PLANNED DIFFUSION

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ABSTRACT

A central challenge in large language model inference is the trade-off between generation speed and output quality. Autoregressive models produce high-quality text but generate tokens sequentially. Diffusion models can generate tokens in parallel but often need many iterations to match the same quality. We propose *planned diffusion*, a hybrid method that combines the strengths of both paradigms. Planned diffusion works in two stages: first, the model creates a short autoregressive outline that breaks the output into smaller, independent spans. Second, the model generates these spans simultaneously using diffusion. This approach expands the speed–quality Pareto frontier and provides a practical path to faster, high-quality text generation. On AlpacaEval, a suite of 805 instruction-following prompts, planned diffusion achieves Pareto-optimal trade-off between quality and latency, achieving 1.84x speedup over autoregressive generation with only a 6.8% drop in win rate. Our sensitivity analysis confirms that the internal planning of our model is reliable and offers tunable control over the trade-off between generation speed and quality.

1 INTRODUCTION

Language model text generation is subject to a fundamental tradeoff between modeling textual dependencies and leveraging the parallel processing capabilities of modern hardware. Autoregressive (AR) models have defined the state-of-the-art in quality by excelling at the former (Radford et al., 2019); generating tokens sequentially allows them to capture dependencies with high fidelity, but this process inherently creates a latency bottleneck. Conversely, diffusion language models (Sahoo et al., 2024) are designed for parallelism but can struggle with coherence when generating with a low number of iterative steps needed for low latency (Wu et al., 2025). This establishes a Pareto frontier for LLMs, in which there exists a difficult compromise between inference speed and output quality.

We propose *planned diffusion*, a framework that challenges this compromise by treating text generation as a dynamic parallel scheduling problem. The motivation behind this technique is that the dependency structure among tokens is context-dependent; typical language model responses include semantically independent spans of tokens that can generate concurrently. For example, an answer that contains a bulleted list can generate each bullet point in parallel (Ning et al., 2024).

Planned diffusion realizes this concept through a novel hybrid architecture where a single, unified model transitions between autoregressive and diffusion-based generation. First, in a sequential planning stage, the model operates autoregressively to generate a high-level "execution plan" composed of structural control tags. This plan partitions the task into a set of conditionally independent sub-tasks. Second, in a parallel diffusion stage, the model executes this plan, simultaneously generating the text for all planned segments. By integrating these two modes, our method optimizes for parallel generation while preserving coherence and quality. This single-model, hybrid approach offers a distinct architectural advantage over other acceleration techniques, such as speculative decoding, which require multiple, separate models. To the best of our knowledge, this is the first text-only model that uses both discrete diffusion and autoregression. Figure 1 presents a sample generation produced by our planned diffusion model.

Figure 1: A real example of planned diffusion. **(1) Autoregressive Plan**: The model first generates a sequential plan using control tags to define the structure and length of independent text spans. **(2) Programmatic Scaffold**: This plan is then translated into a scaffold where each span is initialized with a corresponding number of mask tokens. **(3) Diffusion Denoise**: Finally, the model denoises all spans in parallel with diffusion, generating the text for each section simultaneously to produce the complete response.

We make the following contributions:

1. We introduce *planned diffusion*, a new parallel generation technique that decomposes text generation into a sequential planning stage and a parallel diffusion stage.
2. We design the control tag language, model training methodology, and inference algorithm that enable a single model to perform this hybrid generation process.
3. We demonstrate that planned diffusion achieves a state-of-the-art trade-off between speed and quality. On the AlpacaEval benchmark, it achieves a 1.84x speedup over autoregressive generation while incurring only a 6.8% drop in win rate.
4. We present sensitivity analysis which validates that the internal planning of our model is reliable and offers tunable control over the trade-off between generation speed and quality.

2 Related Work

Our work builds upon recent developments in non-autoregressive and parallel decoding strategies. We position our contributions in the context of two primary research areas: diffusion-based language models and methods for achieving semantic parallelism.

