AR MODELS CAN BE FASTER AND MORE ACCURATE PARALLEL DECODERS THAN DIFFUSION LLMS

Anonymous authors
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ABSTRACT

Multi-token generation has emerged as a promising paradigm for accelerating transformer-based large model inference. Recent efforts have primarily explored diffusion-based LLMs (dLLM) for parallel decoding to reduce latency while preserving model generation quality. However, non-diffusion approaches remain largely underexplored and it's unanswered whether AR models can be adapted as faster parallel decoders than dLLMs while maintaining generation quality. We present pcLLM, a progressive consistency distillation paradigm that transforms autoregressive (AR) models into efficient parallel decoders while preserving the causal inference property. pcLLM achieves $3.6\times$ wall-clock speedup on coding benchmarks with minimal loss in performance. Based on pcLLM's trajectory characteristics, we introduce multi-block decoding with rejection recycling, which enables up to $4.2\times$ higher token acceptance count per iteration and nearly $4\times$ speedup, effectively trading additional compute for lower inference latency.

1 INTRODUCTION

Modern Large Language Models (LLMs), such as GPT-5 (OpenAI, 2025), Gemini-2.5 (DeepMind, 2025), and DeepSeek-R1 (Ren et al., 2025), demonstrate impressive capabilities across a wide range of complex reasoning and agentic tasks. However, the strong performance come at the cost of high inference latency, particularly during the generation of long token sequences using chain-of-thought (Wei et al., 2022; Hou et al., 2025; Ren et al., 2025; Muennighoff et al., 2025) under autoregressive (AR) decoding. Since each token generation requires a full forward pass through the model, the sequential nature of decoding limits parallelism and underutilizes the massive parallel processing capabilities of modern GPUs. This results in significantly increased inference latency and high computational costs, degrading user experience in real-time and interactive applications.

Diffusion-based language models (dLLMs) offer an alternative to AR models by relaxing token-by-token causality and enabling multi-token generation per iteration with improved controllability (Li et al., 2024a; Nisonoff et al., 2024; Schiff et al., 2024). dLLMs reframe decoding as a more parallelizable computation that better utilizes the compute from modern accelerators. Mercury (Inception Labs, 2025), Gemini Diffusion (Google DeepMind, 2025) and Seed Diffusion (Song et al., 2025b) demonstrate that diffusion-based LLMs (dLLMs) can achieve up to a $5\times$ increase in throughput while maintaining coding and text generation quality on par with autoregressive (AR) models. Community-driven efforts (Ye et al., 2025; Zhu et al., 2025; Nie et al., 2025a; JetAstra, 2025; Gong et al., 2025) are rapidly advancing in this direction; however, a performance gap remains. In particular, current open implementations often exhibit lower generation quality and face challenges in adapting widely used inference optimizations for AR models, such as KV caching, to the bi-directional attention setting of dLLMs. While recent work have made significant gains in further improving dLLMs' efficiency (Arriola et al., 2025; Wu et al., 2025a; Liu et al., 2025), it remains an open question whether AR models possess the same potential for parallel decoding, or the ability to train an efficient parallel decoder is a unique advantage of dLLMs.

One commonly used parallel decoding technique for AR models is Jacobi decoding (Song et al., 2021; Santilli et al., 2023), which is training-free and requires no architecture modification. While this method has inspired several extensions (Fu et al., 2024; Teng et al., 2024; Wu et al., 2025b), in practice these techniques deliver only modest speedups. Prior works including CLLM (Kou et al., 2024) and CEED-VLA (Song et al., 2025a) train LLMs and Vision-Language-Action (VLA) models

with consistency distillation (Song et al., 2023) to predict multiple correct tokens simultaneously in each iteration. Kou et al. (2024); Gat et al. (2025) observes that when inference with larger block sizes, the speedup achieved during inference plateau: as the block size increases, the number of tokens "fast-forwarded" per iteration remains essentially constant. A natural question is whether we can train models to better predict future tokens under Jacobi decoding, such that increasing the block size yields useful predictions. Modern AI accelerators offer high FLOPs, and if decoding more future tokens in each iteration could reduce the total number of iterations to generate the same number of tokens, total latency drops.

In this work, we introduce a progressive consistency distillation technique that address the limitation by progressively teaching to predict more tokens within each block and to perform better fast forwarding with increasing block size. We further introduce a noise-aware causal attention that teaches to model to predict correct tokens within each block conditioned on unconverged blocks, and we show it enables more useful future tokens to emerge in each block's trailing tails. We show applying rejection-recycling and multi-block decoding to leverage this model behavior from progressive consistency LLMs (pcLLM) for further efficiency improvement.

Experiments show pcLLM can serve as very efficient parallel decoders with up to $3.8\times$ improvement in generation speed across coding and math benchmarks. It also effectively generate higher quality draft n-grams from future tokens within each block, as observed in Section 4. Using rejection-recycling and multi-block decoding makes use of future n-grams and further boost speedup to $4.2\times$.

