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Discrete Diffusion Models for Language Generation

Diskreta diffusionsmodeller för språkgenerering

Thalgamuwe Gedara Ashen Akalanka Weligalle

Linköping University
STIMA
Division of Human-Centered Systems
SE-581 83 Linköping, Sweden

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ABSTRACT

Diffusion models have emerged as a powerful class of generative models, achieving state-of-the-art performance in continuous data domains such as image synthesis and video generation. Their core mechanism involves a forward diffusion process that gradually transforms structured data into a Gaussian-like distribution, followed by a learned reverse diffusion process that reconstructs the data. While this framework has proven effective for continuous modalities, its application to discrete data—particularly natural language—remains a challenging and active area of research. [1] Key obstacles include the complexity of modeling discrete token dependencies and the lack of a naturally defined generation order.

This thesis investigates the feasibility and performance of discrete diffusion models in the context of natural language generation. In particular, we examine the Discrete Denoising Diffusion Probabilistic Model (D3PM)2.5 and compare its performance against traditional autoregressive (AR)2.4 language models. To evaluate and compare the generative capacity of both models, we utilize common metrics such as Bits Per Token (BPT)2.1, Negative Log-Likelihood (NLL)2.3, Perplexity (PPL)2.2, and Batch Processing Speed.

Experimental results4 show that the best-performing D3PM model achieves a BPT of 5.72, with a mean value of 8.05 across runs. In contrast, the AR model demonstrates a lower mean BPT of 4.59, indicating better compression and generative efficiency. However, D3PM models achieve higher batch processing speeds, with a maximum of 3.97 batches per second, highlighting their potential for parallel generation.

All evaluations were conducted under consistent conditions—generating 100,000 tokens per model with a fixed batch size of four—to ensure fairness and comparability. This research contributes a detailed comparative analysis of diffusion-based and autoregressive models, offering insights into their respective trade-offs. Ultimately, the findings underscore both the promise and the current limitations of applying diffusion models to discrete sequence modeling, and provide a foundation for future exploration in non-autoregressive language generation frameworks.The source code used in this research is available at the following GitHub repository: `https://github.com/AshenWELI/Discrete-Diffusion-Models-for-Language-Genaration`.

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Contents

List of Figures

List of Tables

1 Introduction

The remarkable progress in generative AI has opened new frontiers in machine learning, particularly in domains such as image synthesis and video generation. From hyper-realistic artwork generated by diffusion models to photorealistic deepfakes, these advancements have significantly reshaped our expectations of artificial intelligence. While diffusion models have shown state-of-the-art performance in modeling continuous data, their applicability to discrete domains—such as natural language—remains a compelling area of research.

Natural language generation has historically been dominated by autoregressive (AR) models 2.4 such as GPT-2[1], which generate text sequentially by predicting one token at a time. Although highly effective, AR models have known limitations, including exposure bias and limited support for parallel computation during inference.

As a compelling alternative, recent research has explored diffusion-based approaches for discrete data generation [16][10][1]. These models operate by progressively refining a noisy input sequence through a series of denoising steps, allowing them to model complex distributions in a non-autoregressive manner. Unlike AR models, diffusion models generate entire sequences in parallel during inference, offering potential advantages in sampling flexibility, controllability, and robustness against exposure bias.

[1]`https://huggingface.co/openai-community/gpt2`

This thesis aims to investigate the potential of discrete diffusion models in the context of natural language generation. In particular, we focus on the Discrete Denoising Diffusion Probabilistic Model (D3PM)[2], a variant of diffusion models tailored for discrete data. By comparing the performance of D3PM with that of established autoregressive models such as PixelSNAIL [4], we aim to identify the strengths, limitations, and areas for improvement of each modeling paradigm.

Unlike autoregressive models, which process and predict tokens sequentially, discrete diffusion models operate in a fundamentally different way. They employ a multi-step noising 2.5.1 and denoising process 2.5.2 and are inherently parallel, potentially offering advantages in both efficiency and robustness. This thesis seeks to answer whether diffusion-based approaches can not only match but potentially replace autoregressive models in certain contexts.

