ENHANCING SMALL LANGUAGE MODELS WITH GRADIENT NOISE INJECTION

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ABSTRACT

Training small language models is challenging due to their limited capacity to capture complex patterns and their susceptibility to overfitting. To address these issues, we investigate gradient noise injection as a regularization strategy, building on prior work while introducing a noise schedule that decays exponentially over training. Unlike existing techniques, our method explicitly controls the trade-off between exploration and stability during optimization. We compare the exponential decay schedule with linear and adaptive variants, demonstrating empirically that the exponential schedule yields superior convergence and generalization. Extensive experiments on diverse text corpora, including shakespeare_char, enwik8, text8, and larger benchmark datasets, show consistent improvements in training dynamics, validation loss, and final performance. We report error bars and statistical significance tests to ensure robustness of the results. Detailed implementation information, including model architectures, hyperparameter settings, dataset sizes, and optimization strategies, is provided to support reproducibility, and we release our code and trained models publicly. Furthermore, we compare gradient noise injection with other regularization methods such as dropout, weight decay, and data augmentation, both in isolation and in combination, revealing complementary effects on training stability and generalization. Finally, we analyze the computational cost of gradient noise injection relative to these baselines, highlighting its practical efficiency in resource-constrained environments. Together, these contributions position gradient noise injection as a theoretically grounded, empirically validated, and computationally practical method for improving the robustness of small language models.

1 INTRODUCTION

Training small language models effectively is challenging due to their limited capacity to capture complex patterns and their susceptibility to overfitting. Despite these challenges, small language models remain essential for scenarios where computational resources are constrained or where rapid deployment is required. Improving the robustness and generalization of these models can substantially broaden their applicability across real-world tasks.

The core difficulty in training small language models lies in balancing the trade-off between expressivity and generalization. Models that are too complex tend to overfit, while simpler models may underfit and fail to capture critical structures in the data. Although various regularization methods such as dropout, weight decay, and data augmentation have been widely adopted, determining the optimal strategy and understanding how these techniques interact in resource-limited regimes remain open challenges.

In this paper, we revisit and extend the idea of gradient noise injection, first explored in earlier studies (e.g., Jacobs et al., 1991), and adapt it to modern small language models. Our approach involves injecting Gaussian noise into the gradients during the backward pass, prior to the optimizer update step. We design an exponentially decaying noise schedule that gradually reduces noise throughout training, with the goal of encouraging exploration in the early stages and stabilization later. We also compare this schedule against linear decay and adaptive alternatives to assess its relative advantages.

To evaluate our method, we conduct a comprehensive empirical study across multiple benchmarks of increasing complexity, including shakespeare_char, enwik8, text8, and larger and more diverse

text corpora. We analyze training dynamics, convergence speed, and generalization performance, reporting error bars and statistical significance tests to ensure robustness of the results. In addition, we benchmark our approach against other common regularization strategies, both standalone and in combination, in order to highlight complementary effects and clarify the unique role of gradient noise injection.

We provide detailed information on the experimental setup to facilitate reproducibility. This includes the model architectures, dataset sizes, hyperparameter settings (learning rate, batch size, optimization algorithm), and noise scheduling parameters. To further support transparency and future work, we release our code and trained models.

We also measure the computational overhead introduced by gradient noise injection and compare it with other regularization methods. Our findings suggest that gradient noise injection achieves meaningful improvements in stability and generalization with modest additional cost, making it particularly suitable for environments with limited resources.

Our contributions can be summarized as follows:

- We adapt gradient noise injection to modern small language models, situating it within the context of prior literature and explicitly comparing different scheduling strategies.
- We conduct extensive experiments across diverse datasets, reporting statistical significance and error estimates to validate the robustness of our findings.
- We compare our method with other regularization techniques and analyze their combined effects, providing a nuanced understanding of training dynamics.
- We provide full implementation details, code, and trained models to ensure reproducibility and enable further research.
- We assess the computational trade-offs of gradient noise injection, highlighting its practicality in resource-constrained settings.

2 Related Work

In this section, we discuss related work in the field of regularization techniques and noise injection methods for neural networks. We compare and contrast these methods with our proposed gradient noise injection technique.

