

Diffusion Beats Autoregressive in Data-Constrained Settings

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Abstract

Autoregressive (AR) models have long dominated the landscape of large language models, driving progress across a wide range of tasks. Recently, diffusion-based language models have emerged as a promising alternative, though their advantages over AR models remain underexplored. In this paper, we systematically study masked diffusion models in data-constrained settings—where training involves repeated passes over limited data—and find that they significantly outperform AR models when compute is abundant but data is scarce. Diffusion models make better use of repeated data, achieving lower validation loss and superior downstream performance. We interpret this advantage as implicit data augmentation: masked diffusion exposes the model to a diverse distribution of token orderings and prediction tasks, unlike AR’s fixed left-to-right factorization. We find new scaling laws for diffusion models and derive a closed-form expression for the critical compute threshold at which diffusion begins to outperform AR. These results suggest that when data, not compute, is the bottleneck, diffusion models offer a compelling alternative to the standard AR paradigm. Our code is available at: <https://github.com/wmn-231314/diffusion-data-constraint>.

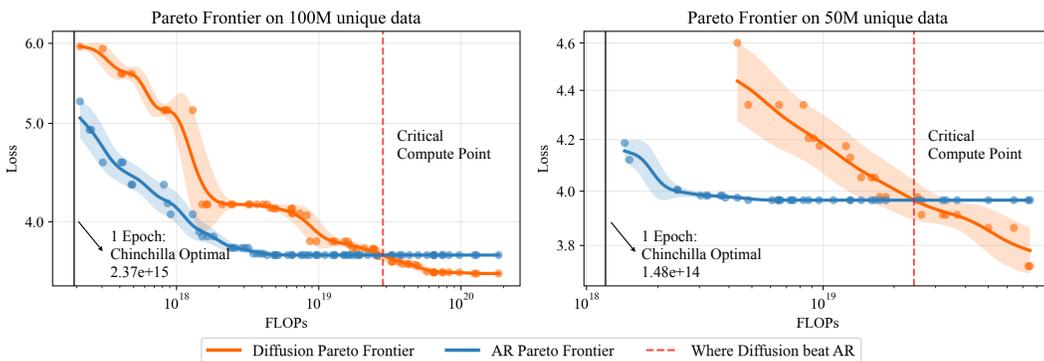


Figure 1: Pareto frontier of validation loss versus training FLOPs for autoregressive (AR) and masked diffusion models under data-constrained settings. Each point represents a model trained until convergence; we report the best validation loss achieved among all models using less than or equal to the FLOPs shown on the x-axis. AR models initially outperform diffusion models, particularly near the Chinchilla-optimal compute point [15] (indicated on the plot). However, as training continues beyond this regime with repeated data, AR models quickly saturate and begin to overfit. In contrast, diffusion models continue to improve with more compute and exhibit no signs of overfitting.

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1 Introduction

Training large language models (LLMs) on massive corpora of internet text has become the driver of recent AI breakthroughs [4, 30, 43]. This progress has been fueled by scaling two core resources proportionately: compute and data [18, 14]. While compute availability has steadily grown—enabled by advances in hardware and the construction of larger data centers—the growth in high-quality data has been comparatively stagnant. Recent projections, such as those by Villalobos et.al. [45], estimate that the global supply of publicly available, human-generated data may be exhausted by 2028, posing a serious bottleneck to further scaling. This looming constraint makes it increasingly important to develop modeling strategies that are more data-efficient. Furthermore, there are several domains, such as robotics and healthcare, where the data, not compute, is a scarce resource even to begin with.

LLM development has so far been dominated by autoregressive (AR) models, which factorize the joint distribution of text in a fixed left-to-right order, i.e., $p(x) = p(x_0)p(x_1 | x_0)p(x_2 | x_1)p(x_3 | x_1, x_2)$. While this modeling approach has delivered state-of-the-art performance across a range of benchmarks, it remains unclear whether it is the optimal strategy going forward. Recently, diffusion-based models—specifically masked diffusion models [2, 33, 21, 37, 1]—have emerged as an alternative strategy, where they model text via a random-order factorization, e.g., $p(x) = p(x_2|x_3)p(x_3|x_0)p(x_0|x_1)p(x_1)$. These models learn across many different masked versions of the text, allowing them to train on diverse token orderings. Although diffusion language models have demonstrated similar scaling behavior to AR models [25, 42], their practical benefits have, so far, been modest—largely due to their high training compute requirements.

This high compute demand has become the central obstacle to wider adoption of diffusion-based language models. As noted by Nie *et al.* [25] and Swerdlow *et al.* [42], masked diffusion models require up to 16× more compute than AR models to match validation NLL—a clear disadvantage for most applications.

But a critical nuance is often overlooked: these comparisons are based entirely on single-epoch training, where each token is seen only once. This conflates compute efficiency with data efficiency, making it unclear whether diffusion models truly need 16× more compute—or simply 16× more data.

To resolve this ambiguity, we systematically study masked diffusion models in data-constrained settings, where repeated training on limited data is the norm rather than the exception. We find that under such regimes, diffusion models substantially outperform autoregressive models across a variety of data scales and compute budgets. We train hundreds of models spanning multiple orders of magnitude in model size, data quantity, and number of training epochs to fit scaling laws for diffusion models in the data-constrained setting. We summarize some of our key findings below.

1. **Diffusion models surpass autoregressive models given sufficient compute.** Across a wide range of unique token budgets, we observe a consistent trend: autoregressive models initially outperform diffusion models at low compute, but quickly saturate. Beyond a critical compute threshold, diffusion models continue improving and ultimately achieve better performance (Section 4.1)
2. **Diffusion models benefit far more from repeated data.** Prior work [24] showed that repeating the dataset up to 4 epochs is nearly as effective as using fresh data for autoregressive models. In contrast, we find that diffusion models can be trained on repeated data for up to **100 epochs**, while having repeated data almost as effective as fresh data (Section 4.2).
3. **Diffusion models have a much higher effective epoch count.** Muennighoff *et al.* [24] fit scaling laws for AR models in data-constrained settings and define R_D^* as a learned constant that characterizes the number of epochs after which training more epochs results in significantly diminished returns. For autoregressive models, they estimate $R_D^* \approx 15$. In contrast, we find $R_D^* \approx 500$ for diffusion models, suggesting they can benefit from repeated data over far more epochs without major degradation (Section 4.2).
4. **Critical compute point follows a power law with dataset size.** We find that the amount of compute required for diffusion models to outperform autoregressive models—the critical compute point—scales as a power law with the number of unique tokens. This yields a closed-form expression that predicts when diffusion becomes the favorable modeling choice for any given dataset size (Section 4.3).