In summary, key contributions of this paper includes:

- We introduce progressive consistency distillation to train AR models as fast parallel decoders, pcLLM, with up to $4\times$ generation speedup.
- We empirically observe and qualitatively verify pcLLM have both higher fast-forwarded token count and a useful n-gram count in comparison with baseline models.
- We propose rejection-recycling and multi-block decoding to make use of higher quality draft n-grams from future tokens within each block, and apply them to pcLLM boost generation speed to $4.2\times$ across various benchmarks.

2 PRELIMINARY

This section reviews the basics of Jacobi decoding and consistency distillation training to accelerate Jacobi decoding of AR models.

2.1 JACOBI DECODING

Given a prompt $\boldsymbol{x}$ and a pre-trained LLM $p_\theta(\cdot|\boldsymbol{x})$ parametrized by θ, the standard AR decoding under the greedy strategy produces a response sequentially as follows:

$$y_i = \arg\max_y p_\theta(y \mid \boldsymbol{y}_{<i}, \boldsymbol{x}), \quad \text{for } i = 1, \ldots, n, \tag{1}$$

where $\boldsymbol{y}_{<i} = \{y_1, \ldots, y_{i-1}\}$. This process requires n forward passes of the LLM to generate n tokens $\boldsymbol{y}_{\le n}$. The inherently sequential nature of AR decoding limits practical efficiency when generating long sequences. Jacobi decoding (Song et al., 2021; Santilli et al., 2023) addresses this bottleneck by reformulating token generation as solving a system of nonlinear equations:

$$f(y_i, \boldsymbol{y}_{<i}, \boldsymbol{x}) = 0, \quad \text{for } i = 1, \ldots, n, \tag{2}$$

where $f(y_i, \boldsymbol{y}_{<i}, \boldsymbol{x}) := y_i - \arg\max_y p_\theta(y|\boldsymbol{y}_{<i}, \boldsymbol{x})$. This system can be solved in parallel using Jacobi fixed-point iteration (ort, 2000). Starting from a randomly initialized n-token sequence $\boldsymbol{y}^{(0)} = \{y_1^{(0)}, \ldots, y_n^{(0)}\}$, the update at each iteration j is:

$$\begin{cases} y_1^{(j+1)} & = \arg\max_y p_\theta(y|\boldsymbol{x}) \\ y_2^{(j+1)} & = \arg\max_y p_\theta(y|\boldsymbol{y}_1^{(j)}, \boldsymbol{x}) \\ & \vdots \\ y_n^{(j+1)} & = \arg\max_y p_\theta(y|\boldsymbol{y}_{<n}^{(j)}, \boldsymbol{x}). \end{cases} \tag{3}$$

Notably, for LLM, the above n maximization problems can be solved in parallel by using a causal attention mask, i.e., only one forward pass of the LLM is required to obtain $\boldsymbol{y}^{(j+1)}$ based on $\boldsymbol{y}^{(j)}$. The iteration exits at some k such that $\boldsymbol{y}^{(k)} = \boldsymbol{y}^{(k-1)}$ and we define $\boldsymbol{y}^* := \boldsymbol{y}^{(k)}$ as the fixed point. Let $\mathcal{J} := \{\boldsymbol{y}^{(0)}, \ldots, \boldsymbol{y}^{(k)}\}$ denote the Jacobi trajectory. It can be proven that $\boldsymbol{y}^*$ is identical to AR decoding under greedy strategy (Song et al., 2021).

To generate a long response $\boldsymbol{l}$ of length $L \gg n$, Jacobi decoding is applied sequentially over blocks of size n until the <eos> token appears in a fixed point. Let $\boldsymbol{y}^*_{B_i}$ denote the fixed point obtained for the i-th block. The full output $\boldsymbol{l}$ is then constructed by concatenating fixed points from consecutive blocks:

$$\boldsymbol{l} = [\boldsymbol{y}^*_{B_1}, \ldots, \boldsymbol{y}^*_{B_N}], \tag{4}$$

where N denotes the number of blocks generated before termination.

2.2 Consistency Distillation

Despite the promise, Jacobi decoding achieves little speedup over standard AR decoding (Santilli et al., 2023; Fu et al., 2024), as it rarely predicts more than one correct[1] token within one fixed-point iteration. To address this, recent works such as CLLMs (Kou et al., 2024) propose consistency distillation, a training approach designed to accelerate convergence to the fixed point from arbitrary states on a Jacobi trajectory. The key idea is to introduce a consistency loss that encourages an LLM $p_\theta(\cdot|\boldsymbol{x})$ to predict multiple tokens simultaneously:

$$\mathcal{L}_{\text{c}} = \mathbb{E}_{i\sim\mathcal{U}\{1,\ldots,N\},\boldsymbol{y}_{B_i}\sim\mathcal{J}_i}\left[D_{\text{KL}}\left(p_{\theta^-}(\boldsymbol{y}^*_{B_i}|\boldsymbol{x}, \boldsymbol{y}^*_{B_1}, \ldots, \boldsymbol{y}^*_{B_{i-1}})||p_\theta(\boldsymbol{y}_{B_i}|\boldsymbol{x}, \boldsymbol{y}^*_{B_1}, \ldots, \boldsymbol{y}^*_{B_{i-1}})\right)\right], \tag{5}$$

where $\theta^- = \text{stopgrad}(\theta)$ and D_{KL} denotes the KL divergence aggregated across the n tokens in a block. Here, $i \sim \mathcal{U}\{1, \ldots, N\}$ denotes sampling a block index uniformly at random, and $\boldsymbol{y}_{B_i} \sim \mathcal{J}_i$ denotes randomly sampling from the Jacobi trajectory of the i-th block.