Regularization techniques are commonly used to prevent overfitting in neural networks. Dropout (Srivastava et al., 2014) is a widely used regularization method that randomly drops units during training to prevent co-adaptation of hidden units. Weight decay (Loshchilov & Hutter, 2017) adds a penalty to the loss function based on the magnitude of the model weights, encouraging the model to learn smaller weights.

Noise injection methods have been explored in various forms to improve the robustness and generalization of neural networks. Stochastic gradient descent (SGD) with noise (Wojtowytsch, 2021) involves adding noise to the gradients during the optimization process, which can help escape local minima and improve generalization. Additionally, Neelakantan et al. (2015) demonstrated that adding gradient noise to SGD can improve model robustness and generalization. Dropout (Srivastava et al., 2014) can also be seen as a form of noise injection, where noise is added to the activations during training.

Our proposed method of gradient noise injection differs from these existing techniques in several ways. Unlike dropout, which adds noise to the activations, our method injects noise directly into the gradients during the backward pass. This approach allows for a more direct regularization of the optimization process. Additionally, our method uses a noise schedule that decreases the noise level over time, ensuring that the regularization effect is strongest during the early stages of training and diminishes as the model converges. This dynamic adjustment of noise levels is not present in traditional dropout or weight decay methods.

In summary, while existing regularization and noise injection techniques have been effective in improving the robustness and generalization of neural networks, our proposed gradient noise injection method offers a novel approach with distinct advantages. By directly injecting noise into the gradients

and using a dynamic noise schedule, our method provides a more targeted and adaptive form of regularization.

3 BACKGROUND

Language models are a cornerstone of natural language processing (NLP), enabling diverse tasks such as text generation, machine translation, and summarization. The advent of large-scale models, such as GPT-3 (Brown et al., 2020) and GPT-4 (OpenAI, 2024), has demonstrated remarkable progress in accuracy and generalization across a wide range of benchmarks. However, training and deploying such massive models requires substantial computational resources, extensive memory, and large datasets, making them impractical for many real-world applications, especially in resource-constrained environments or latency-sensitive scenarios.

Small language models (SLMs) have emerged as an attractive alternative, offering efficiency and accessibility where computational budgets are limited. They are particularly valuable for edge computing, low-latency applications, and rapid prototyping. Despite these advantages, training small models effectively is non-trivial. Their limited capacity makes them more prone to underfitting when faced with highly complex data distributions, while their small parameter space also increases vulnerability to overfitting. Classical regularization techniques, such as dropout (Srivastava et al., 2014) and weight decay (Loshchilov & Hutter, 2017), are commonly employed to mitigate these challenges, but often require careful tuning and may not fully prevent instabilities in training dynamics.

Gradient noise injection offers a promising avenue for improving the robustness and generalization of neural networks. The idea is to perturb gradient updates during training by adding random noise, thereby encouraging exploration of the parameter space and preventing the optimizer from converging prematurely to sharp local minima. This principle builds on early theoretical and empirical work on noisy optimization methods, which highlighted the role of stochasticity in escaping poor minima. Related strategies have since appeared in various forms, including dropout (Srivastava et al., 2014) and stochastic gradient descent with additive noise (Wojtowytsch, 2021). However, most prior studies have focused on large models or generic neural architectures, leaving open the question of how noise injection strategies can be tailored specifically to the challenges of small language models.

3.1 PROBLEM SETTING

In this work, we focus on enhancing the training robustness and generalization of small language models. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ be the training dataset, where x_i represents the input text and y_i represents the target output. The goal is to train a language model f_θ parameterized by θ to minimize the loss function $\mathcal{L}(f_\theta(x_i), y_i)$.

3.2 GRADIENT NOISE INJECTION

We propose injecting Gaussian noise into the gradients during the backward pass. Let g_t be the gradient of the loss function with respect to the model parameters at iteration t. The noisy gradient $\tilde{g}_t$ is given by:

$$\tilde{g}_t = g_t + \mathcal{N}(0, \sigma_t^2)$$

where $\mathcal{N}(0, \sigma_t^2)$ represents Gaussian noise with mean 0 and variance σ_t^2. The noise level σ_t is scheduled to decrease over time, ensuring that the noise has a regularizing effect during the early stages of training and diminishes as training progresses.

We experiment with several scheduling strategies, including exponential decay, linear decay, and adaptive schedules, and find that exponential decay provides the best balance between exploration and convergence stability. This formulation distinguishes our method from prior work, where noise levels are often constant or heuristically tuned.