5. **Diffusion models yield better downstream performance.** We find the above benefits extend beyond validation loss: the best diffusion model trained in data-constrained settings consistently outperform the best autoregressive model on a range of downstream language tasks (Section 4.4).

Through detailed scaling law analysis and downstream task evaluations, we demonstrate that diffusion models make significantly better use of repeated data, achieving lower validation loss and better generalization to downstream tasks. These results suggest that diffusion models may offer a compelling and underappreciated advantage in scenarios where data—not compute—is the primary bottleneck.

2 Related Work

Deep Learning in Data-Constrained Settings. Deep learning progress has been largely driven by the scaling of both data and compute. However, recent analyses suggest we may soon face a data bottleneck that could inhibit continued advancement [45]. In language modeling, the dominant paradigm has been autoregressive (AR) models [44, 30, 4], which are typically trained for a single epoch to maximize exposure to unique tokens [14]. In light of looming data constraints, Muennighoff et al. [24] show that AR models can still benefit from data reuse: training for up to four epochs on repeated data achieves performance nearly on par with training on fresh data, suggesting an effective strategy for improving data efficiency. In contrast, computer vision has long embraced multi-epoch training along with aggressive data augmentation—such as random cropping, flipping, and color jittering—to expand effective dataset size and improve generalization [39, 46], particularly for discriminative tasks like classification and detection. Despite these practices, data efficiency in generative modeling remains underexplored, and the trade-offs between leading paradigms such as diffusion and AR models under constrained data regimes are still poorly understood.

Diffusion-Based Language Models. Diffusion models, originally developed for image generation [13], have recently been adapted to text, offering a fundamentally different paradigm for language modeling [2, 20, 11]. Broadly, diffusion language models fall into two categories: *continuous* and *discrete*. Continuous approaches [11] inject Gaussian noise in the forward process, whereas discrete methods [2] corrupt tokens with noise sampled from distributions such as Bernoulli. Among the two classes, continuous diffusion has proven more difficult to scale on language data [11, 22]. In contrast, recent advances in *discrete* diffusion—particularly masked diffusion—have shown encouraging results. Recent work [1, 9, 33, 22] has significantly narrowed the performance gap between diffusion and AR models. Notably, LLaDA [26] scales masked diffusion models to 8B parameters and achieves results similar to LLaMA3-8B across both pretraining and instruction-tuned evaluations. Furthermore, Nie et al. [25] provide scaling law analysis showing that diffusion models follow similar power-law trends as AR models, though they may require up to $16\times$ more compute under single-epoch training, Swerdlow et al. [42] find similar trends on multimodal data containing both image and text. However, these evaluations are restricted to single-pass training and do not examine the data-constrained, multi-epoch regimes which is the focus of our work.

3 Method

Our objective is to determine whether masked diffusion language models are more effective than standard autoregressive models in data-constrained settings. The main difference between AR and diffusion models is the way they factorize the joint distribution of the sequence. Masked diffusion factorizes the joint distribution of the sequence in a random order, while AR factorizes the joint distribution of the sequence in a left-to-right order. To isolate the impact of this, we keep the architecture and data pipeline fixed across both families and vary only the factorization of the joint distribution.

3.1 Preliminaries:

Autoregressive models. In Autoregressive LLMs [43, 30, 4] we predict each token based on a growing prefix of prior tokens, defining a left-to-right factorization of the sequence probability:

$$p_{\text{AR}}(x_1, \dots, x_L) = \prod_{j=1}^L p(x_j | x_{<j}).$$

This structure is implemented using a *causal attention mask*, which prevents each token from attending to future positions. The model is trained via next-token prediction over clean, uncorrupted sequences.

Diffusion models. Masked diffusion language models [2, 33, 25, 42] treat generation as iterative denoising. For each training sequence $x = (x_1, \dots, x_L)$ we

1. Corrupt the sequence by sampling a masking ratio $r \sim \mathcal{U}(0, 1)$ and independently replacing each token with a special [MASK] symbol with probability r . This yields a corrupted sequence \tilde{x} and a mask set

$$\mathcal{M} = \{i \in [1, L] : \tilde{x}_i = [\text{MASK}]\}.$$

2. Denoise by predicting the original tokens at the masked positions with full (bidirectional) attention over \tilde{x} :

$$p_{\text{Diffusion}}(x | \tilde{x}) = \prod_{i \in \mathcal{M}} p_{\theta}(x_i | \tilde{x}).$$

Because the mask pattern is resampled for every example, the model is implicitly trained on a vast collection of token-ordering tasks; the standard left-to-right ordering used by AR models is just one ordering within this ensemble. The absence of a causal mask allows each prediction to attend to *both* past and future unmasked tokens, making the factorization fundamentally non-sequential.

3.2 Modeling Details for AR and Masked Diffusion

Our goal is to isolate the impact of the factorization—fixed left-to-right versus random-order denoising—while keeping every other design choice constant. Unless noted otherwise, both model families share the same Transformer backbone (GPT-2 style with rotary positional embeddings, RoPE [41]) and identical training hyper-parameters across the full parameter sweep (7 M – 2 B).

Given a clean input sequence $x = (x_1, \dots, x_L) \in \mathcal{V}^L$, both models minimize a token-level cross-entropy loss, yet they differ in the conditioning context:

Autoregressive (AR) objective. AR models predict each token conditioned on its prefix using a causal attention mask:

$$\mathcal{L}_{\text{AR}} = - \sum_{j=2}^L \log p_{\theta}(x_j | x_{<j}).$$

Masked Diffusion objective. For masked diffusion we first sample a masking ratio $r \sim \mathcal{U}(0, 1)$ and construct a corrupted sequence \tilde{x} by independently replacing each token with [MASK] with probability r . Let $\mathcal{M} = \{i : \tilde{x}_i = [\text{MASK}]\}$ be the set of masked positions. The loss is then

$$\mathcal{L}_{\text{Diffusion}} = -\mathbb{E}_r \mathbb{E}_{\tilde{x} \sim q_r} \sum_{i \in \mathcal{M}} \log p_{\theta}(x_i | \tilde{x}).$$

Unlike Nie *et al.* [25], we do not add auxiliary losses (e.g., classifier-free guidance) in order to ablate only the factorization.