Diffusion Language Models. Diffusion models have recently emerged as a new paradigm for generative language tasks (Austin et al., 2021; Sahoo et al., 2024). A significant body of research is focused on accel-

erating the inference process, which traditionally involves many iterative denoising steps (Liu et al., 2025a). These acceleration techniques include KV caching for diffusion models (Ma et al., 2025; Liu et al., 2025c), the use of autoregressive verification (Hu et al., 2025; Israel et al., 2025a), and the development of fast sampling strategies that reduce the number of required steps (Wu et al., 2025; Li et al., 2025; Hong et al., 2025). Our proposed planned diffusion framework is orthogonal and complementary to these methods; any diffusion sampling strategy can be integrated into the diffusion component of our algorithm to further increase performance. Other related work include block diffusion (Arriola et al., 2025) which enforces an autoregressive structure over blocks and planned denoising (Liu et al., 2025b) which learns an adaptive denoising schedule. While relevant, neither targets semantic parallelism, which is the purpose of planned diffusion.

Semantic Parallelism. While diffusion models achieve token-wise parallelism, they are not trained to achieve parallelism across larger portions of text at the semantic level. We define *semantic parallelism* as a broad class of techniques that produce models capable of parallelizing over semantically independent segments. Many recent works explore semantic parallelism (Ning et al., 2024; Liu et al., 2024; Jin et al., 2025; Wen et al., 2025; Yang et al., 2025; Pan et al., 2025; Rodionov et al., 2025). While existing works operate within a purely autoregressive framework, to the best of our knowledge, our work is the first to propose a hybrid autoregressive-diffusion model for text. By combining an autoregressive planning phase with a parallel diffusion phase, our method leverages the inherent parallelism of diffusion-based decoding in a structured manner, presenting a novel approach for efficient text generation.

Other Parallel Generation Techniques. There is a rich line of work on parallel generation. Insertion-based models parallelize by inserting tokens into partial positions, reducing decoding depth via simultaneous span updates (Stern et al., 2019). Non-autoregressive translation predicts many tokens at once and often refines them iteratively, trading some quality for much lower latency (Gu et al., 2018; Ghazvininejad et al., 2019). Speculative decoding accelerates autoregressive models by drafting multiple tokens and verifying them in parallel (Leviathan et al., 2023; Chen et al., 2023; Zhang et al., 2024). Planned diffusion differs conceptually as we use a single hybrid model to generate both autoregressively and in parallel.

3 PRELIMINARIES

Generative language models learn a probability distribution over sequences of discrete tokens. In this work, our focus is on two main paradigms: autoregressive and discrete diffusion.

Autoregression. Autoregressive models are the standard for sequential text generation. They factorize the joint probability of a token sequence $x = (x_1, x_2, \cdots)$. The probability distribution under this model, which we denote as p_{AR}, is given by:

$$p_{\text{AR}}(x) = \prod_{i=1}^{|x|} p_\theta(x_i | x_{<i}) \tag{1}$$

where p_θ is a parameterized conditional distribution over tokens. In autoregression, each token is sequentially sampled conditioned on all previously generated tokens.

Discrete Diffusion. Discrete diffusion models learn to reverse a fixed data corruption process that gradually introduces noise into a clean sequence. For language, this process often involves incrementally replacing tokens with a special "mask" token (Austin et al., 2021). Let x^0 be a clean sequence of tokens. The forward corruption process q produces a noisy version x^t at a timestep $t \in [0, 1]$. The distribution of a corrupted sequence x^t follows

$$q_{t|0}(x_i^t \mid x_i^0) = \begin{cases} t, & \text{if } x_i^t = \text{[MASK]} \\ 1 - t, & \text{if } x_i^t = x_i^0 \\ 0 & \text{otherwise} \end{cases} \qquad q_{t|0}(x^t \mid x^0) = \prod_i q_{t|0}(x_i^t \mid x_i^0) \tag{2}$$