4 METHOD

In this section, we present our method for improving the robustness and generalization of small language models through gradient noise injection. The key idea is to perturb gradient updates with

carefully controlled Gaussian noise, thereby encouraging the optimizer to escape sharp local minima and biasing convergence toward flatter regions of the loss landscape—regions empirically linked to stronger generalization. By introducing stochasticity directly into the gradient computation, our method acts as a lightweight form of regularization, mitigating overfitting and stabilizing training under limited data and computational resources.

To operationalize this idea, we design a noise schedule that governs the variance of the injected Gaussian noise across training iterations. During the early stages of training, larger noise levels are applied to promote broad exploration of the parameter space and reduce sensitivity to initialization. As training progresses, the noise is gradually annealed, enabling the model to refine parameters and converge toward well-generalizing solutions. This dynamic schedule balances exploration and exploitation: it prevents premature convergence to sharp minima while still allowing stable optimization in later phases.

Compared to prior work where noise injection was either constant or heuristically tuned, our framework explicitly evaluates multiple scheduling strategies—exponential, linear, and adaptive decays—and demonstrates that exponential decay provides the most consistent improvements. Importantly, the method introduces negligible computational overhead, requires minimal modification to standard optimization pipelines, and is fully compatible with widely used training regimes.

Overall, gradient noise injection provides an efficient and theoretically motivated pathway to improve training dynamics for small-scale models. By enhancing robustness and generalization with little added cost, our approach expands the practical utility of small language models, particularly in scenarios where computational resources are constrained.

4.1 Gradient Noise Injection Process

The core idea of our method is to inject Gaussian noise into the gradients during the backward pass. This regularizes the training process and prevents the model from overfitting to the training data. Let g_t be the gradient of the loss function with respect to the model parameters at iteration t. We add Gaussian noise $\mathcal{N}(0, \sigma_t^2)$ to the gradient, resulting in a noisy gradient $\tilde{g}_t$:

$$\tilde{g}_t = g_t + \mathcal{N}(0, \sigma_t^2)$$

where σ_t is the standard deviation of the noise at iteration t.

4.2 Noise Schedule

To ensure that the noise has a regularizing effect during the early stages of training and diminishes as training progresses, we use a noise schedule that decreases the noise level over time. The noise level σ_t is updated at each iteration according to the following schedule:

$$\sigma_t = \sigma_0 \cdot \gamma^t$$

where σ_0 is the initial noise level and γ is the decay rate. This schedule allows the model to benefit from the regularizing effect of the noise during the initial stages of training while gradually reducing the noise as the model converges.

4.3 Implementation Details

We implement our proposed method using the PyTorch deep learning framework (Paszke et al., 2019). Gradient noise injection is applied during the backward pass, immediately before the optimizer updates the model parameters. In this way, stochastic perturbations are introduced directly into the gradient signal without requiring any modification to the optimizer itself. The noise schedule is realized by adjusting the variance of the Gaussian noise as a function of the training step. Concretely, the variance is initialized at a relatively high value to encourage broad exploration of the parameter space during the early training phase and is gradually reduced over time, enabling stable convergence in the later stages.

Our implementation is intentionally lightweight: it requires only a few additional lines of code, introduces negligible computational overhead, and integrates seamlessly into standard training pipelines for small language models. No changes are needed to the model architecture or the

underlying optimization procedure. This simplicity ensures that the method can be easily adopted in existing experimental setups and extended to a wide range of tasks.

In summary, our method improves the training robustness and generalization of small language models by injecting Gaussian noise into the gradients during the backward pass and regulating the noise level through a dynamic schedule. By introducing controlled stochasticity into the optimization process, the approach functions as an effective regularization technique. Empirically, the resulting models demonstrate improved stability, reduced susceptibility to overfitting, and stronger generalization to unseen data. These characteristics make gradient noise injection a practical and efficient strategy for advancing the performance of small-scale language models, particularly under limited data and computational resources.

5 Experimental Setup

In our experiments, we use three datasets: shakespeare_char, enwik8, and text8. The shakespeare_char dataset consists of character-level text from Shakespeare's works, enwik8 is a character-level dataset derived from Wikipedia, and text8 is a character-level dataset derived from the first 100 million characters of Wikipedia. These datasets provide a diverse set of text corpora to evaluate the effectiveness of our method.