Beyond the attention mechanism and input corruption, *all* other variables are held constant. We follow the hyperparameter configuration proposed by Muennighoff *et al.* [24] for all training runs. In particular, we use a dynamic learning rate schedule that adapts to the number of training epochs. The only distinctions between AR and diffusion models in our implementation are:

1. **Attention mechanism:** Causal attention for AR; full self-attention for masked diffusion.
2. **Prediction target:** AR models predict the next token; diffusion models predict the masked tokens.

3.3 Scaling Framework in Data-Constrained Settings

Classical scaling laws, such as those proposed by [18, 15], model validation loss as a function of total parameters (N) and training tokens (D), assuming all data is unique. These laws have been instrumental in guiding compute-optimal training of language models. However, this assumption becomes unrealistic as the community approaches the limits of high-quality text data available on the internet.

To address this, Muennighoff *et al.*[24] extend the Chinchilla framework to explicitly account for repeated data — a common necessity in data-constrained regimes. They show that repeating training data beyond a few epochs yields diminishing returns and propose a new scaling law that incorporates the decaying utility of repeated tokens.

We briefly outline their formulation below.

Definitions:

- U : number of **unique** tokens available for training,
- E : number of **epochs** (i.e., how many times each unique token is reused),
- $D = U \cdot E$: total number of tokens seen by the model.

To model diminishing returns from repeated data, Muennighoff *et al.* [24] introduce an *effective unique data size* D' , motivated by the idea that each additional epoch contributes less useful signal than the previous. Specifically, they assume the value extracted from the k^{th} exposure to the same data follows a geometric progression, where the utility of a token on its k -th repetition is $(1 - \delta)^{k-1}$. Summing over all epochs the total effective data becomes: $D' = U \cdot \sum_{k=1}^E (1 - \delta)^{k-1} = U \cdot \frac{1 - (1 - \delta)^E}{\delta}$ where δ is the decay factor. Defining $R_D^* = \frac{1 - \delta}{\delta}$, the expression simplifies to the exponential-decay form:

$$D' = U + U \cdot R_D^* \left(1 - e^{-(E-1)/R_D^*}\right).$$

here R_D^* represents the half-life of data reuse, repeating data beyond R_D^* epochs will result in significant diminishing returns. This form approximates the geometric sum well and captures diminishing returns over repeated epochs. As the number of epochs $E \rightarrow \infty$, the exponential term vanishes and D' asymptotically approaches: $D' \rightarrow U + U \cdot R_D^*$, implying that no matter how many times data is repeated, the maximum usable signal is bounded by $(1 + R_D^*) \cdot U$. This defines a natural saturation point on returns: even infinite compute yields no additional effective data beyond this limit.

A symmetric formulation is applied to model parameters for mathematical convenience which is used to define N' . Finally, a modified Chinchilla-style loss function incorporates these effective quantities N' and D' :

$$\mathcal{L}(N, D) = \frac{A}{(N')^\alpha} + \frac{B}{(D')^\beta} + E_0,$$

with $A, B, \alpha, \beta, E_0, R_D^*, N_D^*$ fitted empirically from training runs. This formulation accurately captures loss behavior in regimes where data is reused multiple times and serves as a powerful tool for guiding training under data scarcity.

In this work, we adopt this framework to study how diffusion models and autoregressive models compare in their ability to extract value from repeated data, enabling apples-to-apples comparisons across compute, data, and model scale.

3.4 Training setup

We use the English C4 corpus [31], tokenized with the GPT-2 BPE vocabulary and truncated or padded to 2048 tokens per sequence. We consider unique-token budgets of $U \in \{25, 50, 100\}$ M and train for up to 800 epochs (80B tokens total). Models are trained ranging from 7M to 2.5B parameters, following the Chinchilla scaling strategy where both width and depth are increased proportionally. The detailed architectural configurations of each model are provided in Appendix 10. For all training runs, we adopt the hyperparameter configuration introduced by Muennighoff *et al.* [24]. This may provide a slight advantage to autoregressive models, as these hyperparameters were originally tuned for that family. For all models, we use the following hyperparameters: batch

size of 256 sequences, AdamW optimizer with $\beta_1=0.9$, $\beta_2=0.95$, $\epsilon=10^{-8}$, a learning rate schedule with peak $2e-4$, minimum $2e-5$, 1% warm-up, cosine decay, weight decay 0.1, and gradient clipping of 1.0.

4 Experiments

Our goal is to compare the performance of masked diffusion models and autoregressive models in data-constrained settings. To this end, we train a total of 200 models—100 diffusion models and 100 autoregressive models—across varying unique data sizes, model scales, and epoch counts. We present the empirical results in Section 4.1. In Section 4.2, we fit scaling laws tailored to data-constrained regimes for both model types, following the methodology introduced by Muennighoff *et al.*[24]. These scaling laws allow us to analyze performance trends and identify scenarios where diffusion models should be preferred over autoregressive ones (Section 4.3). Finally, in Section 4.4, we demonstrate that the superior validation loss of diffusion models indeed correlates with improved downstream task performance.