Because the true posterior over a forward noising process is intractable to compute exactly (Lou et al., 2024), diffusion models learn an approximation by maximizing a variational lower bound on the log-likelihood (Sahoo et al., 2024).

$$\log p_{\text{D}}(x^0) \geq \mathbb{E}_{t\sim U(0,1),x^t\sim q(x^t|x^0)} \sum_i \mathbb{1}(x_i^t = \text{[MASK]}) \log p_\theta(x_i^0 \mid x^t) \tag{3}$$

Unlike autoregressive sampling, the above diffusion distribution emits a sampling algorithm capable of sampling multiple tokens in parallel. For brevity, when referring to diffusion we will let $p_{\text{D}}(x)$ denote the clean distribution obtained through the above process.

In planned diffusion, we will assume p_{AR} and p_{D} can be conditioned on prior context tokens $c = (c_1, c_2, \cdots)$. Thus, we shall utilize the distributions $p_{\text{AR}}(\cdot \mid c)$ and $p_{\text{D}}(\cdot \mid c)$ respectively.

4 Planned Diffusion

Planned diffusion can be described probabilistically as a model that factorizes the text generation process into distinct planning and diffusion components. While this formalization is a useful description, it abstracts away technical details regarding implementation. The details comprise of three key contributions: (i) a synthetic data curation pipeline to produce text annotated with planning control tags, (ii) a tailored training objective with a custom attention masking to enforce the specified conditional independencies, and (iii) an optimized inference procedure that utilizes KV caching to facilitate efficient parallel decoding.

4.1 Formal Description

We formalize the generative process for a single stage of planned diffusion. A stage begins with an initial context c which may contain the prompt or any previously generated tokens. It then produces a plan $z = (z_1, z_2, \dots)$ followed by its corresponding asynchronous execution x, where both are sequences of tokens. The plan z defines the structure for the subsequent parallel generation, specifying a set of $b(z)$ asynchronous spans. For each span $k \in \{1, \dots, b(z)\}$, the plan also specifies its length $l_k(z)$.

Let $x(k)$ be the sequence of tokens corresponding to the k-th span, where $|x(k)| = l_k(z)$. The complete sequence generated in the diffusion phase is the union of these spans, $x = \bigcup_{k=1}^{b(z)} x(k)$. The joint probability of generating the plan z and the content x within a single stage of planning and diffusion, conditioned on the context c, is given by the following factorization:

$$p_{\text{PD}}(z, x|c) = \underbrace{p_{\text{AR}}(z|c)}_{\text{Planning}} \underbrace{p_{\text{D}}(x|z, c)}_{\text{Diffusion}} \tag{4}$$

where p_{PD} denotes the distribution of planned diffusion. In this definition, we note that the diffusion distribution p_{D} is conditioned on the plan z, which guarantees additional properties. In planned diffusion, each span $x(k)$ are generated independently of one another. Thus, the probability of a whole span x factorizes over individual spans $x(k)$.

$$p_{\text{D}}(x|z, c) = \prod_{k=1}^{b(z)} p_{\text{D}}(x(k)|z, c) \tag{5}$$

Thus, planned diffusion is able to exploit conditional independence between spans to achieve significant parallelism. In this formulation, we describe one stage of planned diffusion composed of autoregressive planning and conditional diffusion. In general, this framework can be extended to multiple stages of planning and diffusion chained together by setting c to the output of the previous stage. This multi-stage process can be seen in Algorithm 1

Algorithm 1 Planned Diffusion

function PLANNED_DIFFUSION(c)
  loop
    Sample plan $z \sim p_{\text{AR}}(\cdot|c)$
    Parse z to get spans $b(z)$ and their lengths $\{l_k(z)\}_{k=1}^{b(z)}$
    Sample $\{x(k)\}_{k=1}^{b(z)}$ in parallel from $p_{\text{D}}(\cdot|z, c)$
    $x \leftarrow \bigcup_{k=1}^{b(z)} x(k)$
    $c \leftarrow c \oplus z \oplus x$
    if z[end] = <eos/> **then**
      break
    end if
  end loop
  $c \leftarrow$ REMOVECONTROLTAGS(c)
  return c
end function