CLLMs build upon this idea by first collecting Jacobi trajectories, obtained by running Jacobi decoding with p_θ on a set of prompts. The model is then trained with a joint objective that combines the consistency loss in Eq. 5 with the standard AR loss, achieving up to a $2\times$ speedup over AR decoding while maintaining quality. Similar training objectives have also been adopted for inference acceleration in other domains, such as action prediction in VLA models (Song et al., 2025a).

3 Methodology

In this section, we first discuss the training challenges of consistency distillation with larger block sizes n, and then present progressive consistency distillation, a refined paradigm designed to mitigate this bottleneck, and denote LLMs trained under this paradigm as pcLLM. Furthermore, by observing pcLLM's trajectories under vanilla Jacobi decoding, we introduce rejection-recycling and multi-block decoding strategies to improve its efficiency.

3.1 Progressive Consistency Distillation

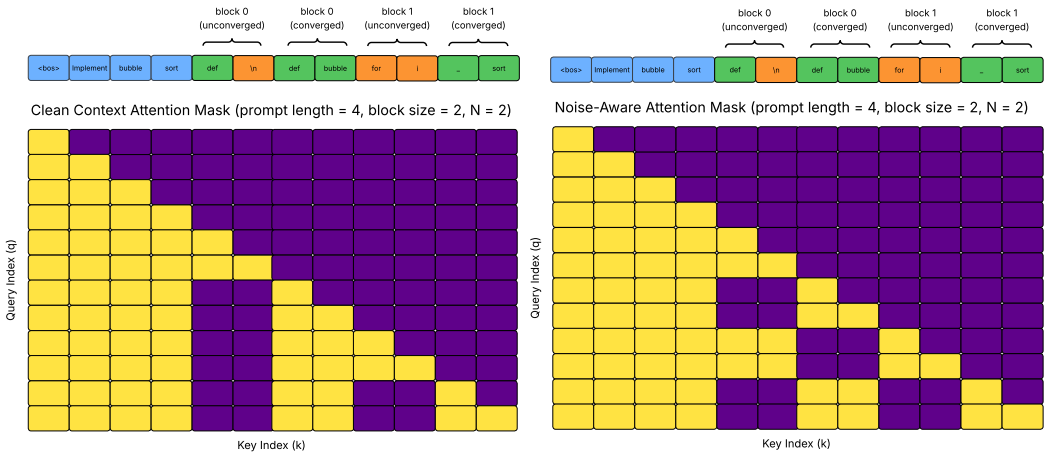
Progressive Noise Schedule. In Jacobi decoding, we maintain strict causality within each block, where each token is updated in accordance with Eq. 3. Consider the i-th block $\boldsymbol{y}^{(j)}_{B_i}$ of size n is been decoded at some iteration step j. Assume the first $c-1$ tokens have been accepted, and we denote y_f as the future token as shown in Eq. 6.

$$y_f = \arg\max_y \; p\big(y \mid \boldsymbol{x}_c,\; \boldsymbol{y}'_{c:f-1}\big), \quad \text{for } f = c+1, \ldots, n, \tag{6}$$

where $\boldsymbol{x}_c = [\boldsymbol{x}, \boldsymbol{y}_{<c}]$ is the clean context, $\boldsymbol{y}'_{c:f-1}$ is the noisy[2] context. While the training objective in Eq. 5 is designed to optimize correct token prediction in this setting, it's observed from Kou et al.

[1] By correctness, we mean alignment with the AR decoding result under a greedy sampling strategy.

[2] By noisy, we refer to tokens in the non-converged point along the Jacobi trajectory that that differ from those in the fixed point at the same positions.



(a) clean-context conditioned causal mask.

(b) noisy-context conditioned causal mask.

Figure 1: Sequence packing with two attention mask implementations, both allow logits from clean blocks and noisy blocks to be generated with single forward pass to calculate the progressive consistency loss and AR loss in Eq. 9.

(2024) that predicting y_f is hard when it's conditioned on a long noisy context $\boldsymbol{y}'_{c:f-1}$ under large block sizes (e.g., $n = 256$).