4.1 Does Diffusion beat AR in Data Constrained Settings?

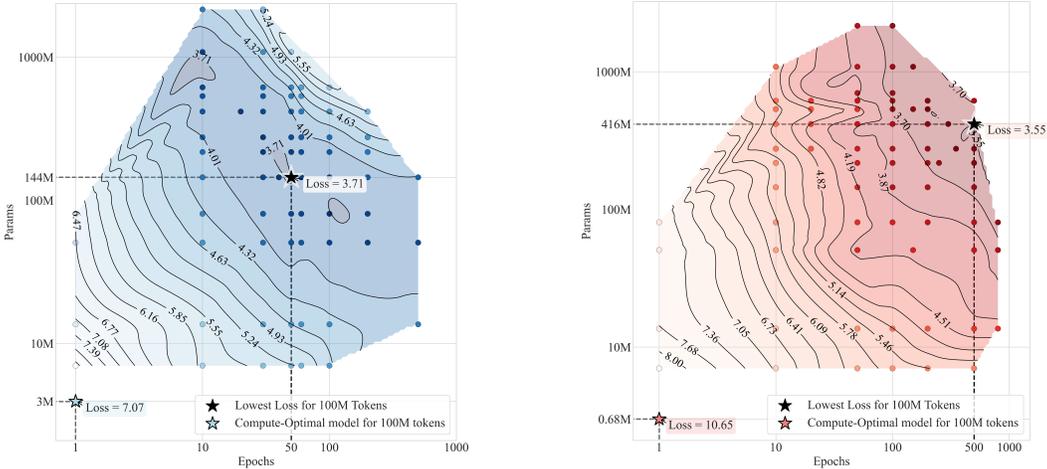
Previous studies comparing diffusion models and autoregressive (AR) models have predominantly focused on the single-epoch regime [34, 25, 42], where each data point is seen only once during training. In this setting, diffusion models have consistently been reported to require substantially more training compute to match the validation loss of AR models. For example, Nie *et al.*[25] and Swerdlow *et al.*[42] derive scaling laws that indicate that masked diffusion models need up to $16\times$ more training compute to achieve comparable performance to AR. However, because total compute C is a function of both model parameters and the number of unique data tokens ($C \sim 6ND$), it remains ambiguous whether this gap reflects a fundamental inefficiency in the use of unique data, or simply a higher compute requirement for diffusion models when trained on the same data. In other words, is the bottleneck for diffusion models data efficiency or compute efficiency?

To resolve this ambiguity, we systematically investigate the performance of masked diffusion models and AR models in data-constrained settings, where the number of unique tokens is limited and data must be reused across multiple epochs. Unlike prior work, we explicitly train both model families for many epochs, thereby disentangling the effects of data reuse from those of model scaling.

We train a large suite of AR and diffusion models across three unique data regimes—25M, 50M, and 100M tokens—and a wide range of training compute budgets. In Figure 1, we report empirical validation loss as a function of training FLOPs for the 50M and 100M regimes; results for the 25M setting are shown in Appendix Figure 7. We find that AR models initially outperform diffusion models when trained with the compute-optimal budget prescribed by Chinchilla scaling laws (denoted by the solid vertical line). However, this advantage disappears as training continues beyond this point. When models are allowed to train for additional epochs on repeated data, diffusion models consistently surpass AR models in validation loss across all data regimes. These findings indicate that the previously observed inefficiency of diffusion models is largely a consequence of evaluating them solely in the single-epoch regime. In data-constrained settings with repeated exposures, diffusion models extract significantly more value from the same data than their AR counterparts.

A key question remains is how should one go about increasing compute for diffusion models: by increasing model size, or by increasing the number of epochs (i.e., data reuse)? To address this, we analyze the trade-off between parameters and epochs in Figure 2, which shows validation loss contours as a function of both axes. In the 100M unique token regime, for example, we find that diffusion achieves its best loss at 500 epochs, while AR model reach its best at just 50 epochs. Each point on the contour plot corresponds to a model trained with a specific parameter count and number of epochs; we report the actual validation loss at each configuration, without early stopping. We find that autoregressive models begin to overfit at high epoch counts, with validation loss worsening as training continues beyond a certain point. In contrast, diffusion models show no signs of overfitting within our compute budget—the best validation loss is achieved at the highest epoch counts we explore. This suggests that diffusion models continue to benefit from additional training on repeated data, and that observing overfitting may require significantly more compute.

To contextualize these results, we highlight two key configurations in Figure 2 for each model family: the compute-optimal point for single-epoch training, as identified by prior scaling law analyses [15, 27] (marked with a colored star in the bottom-left), and the best validation loss achieved under extended multi-epoch training (marked with a black star). At the compute-optimal point, which corresponds to training for a single epoch, diffusion models perform substantially worse than autoregressive models (10.65 vs. 7.07), consistent with prior findings that diffusion performs worse initially. However, as training is extended to hundreds of epochs, diffusion models continue to improve and eventually achieve a lower validation loss (3.55) than the best AR models (3.71). While AR models begin to overfit as training progresses, diffusion models show no signs of overfitting within our budget.



(a) Autoregressive contour: validation loss over epochs and model sizes.

(b) Diffusion contour: validation loss over epochs and model sizes.

Figure 2: Validation loss contours over epochs and model sizes for autoregressive (left) and diffusion (right) models, trained on 100M unique tokens. Each plot shows validation loss as a function of training epochs (x-axis) and model parameters (y-axis). The colored star marks the compute-optimal point for single-epoch training, as predicted by prior scaling laws [15, 27], and the black star indicates the lowest validation loss achieved through extended multi-epoch training. In the single-epoch regime, diffusion models perform worse than AR models (10.65 vs. 7.07). However, when trained longer, diffusion models achieve a substantially lower final loss (3.55 vs. 3.71). This corresponds to a 67% reduction in loss for diffusion models compared to just 48% for AR models, highlighting their superior ability to leverage repeated data. These results underscore that diffusion models require significantly more training—both in epochs and compute—to realize their advantages in data-constrained settings.

4.2 Fitting Data-Constrained Scaling Laws

To gain deeper insight into the trade-offs between diffusion and autoregressive models in data-constrained settings, we fit scaling laws to both model families across single-epoch and multi-epoch regimes, as described in Section 3.3. Our approach systematically varies three key factors: (1) the amount of unique data, (2) model parameter count, and (3) number of training epochs. This grid search allows us to disentangle the effects of data quantity, model capacity, and data reuse on final model performance.

We evaluate the quality of our scaling law fits using the coefficient of determination (R^2) and relative prediction error, as shown in Table 1. For autoregressive models, our R^2 values closely match those reported by Muennighoff *et al.* [24], indicating consistent behavior under repeated training. Interestingly, diffusion models yield significantly higher R^2 values, reflecting a better overall fit. We attribute this to lower variance in validation loss across training runs, likely due to the absence of overfitting in diffusion models even at high epoch counts.