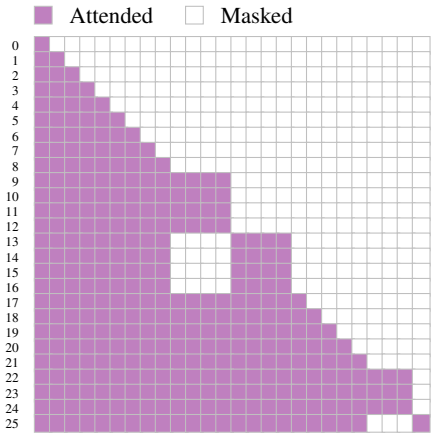
4.2 DATA

Control Tags. A span intended for parallel generation is first defined during a sequential planning stage. This is done using a paired <topic> ... </topic> tag structure. Within this structure, the model generates a concise description of the span's content (e.g., description) and its predicted length (e.g., 3) in multiples of 10 tokens. During the parallel diffusion stage, the tokens for each planned span are generated within a corresponding <async> ... </async> tag pair. Finally, the <sync/> tag conveys generation dependency: tokens that follow <sync/> may require details produced inside the preceding <async> spans, so we continue sequential planning only after those spans are filled and available. We add all control tags to the model's vocabulary for training and inference and strip them during post-processing of final outputs.

Finetuning Dataset. We annotate the SlimOrca instruction–finetuning dataset (Lian et al., 2023) for parallel generation, following Jin et al. (2025). We prompt a GEMINI model with the syntax and semantics of the special tags (attribute schema, complete-coverage and non-overlap constraints). See Appendix A for more details. GEMINI inserts the control tags into the assistant completion. The opening <async> carries two attributes: topic (a concise label, ≤ 3 words) and tokens (a coarse length estimate, e.g., multiples of 10 tokens). We impose complete coverage: every non-tag token lies inside exactly one <async> ... </async> span (no nesting, no overlap). During preprocessing for training, we insert 0–10 tokens of stochastic padding inside each <async> span to create variable reconstruction gaps while preserving tag correctness. We validate well-formedness (balanced tags, coverage, non-overlap, attribute types/ranges) and discard malformed cases. Figure 2 contains a concrete example of the tagging language used by planned diffusion.

4.3 TRAINING

Training Loss. The goal of training is to maximize the joint probability over plan tokens and their content. Suppose we are given access to an annotated dataset $\mathcal{D}$ in which a single "clean" example is given by $Y \in \mathcal{D}$. We can decompose Y into sets of planning tokens Z and content tokens X, such that $Y = Z \cup X$. X^t is a noised sequence of tokens under noise distribution $q_{t|0}$ as previously defined. Thus, X^t will contain masked tokens with probability t. Let f_θ be the function to instantiate planned diffusion, parameterized by θ. We will use the notation $f_\theta(x, i)$ to signify that the model takes input x and makes a prediction at index i of the sequence. Finally, let $M_i(X)$ be a masking function that takes as input a sequence X and outputs a



Plan 1 (0-8)
0: <bos>
1: <topic>
2: task1
3: 3
4: </topic>
5: <topic>
6: task2
7: 2
8: </topic>

Diffusion 1 (9-16)
9: <async>
10: A
11: B
12: </async>
13: <async>
14: C
15: D
16: </async>

Plan 2 (17-21)
17: <sync/>
18: <topic>
19: task3
20: 1
21: </topic>

Diffusion 2 (22-25)
22: <async>
23: E
24: </async>
25: <eos>

Figure 2: The attention mask for planned diffusion combines causal and bidirectional attention. Causal attention is used for sequential planning stages. Bidirectional attention is used within <async> spans for parallel denoising, with concurrent spans isolated from each other. After a <sync/> token, subsequent tokens can to attend to all prior tokens. For illustrative purposes, this example shortens the diffusion spans.