To address this challenge, we instead split a large block into smaller blocks (e.g., $n = 16$) with noise ratios determined by a predefined schedule $\{t_1, \ldots, t_N\}$. Each t_i denotes the fraction of noisy tokens in a block. The noise schedule follows a cyclic strategy with window size w, where the noise ratio linearly increases from 0 to 1 within each window, i.e.,

$$W = \left\{0, \frac{1}{w}, \ldots, \frac{w-1}{w}\right\}, \quad t_i = W[j], \quad j = i \bmod w. \tag{7}$$

This progressive schedule ensures that each block retains a partially clean context, thereby shortening noisy tokens dependencies. In particular, it reduces the longest span of consecutive noisy inputs for any prediction from $O(\lceil tnw \rceil)$ to $O(\lceil tn \rceil)$, which facilitates learning. Empirically, we find this progressive schedule to be more effective than a purely random noise schedule (Table 4).

Progressive Distillation Loss. Let $\boldsymbol{y}_{b_i}^{t_i}$ denote the point along the i-th block Jacobi trajectory with a number of noisy tokens closest to $\lceil t_i n \rceil$. The training objective is to predict tokens correctly within each block, aggregating losses across blocks to reduce gradient variance and stabilize optimization. Accordingly, we introduce a new loss term, *progressive consistency loss*, which optimizes p_θ under the progressive noise schedule in Eq. 7:

$$\mathcal{L}_{\text{pc}} = \frac{1}{N} \sum_{i=1}^{N} D_{\text{KL}}\big(p_{\theta^-}(\boldsymbol{y}_{B_i}^* \mid \boldsymbol{x}, \boldsymbol{y}_{B_1}^{t_1}, \ldots, \boldsymbol{y}_{B_{i-1}}^{t_{i-1}}) \big\| \, p_\theta(\boldsymbol{y}_{B_i}^{t_i} \mid \boldsymbol{x}, \boldsymbol{y}_{B_1}^{t_1}, \ldots, \boldsymbol{y}_{B_{i-1}}^{t_{i-1}})\big). \tag{8}$$

AR Loss. Kou et al. (2024) notes that using only the consistency loss (Eq. 5) must be supplemented with an AR loss to maintain generation quality. Our preliminary experiments show that using only the consistency objective (Eq. 8) produces the same effect. This motivates our inclusion of a conventional AR loss term in the final training objective to safeguard output quality:

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{pc}} + w\mathcal{L}_{\text{AR}} \tag{9}$$

where w is a tunable weight that balances the two learning objectives.

Noise-aware Causal Attention. In CLLM, loss from each training step is computed based on KL divergance from one block instance in Eq. 5. This learning objective is to train correct token prediction in the setting where there is only a big block (Eq. 6). Moreover, in both Eq. 5 and Eq. 8, the loss term computation involves two forward passes using a conventional causal mask since each involves a distinction sequence. As a result, it requires $O(2N)$ forward passes to compute all loss terms in Eq. 8 and $O(N)$ backward passes to compute gradients, resulting in low training efficiency, especially in settings like CoT generation for reasoning models. We reduce the number of forward

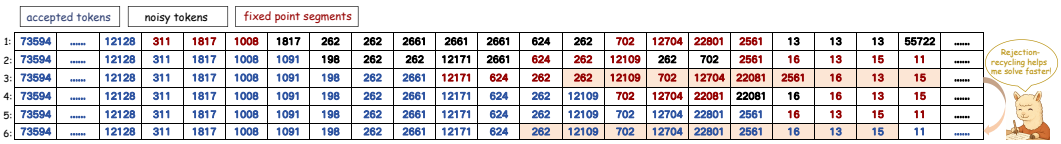


Figure 2: Visualization of pcLLM's trajectory under vanilla Jacobi decoding. The figure shows a partial segment of the trajectory. Blue tokens denote accepted tokens that match the fixed point at their positions. Black tokens denote unconverged noisy tokens, and we highlight them in red if more than three consecutive tokens match the fixed point regardless of position.

and backward passes from $O(N)$ to $O(1)$ by introducing a sequence packing technique and a block-wise sparse attention mask. We illustrate the sequence packing that interleaves $\boldsymbol{y}_{b_i}^{t_i}$ and $\boldsymbol{y}_{b_i}^{*}$ for the entire complete sequence in Figure 1b for $\mathcal{L}_{pc}$ computation, in contrast with conditioning each unconverged y_{b_s} only on clean tokens for consistency distillation with $\mathcal{L}_c$ in Figure 1a.

Progressive Distillation for Larger Block Sizes. In training pcLLM on Jacobi trajectories prepared from the original AR model, we find model speedup scales with the number of training steps and saturate at around 400k steps. We find that collecting additional rounds of Jacobi trajectories from intermediate checkpoints empowered with multi-token prediction capability and train the models on new trajectories with *progressively larger block sizes* can break the ceiling and further improve model speedup by up to 20%, yet with a slight degradation of model performance.