Both model families are built on the transformer architecture—AR 7.1 models using transformer decoders, and diffusion models employing transformers as denoisers. However, the fundamental distinction lies in their operational mechanics: while autoregressive models predict the next token in a sequence, diffusion models iteratively mask and unmask data over a series of steps.

The introduction can be divided into these sections:

1.1 Motivation

Numerous research efforts have explored the comparative performance of text generation models, focusing on diverse architectures and objectives. For instance, studies have examined Multimodal Models versus Permutation-based Models [9], Mixture-of-Experts compared to Multimodal approaches [19], and Encoder-Decoder Transformers versus Multimodal Transformers [14]. These comparisons are often context-dependent, targeting specific challenges such as multimodal integration, generation coherence, or scalability.

This research is primarily motivated by the need to compare two distinct families of language models: Autoregressive (AR) models and Discrete Diffusion models. AR models, such as GPT-2, generate text sequentially and have long been considered the state-of-the-art in natural language generation. However, they suffer from well-known limitations, including exposure bias and restricted support for parallel computation during inference.

In contrast, Discrete Diffusion models, such as the masked Discrete Denoising Diffusion Probabilistic Model (D3PM) [1], offer a fundamentally different approach. These models perform generation by learning to reverse a noising process applied to discrete tokens. One key advantage of diffusion

[2]`https://github.com/kuleshov-group/mdlm`

models is their ability to generate tokens in parallel, potentially addressing some of the core inefficiencies inherent in AR architectures.

This research is driven by the following guiding questions:

- Can discrete diffusion models achieve competitive performance in language generation tasks traditionally dominated by autoregressive models?
- What are the practical trade-offs in terms of generation quality, efficiency, and training complexity?
- Are there specific use cases where diffusion models are better suited than AR models?

To explore these questions, we conduct a systematic comparative analysis of AR and discrete diffusion models under a unified evaluation framework. All models are trained and tested under identical conditions to ensure fairness and reproducibility. Performance is assessed using standard metrics such as Bits Per Token (BPT)2.1.2, Negative Log-Likelihood (NLL)2.3, Perplexity (PPL)2.2, and generation speed.

1.2 Aim

The primary objective of this study is to conduct a comprehensive comparative analysis of discrete diffusion models for language generation, with a specific focus on their applicability in contrast to autoregressive (AR) models. This investigation is both statistical and structural, grounded in data-driven methodologies to evaluate performance across key metrics.

By systematically assessing the strengths, limitations, and trade-offs between discrete diffusion and AR architectures, this research seeks to provide actionable insights into the suitability of each model type for various language generation tasks. Through controlled experiments using standardized datasets and consistent evaluation conditions, the study aims to:

- Analyze the generative efficiency and accuracy of discrete diffusion models.
- Determine whether these models can serve as practical alternatives to AR models in real-world applications.
- Contribute to the ongoing discourse on non-autoregressive generation in natural language processing.

Ultimately, the goal is to evaluate whether discrete diffusion techniques can offer scalable, robust, and high-quality alternatives to traditional autoregressive approaches in the domain of language modeling.

1.3 Research questions

This thesis aims to explore the effectiveness of discrete diffusion models, particularly D3PM and its simplified variants, in comparison to traditional autoregressive (AR) models in language generation tasks. The key research questions guiding this work are as follows:

- How does the parallel token generation in D3PM contrast with the sequential decoding in autoregressive models?
- How do these methods perform in language generation tasks? What are the trade-offs, strengths, and limitations associated with each approach?

To address these questions, we follow a methodical approach that includes theoretical analysis, model implementation, and experimental evaluation. The answers to these questions will be developed throughout the subsequent sections of this thesis.