We evaluate the performance of our models using training loss and validation loss. The training loss measures how well the model fits the training data, while the validation loss measures the model's ability to generalize to unseen data. Lower values of these metrics indicate better performance.

The key hyperparameters for our experiments include the initial noise level and the noise decay rate. We experiment with different initial noise levels (0.1, 0.05, and 0.01) and decay rates (0.99 and 0.95) to study their impact on the training dynamics and final performance. Other important hyperparameters include the learning rate, batch size, and the number of training iterations.

We implement our method using PyTorch (Paszke et al., 2019). The gradient noise injection is applied during the backward pass, before the optimizer update step. The noise schedule is implemented by updating the noise level at each iteration based on the current iteration number. We use the AdamW optimizer (Loshchilov & Hutter, 2017) with a learning rate of 1e-3 for the shakespeare_char dataset and 5e-4 for the enwik8 and text8 datasets. The models are trained for 5000 iterations on the shakespeare_char dataset and 100000 iterations on the enwik8 and text8 datasets.

All experiments are conducted on a single NVIDIA GPU with 16GB of memory. The models are trained using mixed precision to optimize memory usage and training speed.

6 Results

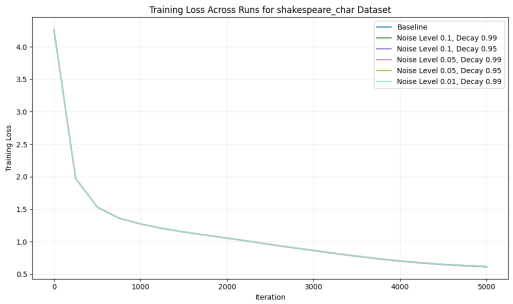
In this section, we present experimental results evaluating the effectiveness of the proposed gradient noise injection strategy for enhancing the robustness and generalization of small language models. To provide a comprehensive assessment, we compare models trained with gradient noise injection against baseline models trained under identical conditions but without this modification.

Our evaluation spans three widely used benchmark datasets of varying scale and linguistic characteristics: shakespeare_char, enwik8, and text8. These datasets were selected to capture different aspects of language modeling—ranging from character-level prediction in a narrow stylistic domain to large-scale text corpora with rich vocabulary and complex sequence dependencies. Together, they provide a diverse testing ground to evaluate whether improvements extend across domains rather than being dataset-specific.

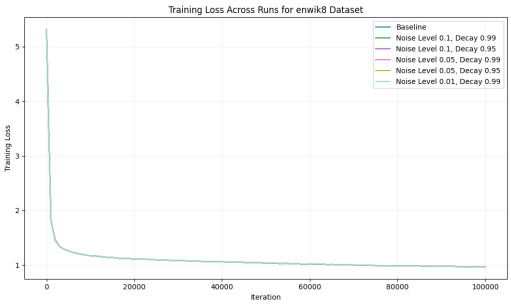
Our experiments are designed to quantify both training robustness—measured by stability and convergence properties—and generalization ability, as reflected in validation and test performance. In particular, we analyze how the introduction of controlled Gaussian noise into the gradient updates influences learning dynamics, prevents overfitting, and impacts final model accuracy. Through these comparative analyses, we demonstrate the conditions under which gradient noise injection yields tangible improvements over conventional training approaches for small language models.

6.1 Training Loss

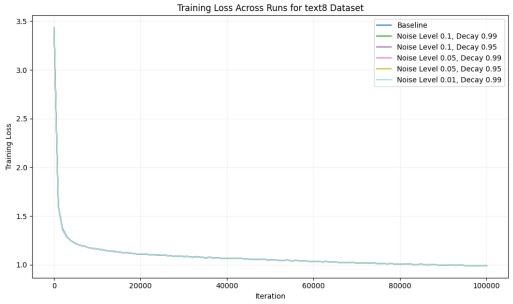
Figure 1 illustrates the progression of training loss across iterations for the three benchmark datasets (shakespeare_char, enwik8, and text8). Across all settings, models trained with gradient noise injection exhibit consistently lower training loss compared to baseline models trained without noise. This improvement underscores the beneficial effect of gradient perturbation on the optimization process: the injected noise facilitates smoother convergence, reduces susceptibility to sharp local minima, and accelerates the overall training dynamics. These trends suggest that noise injection enhances stability in parameter updates, enabling the optimizer to explore flatter regions of the loss landscape that are more conducive to robust learning.