3.2 Inference Optimization

Jacobi Decoding Behavior of pcLLM. pcLLM is trained to have a stronger capability of generating correct future tokens conditioning on noisy tokens. Qualitative analysis in Figure 2 illustrates that it indeed brings the quality improvement: fixed-point segments emerge within the noisy tokens of the unconverged point. Furthermore, these segments progressively extend (e.g., the number of red tokens increases from point 1 to point 2 in Figure 2), even under noisy context, consistent with our training patterns. In this section, we focus on how to translating this qualitative observation of draft quality improvement into qualitative speedup.

Rejection Recycling. Prior work has shown that n-grams produced during Jacobi iterations can be verified in parallel and reused in subsequent iterations (Fu et al., 2024). As illustrated in Figure 2, such n-gram sizes could be large in pcLLM, and if correctly verified many tokens can be fast-forwarded in one iteration. In particular, we initialize a fixed-size n-gram pool by collecting noisy token sequences from unconverged points during Jacobi decoding. If the pool contains an n-gram matching the last accepted token of the current point, we concatenate its subsequent tokens to form new candidates (line 11 in Algorithm 1). At each iteration, we select the candidate with the most accepted tokens. For instance, this strategy enables skipping from point 3 to point 5 in Figure 2, as the fixed-point segments in point 3 yield higher-quality candidates.

Multi-block Decoding. In addition to high-quality n-grams in the draft, we also observe the increasing number of stationary tokens, which are correctly predicted with preceding noisy tokens and remain unaltered through subsequent iterations. Together they yield higher quality drafts. To make use of the property, we introduce *multi-block decoding*, a new decoding paradigm that maintains and refines up to K blocks simultaneously. It marks the block closest to the effective KV cache boundary as the *real-active* block and all the other $K-1$ blocks as *pseudo-active* blocks. Only tokens within the real-active block are accepted and committed to KV cache. Tokens in pseudo-active blocks are only pseudo-accepted, conditioning on prior blocks; once converged, pseudo-active blocks will wait until they are promoted as the

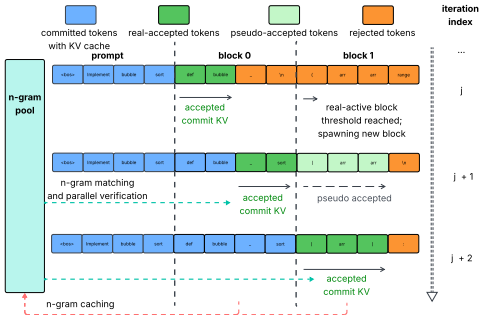


Figure 3: An example of multiblock decoding with rejection recycling at prompt length = 4, block size = 4, $r = 0.5$, $K = 2$.

Algorithm 1 MULTIBLOCK DECODING + REJECTION RECYCLING

Init: Create a set of blocks $\{b\}$ with one *real–active* block RA: draft tokens q_{RA} randomly initialized, accepted tokens $a_{RA} = \varnothing$; For all other blocks b, set $q_b = \varnothing$, $a_b = \varnothing$, and mark as *pseudo-active*.
Initialize candidate pool $\mathcal{N} = \emptyset$, spawn ratio r, threshold $s = \lceil rn \rceil$, block size n.
while iters $<$ max **do**
  Assemble input $\boldsymbol{y}$: Concatenate q_{RA}, then for each pseudo-active b, append a_b (no logits) and q_b (collect logits). Resize cache to batch $\boldsymbol{y}$.
  Forward: Run model $p_\theta(\boldsymbol{y})$ to produce logits.
  for each block b with span $(start, L)$ **do**
    Verification (with rejection-recycling): Greedy prediction $g = \arg\max$ logits; accept longest matching prefix of q_b using g (or $g \cup \mathcal{N}$ if $b = RA$); update a_b.
    if $b = RA$ and EOS encountered in accepted region **then**
      return committed output.
    end if
    Tail update: If partial accept, set $q_b \leftarrow [\text{next} \| g_{\text{tail}}]$ (and if $b = RA$: push rejected tail to update $\mathcal{N}$ and q_{RA}); else $q_b \leftarrow \varnothing$.
  end for
  Cache trim: Delete false KV to committed length: prompt + verified a_b (all accepted blocks) + a_{RA}.
  Spawn: If some block b reaches $|a_b| \geq s$ and active $\{b\} < K$, clone and pad q_{RA} to length n and add as new pseudo-active block.
  Promote: If $|a_{RA}| \geq n$, choose a pseudo-active b with $|a_b| > 0$, rebuild its draft to length n, mark as verified, set $RA \leftarrow b$.
  Stop: If all $|a_b| \geq n$ or EOS emitted by RA, break.
end while
Finalize: Concatenate output = verified a_b for all non-RA blocks, then a_{RA}; trim KV cache $\mathcal{C}$;
Return: $(\text{output}, \mathcal{C}, \text{iters})$

real active block, where all tokens will be verified again, but now with a higher-quality draft. A detailed description is provided in Algorithm 1 (with rejection recycling) and with an example in Figure 4b. Note that both rejection recycling and multi-block decoding are lossless as they employ greedy rejection sampling for token acceptance in the real-active block (Leviathan et al., 2022).