Beyond the overall fit, we extract two key parameters from the scaling laws: R_D^* , which characterizes the effective half-life of data reuse—i.e., the number of epochs after which additional training on

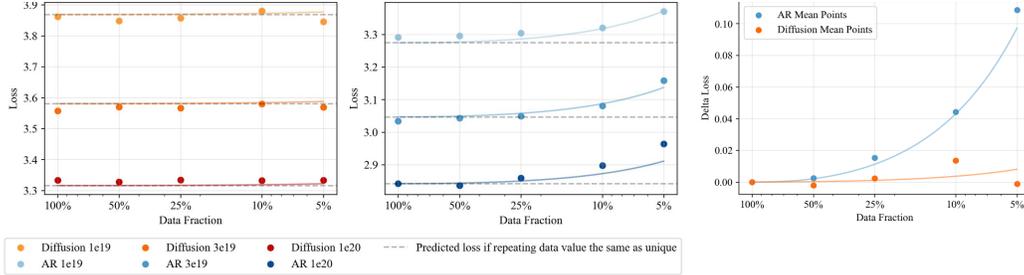


Figure 3: Decay rate of data value under repetition: left shows diffusion, middle AR, and right the average decay rate for both. Points are empirical results (darker color = higher FLOPs, lighter color = lower FLOPs; each line = fixed compute), we find that fitted curves (represented as lines) closely match the empirical points, indicating our scaling laws are representative. The decay rate of value for repeated data is lower for diffusion, reflecting its greater robustness to repeating.

repeated data yields diminishing returns—and R_N^* , which indicates the optimal model size for a given data budget. Our results reveal a sharp contrast in data reuse half-lives: diffusion models exhibit an R_D^* of 512.85, compared to just 31.93 for autoregressive models. A higher R_D^* implies that a model can benefit from many more repeated exposures before saturating. This suggests that diffusion models continue to improve across hundreds of epochs, while AR models quickly saturate—highlighting the superior data efficiency of diffusion models in data-constrained regimes.

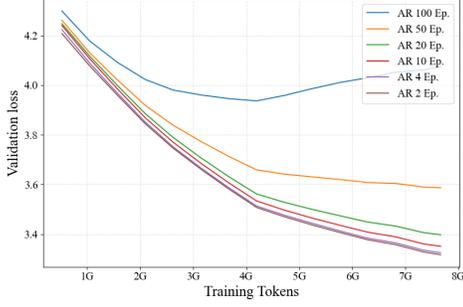
Table 1: Fitting metrics of the scaling law model for Diffusion and AR. Diffusion and AR achieve a strong fit across both phases.

| (a) Initial fit. | | | (b) Second step fit with extracted scaling parameters. | | | | |
|------------------|--------|------------|--|--------|---------|---------|---------|
| Model | R^2 | Loss | Model | R^2 | Loss | R_D^* | R_N^* |
| Diffusion | 0.9447 | 0.0002 | Diffusion | 0.9784 | 0.00079 | 493.89 | 1265.65 |
| AR | 0.9439 | 7.7532e-05 | AR | 0.7628 | 0.00361 | 31.19 | 55.16 |

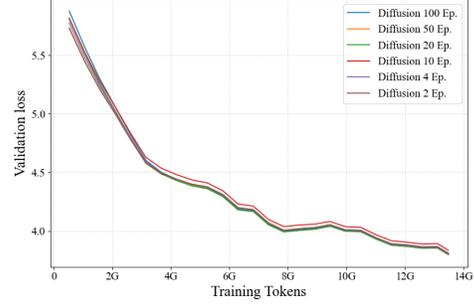
Figure 3 illustrates how the utility of unique data decays with increased repetition. We evaluate this effect across three compute budgets— 1×10^{19} , 3×10^{19} , and 1×10^{20} FLOPs—by varying the proportion of unique data while keeping total compute fixed (e.g., 50% of the data for 2 epochs, 25% for 4 epochs, etc.). This experimental design allows us to directly measure how the utility of data diminishes with increased repetition. We present both empirical results and fitted curves from our parametric scaling law, observing strong agreement between the two. Notably, the decay rate of data value remains consistent across compute budgets for both model families. However, diffusion models consistently exhibit a substantially slower decay rate than AR models, suggesting they are better able to extract value from repeated data.

Figure 4 shows validation loss versus training tokens and reinforces the trend: AR models overfit with increased repetition, showing diverging loss curves. In contrast, diffusion models exhibit overlapping curves across repetitions, indicating no signs of overfitting and a very low decay rate with data reuse.

Figure 5 shows extrapolated training curves at large compute budgets for AR and diffusion models using our fitted scaling laws. For each setting, we use the compute-optimal model and dataset size derived from single-epoch scaling laws and extend training across multiple epochs. The dashed lines represent the ideal Chinchilla-style scaling behavior, where all training tokens are assumed to be unique. We find that for AR models, repeated data provides nearly the same benefit as fresh data only up to about 4 epochs. Beyond this point, additional repetition yields diminishing returns. In contrast, diffusion models continue to match the unique-data curve for up to 100 epochs, indicating a far greater capacity to benefit from repeated data in data-constrained regimes.



(a) AR Training Curves.



(b) Diffusion Training Curves.

Figure 4: Training curves for different epoch counts, all with using the same total compute. Each curve shows a different tradeoff between unique data and repetition. For AR models, validation loss rises with more epochs (overfitting), while for diffusion models, the curves are nearly unchanged, showing much greater robustness to data repetition.

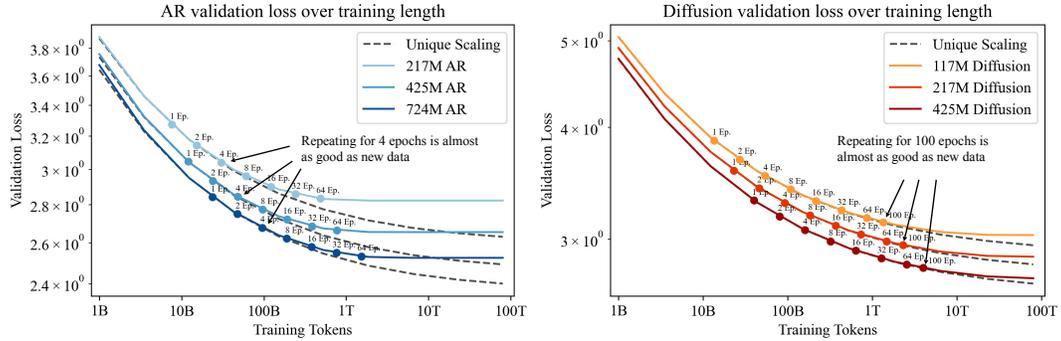


Figure 5: Predicted validation loss for AR models (left) and Diffusion models (right) under compute-optimal settings, extrapolated to larger compute budgets. Dotted lines indicate the hypothetical case where repeated data is as valuable as new data. For AR, this holds up to about 4 epochs; for diffusion, up to 100 epochs, showing that diffusion models are much more robust to data repetition.