subset $M_i(X) \subseteq X$ of the sequence that f_θ will be given access to at a particular index i. A more detailed description of our mask can be found in the following section. Our overall training objective is given by

$$\mathcal{L}(\theta) = \mathop{\mathbb{E}}_{\substack{Y\sim\mathcal{D} \\ t\sim U(0,1)}} \frac{1}{|Y|} \sum_{y_i \in Y} \underbrace{\mathbb{1}(y_i \in Z)\mathrm{CE}(f_\theta(y_{<i}, i),\, y_i)}_{\text{Autoregressive}} + \underbrace{\frac{1}{t}\mathbb{1}(y_i \in X)\mathrm{CE}\big(f_\theta(M_i(X^t \cup Z), i),\, y_i\big)}_{\text{Diffusion}} \quad (6)$$

A subtle characteristic of the training objective is that the same noise is applied to diffusion spans over multiple sequential stages of planning and diffusion. In this decision, we are applying the interpretation of a diffusion model as an any-order autoregressive model capable of supporting arbitrary conditional queries at inference time (Shi et al., 2024). The same technique is used by Llada 7B (Nie et al., 2025), which is trained with a diffusion objective, but during inference used for semi-autoregressive block sampling.

Attention Mask. We implement the following rules via the attention mask M_i. First, sequential-planning tokens, which are composed of control tags and their attributes, are given causal attention (Plan 1 and 2 in Figure 2). Second, tokens inside the same <async>…</async> span use bidirectional attention, as required for diffusion-based parallel denoising (Diffusion 1 and 2 in Figure 2). Third, spans remain isolated until synchronization: before <sync/>, we enforce no cross-span attention; after <sync/>, subsequent tokens may attend to all previously completed <async> spans.

4.4 Inference

Variable Length Denoising. Typically, diffusion models are configured to generate given a fixed number of denoising steps. Generation quality increases and speed decreases with the number of steps. Unlike, vanilla diffusion, planned diffusion does not generate a predetermined number of tokens, so as a consequence the number of denoising steps cannot fixed. We define a parameter r called the *steps ratio*. Given a generation length $|x|$, the number of denoising steps will be $s = r * |x|$. Note that for multiple diffusion spans $x(k)$ for $k \in \{1, ..., b(z)\}$ and a plan z, we will use $s = r * \max_k l_k(z)$. The number of denoising steps may depend

only on the length of the longest span because if all spans are denoised in parallel, the total number of steps will be entirely determined by the longest span.

KV Caching. KV caching plays a substantial role in the efficiency of planned diffusion. The KV cache of planned diffusion can be derived from the model's hybrid attention mask. The general principle is that a token whose key and value embeddings are unaffected by future tokens can be cached. This is determined by whether a token attends to future positions in the sequence. The autoregressive planning stage uses causal attention and a conventional application of KV caching (Pope et al., 2023). In contrast, the diffusion stage employs a bidirectional mask, in which tokens inside an <async> span attend to each other. Because bidirectional attention does not support KV caching (Israel et al., 2025b), tokens inside an <async> span cannot be cached until their respective denoising process is complete. However, subsequent tokens, such as those in a new planning stage following a <sync/> tag, can efficiently attend to the KV cache of the preceding planning and diffusion stages. This caching mechanism is essential for combining the speed of diffusion with the computational savings of autoregressive KV caching.

Diffusion Inference. While diffusion models are trained on an objective that implies a random unmasking order, in practice diffusion does not achieve the best results in this setting. Planned diffusion can integrate any inference algorithm that determines diffusion unmask order. We apply entropy-ordered unmasking, which is a default inference algorithm of Dream 7B (Ye et al., 2025).