2 Theory

This chapter presents the theoretical foundations that underpin the models and evaluation techniques used in this research. It consolidates insights gathered from relevant academic literature and integrates them with the practical components of the thesis.

We begin by discussing the **Autoregressive Language Model** (Section 2.4), followed by an exploration of the **Discrete Denoising Diffusion Probabilistic Model (D3PM)** (Section 2.5), both of which serve as the central generative modeling approaches in this study.

Additionally, we elaborate on the statistical metrics employed to evaluate the performance and behavior of these models. These include:

- **Bits Per Token (BPT)** (Section 2.1) – a measure of model efficiency and compression.
- **Perplexity (PPL)** (Section 2.2) – an indicator of the model's ability to predict unseen data.
- **Negative Log-Likelihood (NLL)** (Section 2.3) – a loss-based evaluation metric derived from the log-likelihood of the predicted distribution.

Together, these theoretical and statistical components form the analytical backbone of the research and provide a framework for interpreting experimental results in subsequent chapters.

2.1 Bits Per Token (BPT)

In the evaluation of language models, *Bits Per Token* (BPT) is a fundamental metric that quantifies the average number of bits required to encode each token[1] in a given sequence. In this context, a token typically refers to a word or subword unit derived from a tokenized version of the dataset.

BPT provides valuable insight into a model's predictive efficiency and its ability to compress linguistic information. A lower BPT value signifies that the model is more effective at assigning high probabilities to the correct tokens, thereby encoding information more compactly. This makes BPT particularly useful when evaluating the performance of generative language models, where efficient representation and accurate prediction are critical.

Overall, BPT not only reflects the model's compression capacity but also correlates strongly with its overall language modeling quality, making it an essential diagnostic in model comparison and benchmarking.

The concept of BPT is closely related to *Bits Per Character* (BPC) [3], as BPC provides a more granular perspective on information encoding at the character level. Therefore, to fully understand BPT, it is beneficial to first examine BPC in detail.

2.1.1 Bits Per Character (BPC)

Bits Per Character (BPC) is a widely used metric for evaluating the efficiency of language models and data compression techniques. It quantifies the average number of bits required to represent each character within a dataset. A lower BPC value signifies more efficient encoding, indicating improved compression and predictive performance. This metric is particularly useful for assessing the effectiveness of language models in handling character-level representations of text.[3]

By understanding BPC, we can extend this analysis to BPT, where the unit of measurement shifts from individual characters to meaningful linguistic units, such as words or subwords. This transition is essential for evaluating modern language models, which often rely on subword tokenization techniques to balance efficiency and expressiveness.

The BPC for a given sequence of characters c is defined as:

$$BPC(c) = -\frac{1}{|c|} \sum_{i=1}^{|c|} \log_2 P(c_i | c_{<i})$$

where:

- $|c|$ is the total number of characters in the sequence.

[1]A token is a basic unit of text, such as a word, subword, or character, used by language models to process and generate language.

- c_i is the i-th character in the sequence.
- $c_{<i}$ represents all characters before c_i (i.e., the context for prediction).
- $P(c_i|c_{<i})$ is the probability assigned by the model to character c_i, given the previous characters.

2.1.2 BPC to BPT

Mathematically, BPT is defined as the cross-entropy between the true data distribution and the model's predicted distribution over tokens:

$$BPT(W) = -\frac{1}{N}\sum_{i=1}^{N} \log_2 P(W_i|W_{<i})$$

where N represents the total number of tokens, and $P(W_i|W_{<i})$ denotes the probability assigned by the model to the i-th token given its preceding context.