4.3 When to Use Diffusion over AR?

A key question for practitioners is: *when should diffusion be preferred over autoregressive models (AR)?* To answer this, we compare the fitted data-constrained scaling laws for both model families (§3.3).

We define the validation loss gap between diffusion and AR as:

$$\Delta\mathcal{L}(C, U) = \mathcal{L}_{\text{Diffusion}}(C, U) - \mathcal{L}_{\text{AR}}(C, U),$$

where C is total training compute and U is the number of unique tokens. Positive values favor AR; negative values favor diffusion. The *critical compute* $C_{\text{crit}}(U)$ is the point where the models perform equally:

$$\Delta\mathcal{L}(C_{\text{crit}}, U) = 0.$$

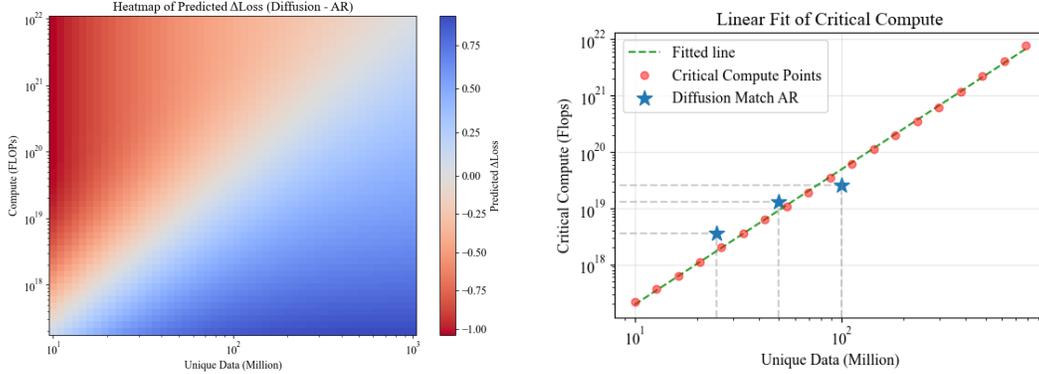
Figure 6(a) shows a heatmap of $\Delta\mathcal{L}$ over compute and data. Red regions indicate regimes where diffusion outperforms AR ($\Delta\mathcal{L} < 0$), while blue regions favor AR. As expected, AR performs better in low-compute settings due to its efficient per-step learning. However, diffusion models begin to outperform AR at higher compute, especially when data is limited and repeated.

Figure 6(b) plots the **critical compute frontier** $C_{\text{crit}}(U)$ —the compute required for diffusion to match or surpass AR at a given unique token count U . This frontier follows a power law:

$$C_{\text{crit}}(U) \propto U^{2.174}.$$

The linear fit in log-log space is:

$$\log_{10}(U) = 0.460 \cdot \log_{10}(C) - 7.052, \quad \text{so} \quad C_{\text{crit}}(U) = 2.12 \times 10^{15} \cdot U^{2.174}.$$



(a) **Loss Gap Heatmap.** Difference in validation loss ($\Delta\mathcal{L} = \mathcal{L}_{\text{Diffusion}} - \mathcal{L}_{\text{AR}}$) across unique data sizes and FLOPs. Red indicates regions where diffusion outperforms AR models and blue where AR outperforms diffusion.

(b) **Critical Compute Curve.** The FLOPs threshold $C_{\text{crit}}(U)$ beyond which diffusion outperforms AR models. This follows a power law: $C_{\text{crit}}(U) \propto U^{2.174}$.

Figure 6: **When does Diffusion beat AR?** Left: Heatmap showing where diffusion models have lower validation loss than AR models. Right: The critical compute curve defining the compute threshold needed for diffusion to match autoregressive models at a given unique token count.

The green dashed line shows the fitted curve, and the blue crosses represent empirical crossover points—where diffusion matches AR performance in experiments. These points align closely with the predicted frontier, confirming our fitted equation’s accuracy.

4.4 Downstream Results

We evaluate the best-performing diffusion and autoregressive (AR) models on several downstream benchmarks to assess whether the gains in validation loss translate to practical improvements in generalization.

Motivated by the critical compute threshold equation identified in Section 4.3, we scale the training data to 500M unique tokens and train a 2.3B parameter diffusion model using the compute budget predicted by the critical compute limit. The model was trained for 130 epochs, during which we observed no signs of convergence. Training was terminated due to compute constraints.

Across a diverse set of tasks and data scales, diffusion models consistently achieve higher accuracy than their AR counterparts. This validates our findings in Section 4.3, also confirms that the data efficiency gains observed in validation loss translate into stronger downstream performance. Additional results, including performance on textbook-style datasets, are provided in Table 3 in the Appendix.

5 Discussion

Why do diffusion models outperform autoregressive (AR) models in low-data regimes? We hypothesize that the key advantage stems from the use of **random masking** in diffusion models, which serves as a form of data augmentation. Unlike AR models, which are trained on a single, fixed left-to-right ordering, masked diffusion models are exposed to a wide variety of token prediction tasks and orderings during training—including, the left-to-right order itself. This broader distribution over prediction tasks encourages better generalization and more effective use of each training example. Analogous to image-based tasks where techniques like random cropping or color jittering boost generalization [5, 8, 12], we believe the corruption process in diffusion plays a similar role. By learning to denoise across many corruptions, the model extracts richer signal per example over time, resulting in improved data efficiency.

