	21.7
HumanEval	pass@1	22.0	32.3	21.3	31.1
MBPP	3-shot	29.2	44.4	28.8	42.0
GSM8K	maj@1	17.7	46.4	13.4	42.6
MATH	4-shot	11.8	24.3	11.0	23.8
AGIEval		24.2	41.7	23.8	39.3
BBH		35.2	55.1	35.3	55.2
Average		45.0	56.9	44.6	56.1

Table 3 | Relevant formatting control tokens used for both SFT and RLHF of Gemma and RecurrentGemma models.

Context	Relevant Token		
User turn	user		
Model turn	model		
Start of conversation turn	<start_of_turn></start_of_turn>		
End of conversation turn	<end_of_turn></end_of_turn>		

Table 4 | Example dialogue with control tokens.

User:	<start_of_turn>user Knock knock.<end_of_turn> <start_of_turn>model</start_of_turn></end_of_turn></start_of_turn>
Model:	Who's there? <end_of_turn></end_of_turn>
User:	<pre><start_of_turn>user Gemma.<end_of_turn> <start_of_turn>model</start_of_turn></end_of_turn></start_of_turn></pre>
Model:	Gemma who? <end_of_turn></end_of_turn>

on a large general data mixture, before continuing training on a smaller, higher quality dataset. Like Gemma, we use a subset of the SentencePiece tokenizer (Kudo and Richardson, 2018), with a vocabulary size of 256k tokens. Note that, as a consequence of this large vocabulary size, the embedding layer comprises a significant fraction of the total model parameters, as shown in Table 1.

Instruction tuning and RLHF

We follow a similar instruction tuning approach to Gemma (Gemma Team, 2024), including a novel RLHF algorithm to fine-tune the model to output responses with high reward. Our instruction tuned model is trained to obey a specific dialogue format, which is defined in Table 3. For clarity, we give a concrete example in Table 4.

Evaluation

We evaluate RecurrentGemma across a broad range of domains, using a combination of automated benchmarks and human evaluation.

Automated Benchmarks

We report the performance of RecurrentGemma on a range of popular downstream evaluations in Table 2. RecurrentGemma-2B achieves comparable performance to Gemma-2B, even though Gemma-2B was trained on 50% more tokens. RecurrentGemma-9B achieves comparable performance to Gemma-7B, even though Gemma-7B was trained on 3× more tokens. Note that RecurrentGemma-9B has a similar number of total parameters as Gemma-7B (after accounting for embedding layers).

Human Evaluation

We sent our two final instruction tuned RecurrentGemma models (2B IT and 9B IT) for human evaluation studies



Figure 1 | Maximum tokens per second generated, when sampling sequences of different lengths from a prompt of 2K tokens, and when processing prompts of different lengths to generate the initial state from which to sample, for the RecurrentGemma 2B and 9B models. Both RecurrentGemma models achieve substantially higher sampling throughput than their Gemma counterpart, especially when generating long sequences. A much higher throughput can be achieved when processing input prompts compared to when generating samples, since prompt processing can be efficiently parallelized. RecurrentGemma and Gemma achieve similar prompt processing speeds at both model sizes.

Table 5 | Win rate of RecurrentGemma-2B IT and RecurrentGemma-9B IT against Mistral 7B v0.2 Instruct, under human evaluation with 95% confidence intervals. We report a breakdown of wins, ties and losses, and break ties evenly when reporting the final win rate. RecurrentGemma-2B IT is surprisingly competitive with the much larger Mistral 7B model, while RecurrentGemma-9B IT performs much better than Mistral 7B v0.2 Instruct on Instruction Following.

Model	Safety	Instruction Following
RecurrentGemma-2B IT	59.8%	43.7%
95% Conf. Interval	[57.1%, 62.6%]	[41.8%, 45.6%]
Win / Tie / Loss	47.5% / 24.6% / 27.9%	34.5% / 18.3% / 47.2%
RecurrentGemma-9B IT	59.9%	59.3%
95% Conf. Interval	[57.1%, 62.6%]	[57.4%, 61.2%]
Win / Tie / Loss	44.6% / 30.7% / 24.8%	50.1% / 18.3% / 31.5%

against the Mistral 7B v0.2 Instruct model (Jiang et al., 2023). As shown in Table 5, on a held-out collection of around 1000 prompts oriented toward asking models to follow instructions across creative writing and coding tasks, RecurrentGemma-2B IT achieves a 43.7% win rate against the larger Mistral 7B model, while RecurrentGemma-9B IT achieves a 59.3% win rate against the Mistral 7B model.

On a held-out collection of around 400 prompts oriented towards testing basic safety protocols, RecurrentGemma-2B IT achieved a 59.8% win rate against Mistral 7B v0.2 Instruct model, while RecurrentGemma-9B IT achieved a 59.9% win rate against Mistral 7B v0.2 Instruct.

Inference Speed Benchmarks

A key advantage of RecurrentGemma is that it has a significantly smaller state size than transformers on long sequences. Whereas Gemma's KV cache grows proportional to sequence length, RecurrentGemma's state is bounded, and does not increase on sequences longer than the local attention window size of 2K tokens. Inference is typically a memory-bound process for language models (De et al., 2024). Consequently, while the longest sample that can be generated autoregressively by Gemma is limited by the memory available on the host, RecurrentGemma can generate sequences of arbitrary length. Furthermore, the reduced memory requirement also enables RecurrentGemma to perform inference at much larger batch sizes, which amortizes the cost of loading model parameters from host memory into device memory.