4 EXPERIMENTS

4.1 EVALUATION SETTINGS

Models and Datasets. We evaluate pcLLM across coding benchmark. For coding benchmarks, we train Qwen2.5-Coder-Insutrct (Hui et al., 2024) on OpenCodeInstruct (Ahmad et al., 2025) and test on the HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021). On OpenCodeInstruct, we curate question instances that come with generations that pass all unit tests, from where we use 450k prompts for trajectory generation and training.

Training Settings. All training and inference are conducted on instances equipped with 8x NVIDIA A100-80GB GPUs, and 8x NVIDIA H200 GPUs. All models are trained with learning rate lr=10^{-6}, max new sequence length at 2048. For pcLLM, we adopt linear progressive noise schedule, initial block size at 16, window size at 16, and a second round of trianing with block size at 32, window size at 8. Ablation studies on parameter choices are presented in Section 4.3.

Baselines. Our main objective in this section is to compare performance and efficiency between diffusion-based parallel decoders and AR-based parallel decoder, pcLLM. The dLLM baselines, also have the capability of generating a single block of tokens or multiple consecutive blocks of tokens together. Specifically, we compare pcLLM with state-of-the-art (SOTA) dLLMs including LLaDA-7B (Nie et al., 2025b), Dream-7B (Ye et al., 2025), fast-dLLM (Wu et al., 2025a) and D2F (Wang et al., 2025). We also compare pcLLM with AR-based parallel decoder including vanilla Jacobi decoding (Santilli et al., 2023) and CLLM (Kou et al., 2024). In this work, we do not focus

Table 1: Performance and efficiency on coding benchmarks, HumanEval and MBPP, grouped by decoding family. For AR-based models, all methods adopt Qwen2.5-Coder-7B-Instruct. For pcLLM, MR stands for employing the multi-block and rejection-recycling decoding algorithm introduced in Algorithm 1. DC stands for using bi-directional dual cache from fast-dLLM. For both Fast-dLLM and D2F, we choose the Dream-7B as it's significantly faster with similar or better performance than LLaDA-7B. For CLLM*, we follow mostly the same recipe in CLLM but with new sequence packing technique (without progressive training on larger block sizes). The speedup ratio is relative to the AR baseline.

Benchmark	Family	Method	TPS ↑	Speedup↑	Accuracy↑	Param Size (B)
HumanEval	*AR-based*	AR	41.3	1.00×	87.9	7
		Jacobi	39.9	0.97×	87.9	7
		CLLM*	103.3	2.50×	88.0	7
		pcLLM	147.6	3.57×	84.8	7
		pcLLM (MR)	**149.3**	**3.62**×	84.8	7
	Diffusion-based	LLaDA-Instruct	2.8	0.07×	36.0	7
		Dream-Base	20.2	0.49×	54.3	7
		Fast-dLLM (DC)	60.0	1.45×	53.0	7
		D2F	73.2	1.77×	54.3	7
MBPP	*AR-based*	AR	43.1	1.00×	74.3	7
		Jacobi	42.4	0.98×	74.3	7
		CLLM*	80.1	1.94×	71.4	7
		pcLLM	90.4	2.10×	73.4	7
		pcLLM (MR)	**106.3**	**2.47**×	73.4	7
	Diffusion-based	LLaDA-Instruct	0.9	0.02×	39.0	7
		Dream-Base	10.4	0.24×	56.2	7
		Fast-dLLM (DC)	73.2	1.70×	51.0	7
		D2F	105.0	2.44×	55.2	7

on speculative decoding methods, because the models themselves don't serve as parallel decoders without supplemental architecture modifications (e.g. via additional heads) (Cai et al., 2024; Li et al., 2024b;c; 2025) or separate draft models (Leviathan et al., 2022; Liu et al., 2024).

4.2 Results

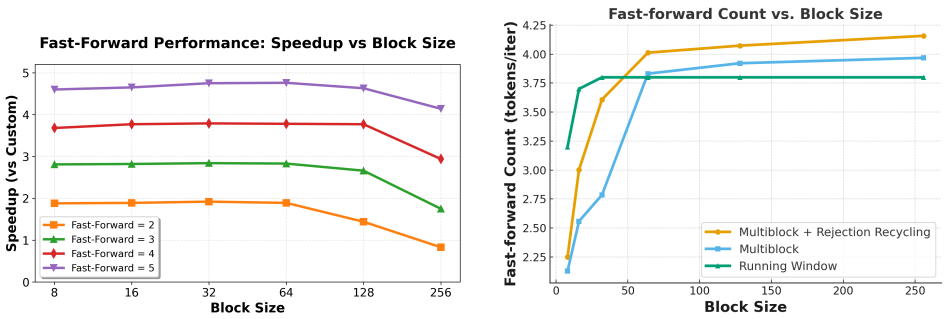
Performance. The performance metrics are the greedy generations' strict accuracy (pass@1) on HumanEval and MBPP. Table 1 compares pcLLM with both dLLMs and Jacobi decoding baselines. On A100 GPUs, our results show that on both benchmarks, pcLLM consistently achieves both better accuracy and better speedup at the same parameter scale. In particular, for structured generations like Python coding, pcLLM achieves $3.6\times$ speedup in comparison with the AR baseline, $53.3 \sim 7.4\times$ speedup comparing to dLLM baselines, and $2.0\times$ comparing to optimized dLLM baselines including Fst-dLLM and D2F with techniques like adding block-wise KV cache, bidirectional KV cache and pipelined parallel decoding. For speedup evaluation, we run all evaluations with block size at 128 except for pcLLM (MR) since MR takes extra FLOPs for multiblock decoding and parallel verification. We also present speedup comparison across different AR-based techniques with pcLLM on H200 in Table 2 as it comes with a better fast-forwward count to TPS conversion rate with mroe compute on H200.