Why are autoregressive (AR) models more compute-efficient than diffusion models? We hypothesize two main contributing factors. (i) Order specialization: AR models are trained with a

Table 2: Downstream Results for the best autoregressive and diffusion trained in different data-constrained settings. We report the results for the models with the best validation loss in 100M and 500M unique data regime. To better understand the difficulty of each benchmark we also report the accuracy of random baseline

| Benchmarks | Random Baseline | 100M unique tokens | | 500M unique tokens | |
|--------------------|-----------------|--------------------|--------------|--------------------|--------------|
| | | AR | Diffusion | AR | Diffusion |
| ARC-Easy [7] | 25.00 | 35.63 | 37.84 | 43.79 | 45.95 |
| BoolQ [6] | 50.00 | 46.00 | 49.38 | 51.87 | 55.26 |
| COPA [32] | 50.00 | 56.33 | 59.00 | 67.00 | 64.83 |
| HellaSwag [47] | 25.00 | 27.37 | 30.24 | 32.28 | 35.33 |
| PiQA | 50.00 | 60.94 | 60.72 | 65.71 | 65.61 |
| RACE [19] | 25.00 | 25.28 | 28.96 | 28.28 | 31.44 |
| WinoGrande XL [35] | 50.00 | 48.87 | 50.97 | 50.61 | 51.51 |
| SciQ [17] | 25.00 | 58.05 | 68.67 | 67.82 | 79.13 |
| Lambada [29] | 00.00 | 10.91 | 15.19 | 15.07 | 22.30 |

Note: All values represent accuracy (%). Best results shown in bold.

fixed left-to-right factorization, so every gradient update reinforces the same prediction task, allowing them to specialize effectively. In contrast, diffusion models must generalize across many random token orderings, which hinders specialization. (ii) Stronger supervision per update: In AR training, every token in a training sequence serves as a supervised target, and the causal structure enables dense gradient updates, resulting in stable, low-variance learning. Diffusion models, however, compute loss only on a subset of masked tokens, making supervision sparser per sequence, even though gradients propagate through the entire input. As a result, each update carries less direct learning signal. Arriola et al. [1] show that tuning the masking schedule can help reduce gradient variance and improve training compute efficiency.

6 Limitations

In this work, we examined two extremes of the generative modeling: masked diffusion models, which learn entirely random token orderings, and autoregressive (AR) models, which learn a fixed left-to-right order. However, we believe that the trade-off between data and compute efficiency need not be binary. In principle, one could interpolate between these two paradigms to achieve a more favorable balance. Prior works have proposed such hybrid approaches that blend diffusion and autoregressive modeling [1, 16], although their interpolations are not motivated by, nor evaluated in terms of, data and compute efficiency trade-offs. Exploring interpolation along this axis remains a promising direction for future research.

7 Conclusion

As the availability of high-quality data plateaus, improving data efficiency becomes essential for scaling deep learning. In this work, we show that masked diffusion models consistently outperform autoregressive (AR) models in data-constrained regimes — when training involves repeated passes over a limited dataset. We establish new scaling laws for diffusion models, revealing their ability to extract value from repeated data far beyond what AR models can achieve. These results challenge the conventional belief that AR models are universally superior and highlight diffusion models as a compelling alternative when data—not compute—is the primary bottleneck. Looking ahead, efficient use of finite data may define the next frontier in scaling deep learning models. Although the studies have been performed in the context of language models, we believe these findings should apply across any kind of sequence modeling data, such as in robotics or healthcare.

For practitioners, our takeaway is simple: *if you are compute-constrained, use autoregressive models; if you are data-constrained, use diffusion models.*

8 Acknowledgement

We thank Alexander Li for his valuable insights and detailed feedback on the manuscript. We are also grateful to Zheyang Qin for his help in improving the figures. Finally, we thank Simo Ryu, Niklas Muennighoff and Colin Raffel for their helpful comments on the final draft of the paper. This work was supported in part by ONR MURI N00014-22-1-2773, ONR N00014-22-1-2096, and AFOSR FA9550-23-1-0747.

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9 Additional Results

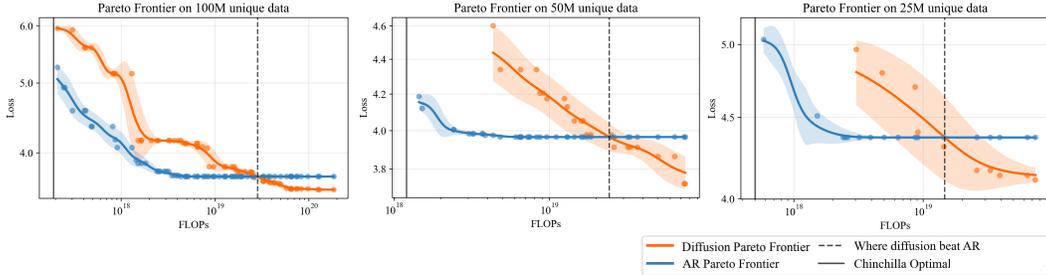


Figure 7: Pareto frontier of validation loss (negative log-likelihood) versus training FLOPs for autoregressive (AR) and diffusion models under data-constrained settings, on three different unique data settings 25M, 50M and 100M.

Table 3 reports the negative log-likelihood (NLL; lower is better) on four diverse corpora: OSCAR [28], TinyStories[10], WikiText [23], and IndustryCorpus2 EN Sub [38]. These datasets span open-domain, narrative, encyclopedic, and industry-specific text.

Table 3: Downstream NLL of best diffusion and AR models at 100M unique data points.

| Model Type | Flops | OSCAR | TinyStories | WikiText | IndustryCorpus2 |
|------------|---------|-------------|-------------|--------------------|-----------------|
| Best ARM | 4.32e18 | 3.98 | 2.96 | 4.94 / 4.96 | 3.58 |
| Best MDM | 1.24e20 | 3.83 | 2.93 | 4.50 / 4.52 | 3.44 |

10 Model Architecture

We adopt the Megatron-DeepSpeed framework as the foundation of our implementation, upon which we build our training and evaluation setup for the masked Diffusion Model. Similar to the “extended version of the architectures” proposed in [25], our model adheres to the general transformer design while introducing several architectural modifications to better align with modern LLM practices.

Specifically, we replace absolute positional embeddings with Rotary Positional Embeddings (RoPE) [40], which improve extrapolation to longer contexts and reduce parameter count. Furthermore, we adopt the SwiGLU activation function in the MLP blocks, which has been shown to outperform standard GELU or ReLU in both convergence and downstream performance [36]. To further simplify the architecture and enhance training stability, we substitute standard LayerNorm with RMSNorm and eliminate all bias terms. These design choices are consistent with [3, 43].

To preserve the original MLP capacity while aligning with hardware-friendly parameter sizes, we compute the feed-forward hidden size h_f as:

$$h_f = \left\lfloor \frac{8 \cdot d_{\text{model}}}{3 \cdot 64} \right\rfloor \cdot 64$$

This rounding scheme ensures that the FFN hidden size remains divisible by 64 while closely matching the effective dimensionality used in SwiGLU layers.