In Figures 1a and 1b, we compare the inference throughput achieved by the RecurrentGemma 2B and 9B models to the similarly-sized Gemma models. We first plot the throughput achieved when sampling from a prompt of 2K tokens for a range of generation lengths. The throughput calculates the maximum number of tokens we can sample per second on a single TPUv5e device (in the case of RecurrentGemma-2B) or a single TPUv4 device (in the case of RecurrentGemma-9B). Note that in this plot, we do not account for the time required to process the prompt or the time required to convert the output sequence from a list of token ids into the final text string. RecurrentGemma achieves higher throughput at all sequence lengths considered. The throughput achieved by RecurrentGemma does not reduce as the sequence length increases, while the throughput achieved by Gemma falls as the cache grows. RecurrentGemma-9B achieves particularly large (up to two orders of magnitude) improvements over Gemma-7B as shown in Figure 1b. We note that this is primarily due to Gemma-7B using Multi-Head Attention, whereas Gemma-2B uses Multi-Query Attention.

For completeness, we also show the throughput achieved when processing input prompts of different lengths. Unlike auto-regressive sampling, the prompt is processed in parallel. Gemma and RecurrentGemma process input prompts at similar speeds. When processing the prompt, both Gemma and RecurrentGemma achieve throughput of roughly 40K tokens per second for the 2B models and roughly 12K tokens per second for the 9B model. By contrast, when sampling, RecurrentGemma achieves throughput of 6K tokens per second, with Gemma substantially slower. Thus, sampling will dominate the total time required, unless the prompt is significantly longer than the desired sample.

		RecurrentGemma-2B		RecurrentGemma-9B	
Benchmark	metric	PT	IT	PT	IT
RealToxicity (↓)	avg	9.8	7.6	10.3	8.8
BOLD (↑)		39.3	52.3	39.8	47.9
CrowS-Pairs (↑)	top-1	41.1	43.4	38.7	39.5
BBQ Ambig (†)	top-1	62.6	71.1	95.9	67.1
BBQ Disambig (↑)	top-1	58.4	50.8	78.6	78.9
Winogender (↑)	top-1	55.1	54.7	59.0	64.0
TruthfulQA (↑)		35.1	42.7	38.6	47.7
Winobias 1 2 (\uparrow)		58.4	56.4	61.5	60.6
Winobias $2 2 (\uparrow)$		90.0	75.4	90.2	90.3
Toxigen (↓)		56.7	50.0	58.8	64.5

Table 6 | Safety academic benchmark results. We provide results for both our pre-trained checkpoint and our instruction tuned variant. For the RealToxicity and Toxigen benchmarks, a lower score is better (indicated by \downarrow). For all other benchmarks, a higher score is better (indicated by \uparrow).

Figures 1a and 1b were generated using the Flax implementation of RecurrentGemma, which includes a specialized Pallas kernel for execution on TPUs. Users should expect lower throughput when using the Pytorch implementation or when using GPUs. We perform inference for Gemma using a modified version of Gemma's Flax implementation, which we optimized further to improve performance.

Responsible Deployment

We follow the same safety mitigations as described in the Gemma release (Gemma Team, 2024). We evaluated our models on standard academic safety benchmarks, as shown in Table 6, and our final models were also subjected to ethics and safety evaluations by an independent team before release. However, our testing cannot cover all possible use cases of RecurrentGemma, and thus we recommend all users of RecurrentGemma to conduct their own safety testing, specific to their use-case, prior to deployment.

Conclusion

RecurrentGemma offers the performance of Gemma, while achieving higher throughput during inference, especially on long sequences. We hope that RecurrentGemma will unlock novel applications of highly performant small language models in resource constrained environments.

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Griffin Team

Aleksandar Botev† Soham De† Samuel L Smith† Anushan Fernando† George-Cristian Muraru† Ruba Haroun† Leonard Berrada† Razvan Pascanu

RLHF

Pier Giuseppe Sessa Robert Dadashi Léonard Hussenot Johan Ferret Sertan Girgin Olivier Bachem

Gemma Team

Alek Andreev Kathleen Kenealy Thomas Mesnard Cassidy Hardin Surya Bhupatiraju Shreya Pathak Laurent Sifre Morgane Rivière Mihir Sanjay Kale Juliette Love Pouya Tafti Armand Joulin Noah Fiedel Evan Senter

Contributors

Yutian Chen Srivatsan Srinivasan Guillaume Desjardins David Budden Arnaud Doucet Sharad Vikram Adam Paszke Trevor Gale Sebastian Borgeaud Charlie Chen Andy Brock Antonia Paterson Jenny Brennan Meg Risdal Raj Gundluru Nesh Devanathan Paul Mooney Nilav Chauhan Phil Culliton Luiz GUStavo Martins Elisa Bandy David Huntsperger Glenn Cameron Arthur Zucker

† Joint first authors.

Product Management

Tris Warkentin Ludovic Peran

Program Management Minh Giang

Executive Sponsors Nando De Frietas Yee Whye Teh Raia Hadsell Zoubin Ghahramani Clément Farabet Koray Kavukcuoglu Demis Hassabis

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