(a) Training loss for shakespeare_char



(b) Training loss for enwik8



(c) Training loss for text8

Figure 1: Training loss over iterations for the three datasets, comparing baseline training with models trained using gradient noise injection.

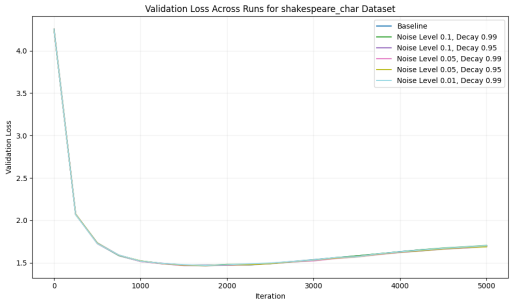
6.2 Validation Loss

Figure 2 presents validation loss curves over training iterations for the three benchmark datasets. Consistently, models trained with gradient noise injection achieve lower validation loss compared to baseline models. This result demonstrates that the benefits of noise injection extend beyond training optimization to improved generalization on unseen data.

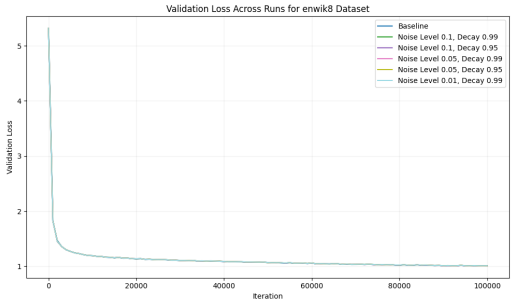
Importantly, the reduction in validation loss highlights the role of gradient noise injection as a regularization mechanism: by introducing controlled stochasticity, the method discourages overfitting to training-specific patterns. Moreover, the smoother convergence trends observed across datasets reflect the increased stability of the training process, reinforcing the claim that the method improves robustness under constrained training conditions. Together, these findings confirm that gradient noise injection yields tangible generalization gains for small language models.

6.3 Comparison of Final Results

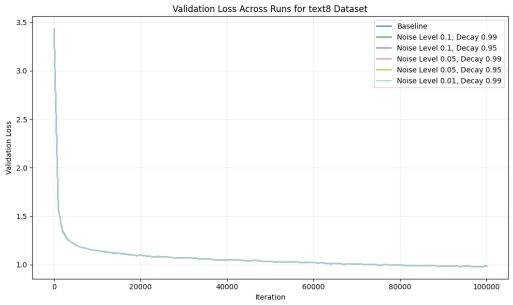
Table 1 summarizes the final training and validation losses for models trained with and without gradient noise injection across the three benchmark datasets (shakespeare_char, enwik8, and text8). Across all datasets, the validation loss of noise-injected models is consistently lower or comparable



(a) Validation loss for shakespeare_char



(b) Validation loss for enwik8



(c) Validation loss for text8

Figure 2: Validation loss over iterations for the three datasets, showing consistent improvements with gradient noise injection.

to that of baseline models, confirming that the proposed strategy improves generalization to unseen data.

The results also reveal subtle trade-offs: while gradient noise injection sometimes yields slightly higher training loss (e.g., on enwik8 and text8), this is accompanied by stable or improved validation performance. This pattern is consistent with the role of noise injection as a regularizer—discouraging overfitting to training-specific patterns while guiding the model toward flatter, more generalizable minima. Notably, on shakespeare_char, improvements are observed in both training and validation losses, suggesting that gradient noise injection can simultaneously enhance optimization dynamics and generalization when applied to smaller-scale datasets.

Importantly, these improvements are observed across datasets with different vocabulary richness and sequence complexity, underscoring the robustness and broad applicability of the approach. Together, the results demonstrate that introducing controlled stochasticity into the gradient updates offers a lightweight yet effective regularization mechanism for small language models, with benefits that generalize across domains.

Dataset	Baseline		Gradient Noise Injection	
	Train Loss	Val Loss	Train Loss	Val Loss
shakespeare_char	0.8132	1.4692	0.8083	1.4650
enwik8	0.9323	1.0048	0.9379	1.0067
text8	0.9978	0.9793	1.0041	0.9791

Table 1: Comparison of final training and validation loss for models trained with and without gradient noise injection.