We slightly modify the parameter count estimation formula from the original:

$$P = 12lh^2 \left(1 + \frac{13}{12h} + \frac{V+s}{12lh} \right)$$

to better reflect our revised architecture. The original formula can be decomposed into: $4lh^2$ (attention), $8lh^2$ (MLP), $13lh$ (LayerNorm and biases), and $(V+s)h$ (token and positional embeddings). After applying our architectural adjustments—namely, using a SwiGLU-based MLP of dimension h_f , switching to RoPE (eliminating sh), and removing bias terms—we arrive at the revised formula:

$$P = 4lh^2 + 3lh \cdot h_f + 6lh + Vh$$

Table 4 presents all model configurations used in our experiments along with their parameter counts.

Table 4: Model Architectures

| Name | param (M) | d_model | origin_ffw_size | ffw_size | kv_size | n_heads | n_layers |
|-------|-----------|---------|-----------------|----------|---------|---------|----------|
| 7 | 7.0 | 128 | 512 | 320 | 32 | 4 | 3 |
| 14 | 13.6 | 224 | 896 | 576 | 32 | 7 | 4 |
| 20 | 19.5 | 288 | 1152 | 768 | 32 | 7 | 5 |
| 35 | 36.6 | 448 | 1792 | 1152 | 32 | 7 | 6 |
| 44 | 50.7 | 512 | 2048 | 1344 | 64 | 8 | 8 |
| 57 | 64.8 | 576 | 2304 | 1536 | 64 | 9 | 9 |
| 74 | 80.5 | 640 | 2560 | 1664 | 64 | 10 | 10 |
| 90 | 95.0 | 640 | 2560 | 1664 | 64 | 10 | 13 |
| 106 | 109.6 | 640 | 2560 | 1664 | 64 | 10 | 16 |
| 117 | 123.6 | 768 | 3072 | 2048 | 64 | 12 | 12 |
| 140 | 144.8 | 768 | 3072 | 2048 | 64 | 12 | 15 |
| 163 | 166.1 | 768 | 3072 | 2048 | 64 | 12 | 18 |
| 175 | 179.2 | 896 | 3584 | 2368 | 64 | 14 | 14 |
| 196 | 198.3 | 896 | 3584 | 2368 | 64 | 14 | 16 |
| 217 | 217.5 | 896 | 3584 | 2368 | 64 | 14 | 18 |
| 251 | 250.8 | 1024 | 4096 | 2688 | 64 | 16 | 16 |
| 278 | 275.7 | 1024 | 4096 | 2688 | 64 | 16 | 18 |
| 306 | 300.6 | 1024 | 4096 | 2688 | 64 | 16 | 20 |
| 425 | 416.9 | 1280 | 5120 | 3392 | 128 | 10 | 18 |
| 489 | 475.6 | 1280 | 5120 | 3392 | 128 | 10 | 21 |
| 509 | 495.9 | 1408 | 5632 | 3712 | 128 | 11 | 18 |
| 552 | 534.4 | 1280 | 5120 | 3392 | 128 | 10 | 24 |
| 587 | 566.7 | 1408 | 5632 | 3712 | 128 | 11 | 21 |
| 632 | 615.3 | 1536 | 6144 | 4096 | 128 | 12 | 19 |
| 664 | 637.6 | 1408 | 5632 | 3712 | 128 | 11 | 24 |
| 724 | 700.3 | 1536 | 6144 | 4096 | 128 | 12 | 22 |
| 816 | 785.2 | 1536 | 6144 | 4096 | 128 | 12 | 25 |
| 893 | 856.4 | 1792 | 7168 | 4736 | 128 | 14 | 20 |
| 1018 | 971.3 | 1792 | 7168 | 4736 | 128 | 14 | 23 |
| 1143 | 1086.3 | 1792 | 7168 | 4736 | 128 | 14 | 26 |
| 1266 | 1207.6 | 2048 | 8192 | 5440 | 128 | 16 | 22 |
| 1424 | 1353.6 | 2176 | 8704 | 5760 | 128 | 17 | 22 |
| 1429 | 1358.2 | 2048 | 8192 | 5440 | 128 | 16 | 25 |
| 1593 | 1508.9 | 2048 | 8192 | 5440 | 128 | 16 | 28 |
| 1609 | 1523.2 | 2176 | 8704 | 5760 | 128 | 17 | 25 |
| 1731 | 1644.9 | 2304 | 9216 | 6144 | 128 | 18 | 24 |
| 1794 | 1692.9 | 2176 | 8704 | 5760 | 128 | 17 | 28 |
| 2007 | 1899.8 | 2304 | 9216 | 6144 | 128 | 18 | 28 |
| 2283 | 2154.7 | 2304 | 9216 | 6144 | 128 | 18 | 32 |
| 2298 | 2165.3 | 2560 | 10240 | 6784 | 128 | 20 | 26 |
| 2639 | 2478.6 | 2560 | 10240 | 6784 | 128 | 20 | 30 |
| 2980 | 2791.9 | 2560 | 10240 | 6784 | 128 | 20 | 34 |
| 3530 | 3257.0 | 2688 | 10752 | 7168 | 128 | 21 | 36 |
| 3802 | 3561.3 | 2816 | 11264 | 7488 | 128 | 22 | 36 |
| 4084 | 3879.2 | 2944 | 11776 | 7808 | 128 | 23 | 36 |
| 4516 | 4231.9 | 3072 | 12288 | 8192 | 128 | 24 | 36 |
| 6796 | 6337.4 | 3584 | 14336 | 9536 | 128 | 28 | 40 |
| 9293 | 8640.6 | 4096 | 16384 | 10880 | 128 | 32 | 42 |
| 11452 | 10889.0 | 4352 | 17408 | 11584 | 128 | 32 | 47 |
| 12295 | 11444.2 | 4608 | 18432 | 12288 | 128 | 36 | 44 |
| 12569 | 12208.7 | 4608 | 18432 | 12288 | 128 | 32 | 47 |
| 13735 | 13560.0 | 4864 | 19456 | 12928 | 128 | 32 | 47 |
| 14940 | 14905.3 | 4992 | 19968 | 13312 | 128 | 32 | 49 |
| 16183 | 15028.3 | 5120 | 20480 | 13632 | 128 | 40 | 47 |