5 Experimental Evaluation

We experimentally assess the performance of planned diffusion, focusing on its trade-off between generation quality and latency. Our results show that planned diffusion expands the latency-quality Pareto frontier for text generation when compared to autoregressive and other diffusion-based approaches. Furthermore, we demonstrate that our method scales better with additional compute; planned diffusion continues to improve with more training, whereas the performance of the autoregressive baseline plateaus.

Training setup. We fine-tune Dream-7B-Base (Ye et al., 2025; Qwen et al., 2025); the base model is first pre-trained autoregressively and then further pre-trained with a diffusion objective. We train with AdamW (Kingma & Ba, 2017; Loshchilov & Hutter, 2019), peak learning rate 5×10^{-5} with linear decay, and bfloat16 precision. We use per-GPU batch size 1 and global batch size 4. Because autoregressive and diffusion language models have different optimal epoch counts (Prabhudesai et al., 2025), we sweep epochs over $\{4, 8, 16\}$. We fine-tune on Gemini-annotated SlimOrca instruction-following data (Section 4.2); for planned diffusion, we keep the control tags, while for autoregressive and diffusion baselines we strip them. Training runs on $4\times$H200 (141 GB) with PyTorch and Hugging Face.

Baselines. We compare four decoding strategies. (i) *Autoregressive* samples tokens sequentially from the autoregressive model. (ii) *Diffusion* samples masked tokens in parallel from the diffusion model; we configure the number of denoising steps to equal the number of new tokens as this produces the highest quality generation (Lou et al., 2024; Shi et al., 2025; Sahoo et al., 2024). (iii) *Fast-dLLM* (Wu et al., 2025) samples from the same diffusion model but with an inference-time only optimization. We configure denoising steps to be half the number of new tokens and use a confidence threshold of 0.9, which Wu et al., 2025 use as the default value. (iv) *Planned diffusion* (ours) samples a plan autoregressively from the planned-diffusion model, then samples masked tokens within each span in parallel from the same model; for each span, we configure denoising steps to equal its predicted token count.

Inference setup. We sample with temperature 0.2 and top-p 0.95 following (Ye et al., 2025), and cap the total sequence length at 2048 tokens. Inference runs on the same H200 hardware configuration.

Benchmark and metrics. We evaluate on AlpacaEval (805 instruction-following prompts) (Li et al., 2023; Dubois et al., 2024). For each method we report: (i) *average latency*—the mean wall-clock time per re-

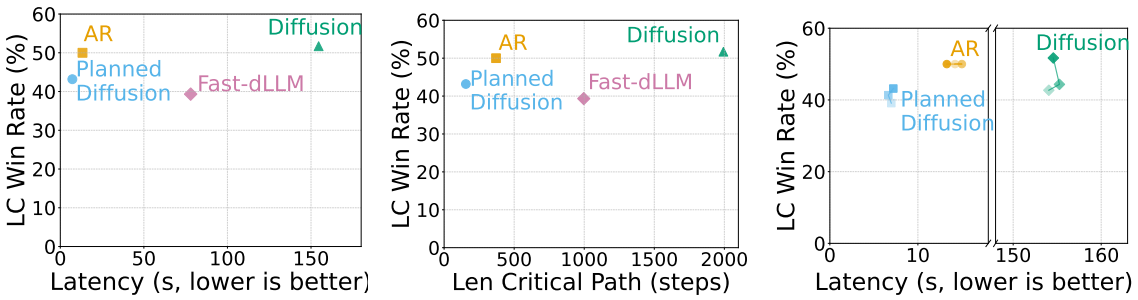


Figure 3: Evaluation of planned diffusion on the AlpacaEval benchmark. **Left:** A comparison of latency versus length-controlled win rate shows planned diffusion establishing a new Pareto frontier, offering a better trade-off between speed and quality. **Middle:** An analysis of the average critical path length reveals that planned diffusion requires substantially fewer sequential forward passes than autoregressive generation. **Right:** A scaling analysis shows that planned diffusion's win rate continues to improve with more training, while the autoregressive baseline's performance flatlines. Within each method, color brightness encodes training epochs: lightest = 4 epochs, medium = 8 epochs, darkest = 16 epochs.

sponse; and (ii) *quality*—length-controlled win rate (LCWR) with an LLM-as-judge. We use the recommended default configuration from (Dubois et al., 2024) due to its high correlation with human preference. We fix the LCWR reference to the best autoregressive baseline. We identify this reference by evaluating the autoregressive variants (4, 8, and 16 epochs) against the 4-epoch variant and choosing the model with the highest LCWR [1]. The 16-epoch model wins and serves as the fixed reference for all LCWR scores.