Table 2: Speedup on HumanEval tested on H200 using same settings and speedup ratio over A100.

Method	TPS ↑	Speedup↑	r (vs. A100)
AR	65.4	1.00×	1.00
Jacobi	63.0	0.96×	1.00
CLLM*	151.3	2.31×	0.92
pcLLM	235.3	3.60×	1.01
pcLLM (MR)	**258.3**	**3.95**×	1.09

4.3 Ablation Study

Block sizes. In this section, we analyze how block size impacts speedup for vanilla Jacobi decoding and multiblock decoding using pcLLM. As shown in Figure 4a, modern GPUs can sustain large block sizes without increasing end-to-end latency compared to the AR baseline. On H200 GPUs,



(a) Speedup vs. (log-scaled) block size at fixed fast-forwarding count per iteration on NVIDIA H200 GPU, using Jacobi decoding at prompt length = 128, generation length = 256.

(b) fast-forward count vs. block size on HumanEval using three decoding strategies on NVIDIA H200 GPU. Notice larger block size provides more fast-forward token count for multi-block decoding with rejection recycling.

Figure 4: Effect of block size choices on fast-forward counts and wall-clock speedup under different settings. We choose the maximum block size on hardware without sacrificing wall-clock speedup.

Table 4: Inference results for block size = 256 with $N = 16$, $t_{\text{min}} = 0.0$ and $t_{\text{max}} = 1.0$. Acc. = pass@1 accuracy (%) on HumanEval. The checkpoints are trained with Qwen2.5-Coder-7B-Instruct on 10k randomly sampled instances from our OpenCodeInstruct trajectory dataset. Notice that for ablation purpose, the checkpoints are not trained with full datascale as in Table 1. Reverse progressive is significantly worse than other schedule and we only conduct ablation for one choice of window size.

Window Size	Random		Linear Progressive		Reverse Progressive	
	Acc.	iter/token	Acc.	iter/token	Acc.	iter/token
8	82.9	0.53	**84.7**	**0.48**	–	–
16	83.5	0.51	81.7	0.46	82.9	0.62

when the number of tokens accepted per iteration with pcLLM are fixed at $2, 3, 4, 5$, Jacobi decoding with block sizes up to 64 incurs no latency penalty, and only minor degradation arises at block size 128, particularly in the high fast-forwarding count regime.

With varying block sizes, we apply multi-block decoding using pcLLM and the results are presented in Figure 4b. The running window method is an optimized variant of Jacobi decoding designed for settings where many tokens are accepted per iteration. It maintains a fixed-size active block by replenishing draft tokens to the original block size as accepted tokens are committed to the KV cache. The results demonstrate that multi-block decoding with rejection recycling consistently achieves the highest number of fast-forwarded tokens per iteration, particularly in the larger block-size regime.

Table 3: Effects of applying noise-conditioned mask (NC) or noise-conditioned mask with intra-window clean context (NC-IC) for pcLLM training, and evaluated on HumanEval with A100.

Method	Speedup↑	Acc.
NC	**3.6**×	**82.3**
NC-IC	1.9×	82.3

Noise schedules. We evaluate three types of noise schedules: random, linear progressive, and reverse progressive. In the random schedule, the noise step t_i for each block is sampled uniformly as $t_i \sim \mathcal{U}(1, \ldots, N)$ during sequence packing in pcLLM training. The linear progressive schedule follows Eq. 7, while the reverse progressive schedule applies a linearly decreasing noise ratio from 1 to 0 within each window. Results in Table 4 show that the linear progressive schedule significantly outperforms the other two when the window size is 8. Intuitively, with $N = 16$, this schedule corresponds to adding noise more aggressively across blocks within each window, roughly two additional noisy tokens per future block, until the final block where all tokens are noisy.