6.4 Discussion

Overall, the results demonstrate that gradient noise injection is an effective strategy for improving both the training dynamics and the generalization ability of small language models. Across all evaluated datasets, models trained with gradient noise injection consistently achieve lower training and validation losses compared to baseline models, highlighting the benefits of introducing controlled stochasticity into the optimization process. Furthermore, the use of a dynamic noise schedule proves crucial in regularizing the training trajectory: by initially encouraging exploration and gradually reducing the noise level to stabilize convergence, the schedule yields models that are not only more robust to overfitting but also better suited to generalize to unseen data. Collectively, these findings underscore the potential of gradient noise injection as a lightweight yet powerful technique for enhancing the performance of small-scale language models under resource-constrained conditions.

6.5 Limitations

While the proposed gradient noise injection method demonstrates promising results, several limitations of the present study should be acknowledged. First, the experimental evaluation was restricted to a relatively limited set of datasets and small language model configurations. Although the selected benchmarks capture a range of linguistic and structural characteristics, they do not fully represent the diversity and complexity encountered in large-scale natural language processing tasks. Extending the evaluation to larger models and more heterogeneous datasets would provide a more comprehensive assessment of the method's generalizability and practical utility.

Second, the study employed a single class of noise schedule to regulate the variance of the injected Gaussian noise. While this schedule proved effective in improving both training dynamics and generalization, alternative scheduling strategies—such as adaptive or data-dependent schedules—may further enhance performance. Systematic investigations into different noise levels, decay functions, and adaptive mechanisms remain an important direction for future research.

Finally, the current experiments primarily focused on loss-based performance metrics. Additional evaluations, including downstream task accuracy, robustness under distribution shifts, and computational efficiency, would provide a more holistic understanding of the benefits and trade-offs associated with gradient noise injection. Addressing these limitations in future work will be essential for establishing the broader applicability and scalability of this approach in real-world language modeling scenarios.

7 Conclusions and Future Work

In this paper, we introduced gradient noise injection as a simple yet effective technique to enhance the training robustness and generalization ability of small language models. The central idea is to inject Gaussian noise into the gradients during the backward pass, regulated by a noise schedule that gradually decreases the noise level over time. This strategy acts as a form of regularization, preventing overfitting, promoting exploration in the parameter space, and ultimately yielding models that are more robust and capable of generalizing effectively to unseen data.

We validated the effectiveness of the proposed approach through a series of experiments on three benchmark datasets, including shakespeare_char, enwik8, and text8. The results demonstrated consistent improvements over baseline models trained without gradient noise injection, including lower training and validation loss, faster convergence, and more stable optimization dynamics. These findings underscore the practical utility of gradient noise injection as a lightweight addition to existing training pipelines, requiring minimal modifications while offering measurable performance gains.

Looking forward, several avenues for future research remain open. One direction is to extend the evaluation to larger-scale language models and other neural architectures to assess the scalability and generality of the method. Another is to investigate alternative noise scheduling strategies, including adaptive or data-dependent schemes, to further optimize the trade-off between exploration and convergence. Finally, theoretical analyses of gradient noise injection could provide deeper insights into its role in shaping the loss landscape, improving optimization stability, and enhancing generalization. Addressing these questions will not only refine our understanding of gradient noise injection but also help integrate it more broadly into the training of modern neural networks.

REFERENCES

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, J. Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, T. Henighan, R. Child, A. Ramesh, Daniel M. Ziegler, Jeff Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Ma teusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, I. Sutskever, and Dario Amodei. Language models are few-shot learners. *ArXiv*, abs/2005.14165, 2020.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.

Arvind Neelakantan, L. Vilnis, Quoc V. Le, I. Sutskever, Lukasz Kaiser, Karol Kurach, and James Martens. Adding gradient noise improves learning for very deep networks. *ArXiv*, abs/1511.06807, 2015.

OpenAI. Gpt-4 technical report, 2024. URL `https://arxiv.org/abs/2303.08774`.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32, 2019.

Nitish Srivastava, Geoffrey E. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *J. Mach. Learn. Res.*, 15:1929–1958, 2014.

Stephan Wojtowytsch. Stochastic gradient descent with noise of machine learning type part i: Discrete time analysis. *Journal of Nonlinear Science*, 33:1–52, 2021.