Quality and Latency. We plot the latency–quality trade-off in the left figure of Figure 3. planned diffusion is 10.8× faster than the fast-dLLM and higher in quality (43.2% vs. 39.3% length-controlled win rate). Relative to autoregressive decoding, it is 1.85× faster while achieving a 43.2% length-controlled win rate against the autoregressive reference. Diffusion reaches the highest quality (51.7% length-controlled win rate) but requires an order of magnitude more inference time than autoregressive decoding or planned diffusion.

Critical Path. We attribute much of planned diffusion's speedup over autoregressive decoding to its shorter *critical path* of generation. We define critical path length as the number of forward passes required to produce the final answer. The middle panel of Figure 3 shows that, on AlpacaEval, the average critical path of autoregressive decoding is 2.39× as long as that of planned diffusion (370.5 vs. 155.2 steps). This is expected, as planned diffusion enables multiple spans to denoise simultaneously. The realized speedup (1.85×) is smaller than this reduction (2.39×) because each planned diffusion step does more work—KV-cache reuse is lower and per-step compute is heavier than an autoregressive token step.

Scaling. The right panel of Figure 3 shows how the latency-quality tradeoff evolves with training epochs for the three training objectives we examine. We evaluate all models against the 16-epoch autoregressive model as the quality reference. Autoregressive training shows no improvement: the length-controlled win rate remains at 50.0% across 4, 8, and 16 epochs. Planned diffusion improves from 39.11% (4 epochs) to 43.18% (16 epochs), gaining 4.07 percentage points. Diffusion shows the largest improvement, rising from 42.71% (4 epochs) to 51.70% (16 epochs), gaining 8.99 percentage points.

Takeaway. Planned diffusion sets a new latency–quality Pareto frontier and keeps improving with more training, while the autoregressive baseline plateaus.

[1] They tie on length controlled win rate, so we break ties using raw win rates.

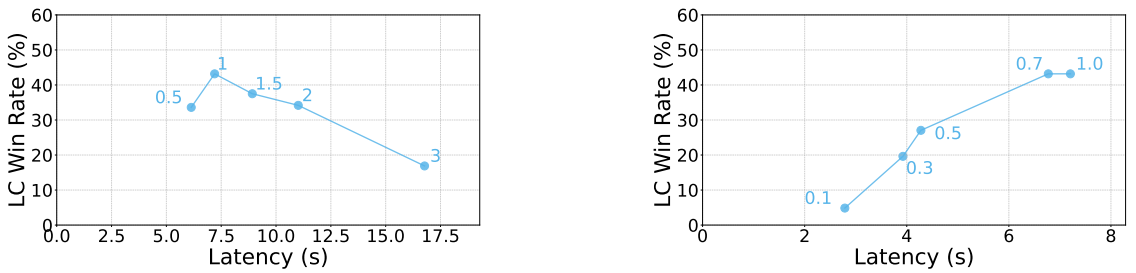


Figure 4: Sensitivity analysis of key hyperparameters in planned diffusion. **Left:** Effect of scaling predicted span lengths. Quality (LCWR) peaks when the scaling factor is 1.0, indicating the model's length predictions are accurate. **Right:** Quality–latency trade-off as the step ratio varies. Smaller step ratios reduce latency but also lower generation quality.

6 Sensitivity Analysis

We present additional analysis on several design decisions key to planned diffusion.