Mask types. We train pcLLM on the objective in Eq. 8 with noise-conditioned mask implementation (Figure 1b). An alternative implementation of the mask is to condition all blocks within a window on clean context. In other words, for every query, it sees blocks from all proceeding windows as of Figure 1a]), and all blocks within its own window as of Figure 1b. Intuitively, it makes token predictions in later windows and blocks easier to learn because now they are conditioned on cleaner context. We summarize results in Table 3, where it shows noise-conditioned mask is more effective in empowering pcLLM with speedup while maintaining generation quality.

5 Related Work

Diffusion-based Large Language Models (dLLMs) represent an new paradigm that challenges traditional autoregressive (AR) modeling by replacing left-to-right causality with iterative denoising, enabling parallel multi-token generation (Li et al., 2024a; Nisonoff et al., 2024; Schiff et al., 2024). Closed-source dLLMs (e.g., Gemini Diffusion (Google DeepMind, 2025; Inception Labs, 2025; Song et al., 2025b)) show huge throughput improvement while maintaining competitive code and text quality, underscoring better accelerator utilization. On the open-source side, community dLLMs with released code and weights delivered strong throughput and controllability via parallel iterative denoising, yet remaining less efficient than autoregressive decoding (Ye et al., 2025; Zhu et al., 2025; Nie et al., 2025a; JetAstra, 2025; Gong et al., 2025). Recent efforts (Arriola et al., 2025; Wu et al., 2025a; Liu et al., 2025) further push the efficiency and scalability of dLLMs.

Jacobi decoding reframes AR generation as a parallel fixed-point update over all positions, with convergence linked to greedy AR, and has been instantiated using Jacobi (Gauss-Seidel) iterations (Song et al., 2021; Santilli et al., 2023). Building on this, follow-ups either refine the decoding procedure or train models as parallel decoders to exploit parall: CLLMs (Kou et al., 2024) fine-tune LLMs with consistency distillation to predict multiple correct tokens per iteration and speed convergence; CEED-VLA (Song et al., 2025a) brings the similar idea to robotics. Other strands adapt Jacobi to new regimes, including FastCoT (Zhang et al., 2023) for reasoning with parallel CoT updates, Speculative Jacobi Decoding (Teng et al., 2024) for sampling in AR Test-to-Image, and MSN, TR-Jacobi (Wang et al., 2024) that injects denoising training and a retrieval-augmented Jacobi strategy.

Speculative decoding speeds up AR generation by letting a lightweight drafter propose several future tokens and having the target model verify them in one pass (Leviathan et al., 2022; Chen et al., 2023). It preserves the target model's distribution while reducing latency. Subsequent work improves proposal quality and verification efficiency: online speculative decoding (OSD) (Liu et al., 2024) adapts draft models to user query distributions via continual distillation, substantially improving token acceptance and reducing inference latency. Medusa (Cai et al., 2024) adds multi-head drafters to the base LM to produce verify-able token blocks; EAGLE, EAGLE-2 (Li et al., 2024b;c) reuse target features for feature-level drafting, and EAGLE-3 (Li et al., 2025) scales this idea with multi-layer fusion. Lookahead Decoding (Fu et al., 2024), PLD (Saxena, 2023; Somasundaram et al., 2024), and REST (He et al., 2023) dispense with a separate drafter, instead synthesizing speculative candidates directly from context or future tokens.

6 Conclusion

In this work, we propose a progressive distillation technique for training AR models as faster and more accurate parallel decoders compared to dLLMs. Unlike CLLM (Kou et al., 2024), which directly trains models to predict large blocks of tokens in parallel, our approach introduces a progressively more difficult learning objective. This is achieved through a progressive noise schedule, combined with a sequence packing strategy and a noise-aware causal mask, enabling parallel token prediction conditioned on noise. The model is further improved through iterative training, where trajectories are regenerated with progressively larger block sizes. The resulting model, pcLLM, achieves a $3.6\times$ speedup while largely preserving accuracy. Analysis of its generated trajectories shows that pcLLM produces high-quality draft tokens toward the tail of sequences. In addition, we introduce rejection recycling and multi-block decoding, which together brings tokens accepted per iteration to $4.2\times$ as high with nearly $4\times$ speedup on HumanEval using an H200 GPU.

Ethics Statement

All authors have read and adhere to the ICLR Code of Ethics. This work does not involve human subjects, sensitive personal data, or experiments with the potential to cause harm. No confidential or proprietary data were used. The methods and experiments were conducted in accordance with principles of research integrity, fairness, and transparency. Potential societal impacts, including limitations and biases of large language models, are explicitly discussed in the paper. All conclusions are the sole responsibility of the authors.

Reproducibility Statement

We have made significant efforts to ensure the reproducibility of our results. Detailed descriptions of the models, datasets been used, as well as hyperparameter choices are included in the main text. All datasets used are publicly available, and the preprocessing steps are fully documented. Ablation studies are provided to validate robustness of results. These resources collectively allow independent researchers to verify and reproduce our work.

7 Use of LLM

During the preparation of this manuscript, large language model was used to refine grammar and improve clarity. The authors carefully reviewed and revised all outputs to ensure the text reflects their original ideas and take full responsibility for the final content, including all statements and conclusions.

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