Span Lengths. We test whether the model predicts span lengths accurately. Accurate length prediction is key to achieving good generation quality for planned diffusion, as the diffusion denoising phase of generation cannot alter the span length. Systematic over-prediction wastes time by adding masks and denoising steps, while systematic under-prediction harms quality by forcing content truncation.

To test for potential systematic deviation from the optimal generation length, we multiply the model's predicted span length by a length scaling factor to set the number of masks, sweeping the factor over $\{0.5, 1.0, 1.5, 2.0, 3.0\}$. We then measure length-controlled win rate (LCWR) and latency under identical inference settings. Quality peaks at the model's originally predicted length (that is, with a scaling factor of 1.0). Deviating by $\pm 50\%$ reduces length controlled win rate: $+50\%$ by 5.7% and -50% by 9.6%. Latency rises with factors above 1.0 as expected because larger spans require more mask tokens and denoising steps. Interestingly, we do not observe additional denoising steps leading to accuracy improvements. The model's length predictions are accurate; we do not observe systematic over/under-prediction.

Step Ratio. By default, we set the number of denoising steps for a span equal to that span's length. Reducing the number of steps can lower latency at the cost of quality. We measure the quality–latency trade-off that results from varying the number of diffusion denoising steps.

We introduce a hyperparameter called step ratio (see Section 4.4), which sets the number of denoising steps relative to the span length. A step ratio of 1 means the number of steps equals the number of tokens in the span (our default). Smaller values mean fewer steps per token. We sweep step ratios of 0.1, 0.3, 0.5, and 0.7 and measure length-controlled win rate (LCWR) and latency under identical inference settings. Figure 4 shows an approximately linear trade-off between quality and latency as the step ratio decreases. Using a step ratio of 0.5 (half as many steps as tokens) yields an LCWR of 27.05% with 4.3 s latency. Step ratio provides a tunable trade-off between generation quality and latency. We use 1.0 by default, but smaller values are useful when latency is the priority and a drop in quality is acceptable.

7 Conclusion

In this work, we introduce planned diffusion, a hybrid architecture that combines the quality of autoregressive generation with the parallelism of discrete diffusion. Our experimental evaluation show that it expands the latency–quality frontier of text generation, providing a promising framework for efficient text generation.

Reproducibility Statement

We specify the starting checkpoint, fine-tuning hyperparameters, inference settings, and hardware/software setup in Section 5. Appendix A includes a shortened version of the data-annotation prompt; we omit in-context examples for brevity.

LLM Use Disclosure

We used LLMs to improve sentence-level writing and to search for related work.

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A Data Annotation Prompt

We present a shortened version of our data-annotation prompt below. We use it to instruct Gemini Flash 2.0 (temperature = 1.0, top-p = 0.95) to annotate our training data.

```
You will first identify whether the given chatbot response may be generated in
parallel. You are to then annotate the chatbot response using specific tags
that highlight segments suitable for parallel generation.

Use <async> tags to denote segments of text that may be generated asynchronously
in parallel with respect to the text that follows. Thus apply <async> tags only
to sentences that do not serve as necessary context for subsequent sentences.
Sentences that are crucial for understanding or generating following text are
not suitable for parallel asynchronous generation. For each <async> tag, include
a very concise topic description of the text surrounded within the <async> tags.
The topic description will be accessible to text generation after the closing
async tag to ensure continuity and coherence.

Use the singleton <sync/> tag for synchronization. All content generated before
<sync/>, including text marked by <async> is accessible to subsequent text
generation after the <sync/> tag, ensuring continuity and coherence.

Detailed Instructions:
- Tagging Rules:
 - Use <async> tag in pairs.
 - Ensure all text content is encapsulated within <async> tags.
 - Ensure that each <async> tag encompasses at least five words.
 - Refrain from altering the content of the response during annotation.
 - Use a maximum of 3 words in the topic description.
 - Use <sync/> sparingly as it introduces significant slowdown.
```