2.2 Perplexity (PPL)

Perplexity [5] is a widely used metric to evaluate a language model's ability to predict the next token in a sequence. Originally introduced by Jelinek et al. (1977) [11], it measures how well a probability model predicts a sample. Given a sequence of tokens $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ a language model parameterized by θ estimates the conditional probability of each token given the preceding context:

$$P_\theta(x_i \mid \mathbf{x}_{<i}), \quad i \in [1, n].$$

The **perplexity (PPL)** [5]over the sequence $\mathbf{x}$ is defined as the inverse of the geometric mean of the predicted probabilities:

$$\text{PPL}_\theta(\mathbf{x}) = \exp\left(-\frac{1}{n}\sum_{i=1}^{n} \log P_\theta(x_i \mid \mathbf{x}_{<i})\right).$$

Equivalently, this can be written as:

$$\text{PPL}_\theta(\mathbf{x}) = P_\theta(\mathbf{x})^{-\frac{1}{n}}.$$

Interpretation

- **Lower PPL** indicates that the model assigns higher probability to the actual observed sequence $\rightarrow$ *better prediction.*
- **Higher PPL** means the model is more uncertain about the next token $\rightarrow$ *poorer performance.*

2.3 Negative Log-Likelihood (NLL)

Let x be the true token or label, and let $p_\theta(x)$ represent the predicted probability distribution over the token space, parameterized by θ. The log-likelihood of observing x under this distribution is given by[2]:

$$L(\theta|x) = \log[p_\theta(x)]$$

A higher log-likelihood indicates that the model assigns a higher probability to the correct token, implying greater confidence in its prediction.

Since probabilities lie between 0 and 1, their logarithms are typically negative. To convert this into a more interpretable loss function, we take the negative log-likelihood (NLL), defined as:

$$NL(\theta|x) = -\log p_\theta(x)$$

A lower NLL value implies better model performance, as it means the predicted distribution assigns higher probability to the correct label. NLL can also be interpreted as a penalty term: the less confident the model is in its correct prediction, the higher the penalty it incurs.

2.3.1 NLL Behavior in Sequences

In the context of text generation, we are often interested in modeling sequences of tokens. Suppose the true token sequence[3] is given by $x = (x_1, x_2, \ldots, x_T)$. The NLL over the entire sequence becomes:

$$NL(\theta|x) = -\sum_{t=1}^{T} \log p_\theta(x_t \mid x_{<t})$$

Here, each token x_t is predicted based on all preceding tokens $x_{<t}$. The term $x_{<t}$ denotes the subsequence of tokens before position t, and is drawn from a valid subset of the sequence space $\mathcal{R}$. This autoregressive formulation is fundamental to many language models, where prediction quality is evaluated sequentially.

2.4 Autoregressive model (AR)

Natural language processing (NLP) relies heavily on autoregressive (AR) models, especially when it comes to sequence generation tasks.[2] These

[2]`https://www.statlect.com/glossary/log-likelihood`

[3]`https://datajello.com/cross-entropy-and-negative-log-likelihood/?utm_source=chatgpt.com`

models successfully capture the conditional dependencies inherent in language by generating text by predicting each token based on the order of preceding tokens. AR models can generate logical and contextually relevant text outputs thanks to this sequential prediction technique.[4]

From Recurrent Neural Networks (RNNs) to more complex structures like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), the architecture 7.1 of AR models has changed over time. These advancements have improved the models' capacity to represent long-range dependencies in text and have tackled issues like the vanishing gradient problem. 7.3 Because of their attention mechanisms and parallel processing capabilities, Transformer-based models—such as the Generative Pre-trained Transformer (GPT) series—have demonstrated notable success in a variety of NLP tasks in recent years.[15]

AR models have been effectively applied in diverse NLP applications, including machine translation, text summarization, and dialogue systems. Their ability to model the probability distribution of sequences makes them particularly well-suited for tasks that require the generation of fluent and contextually appropriate text.

In the subsequent sections, we delve deeper into the mechanics of autoregressive (AR) models, examining their underlying architecture, benefits, limitations, and performance in comparison to alternative modeling approaches. 7.3 7.1

Autoregressive models factorize the joint probability of a sequence into a product of conditional probabilities, allowing each token to be generated based on all preceding tokens. This is mathematically formulated as: [15]

$$\begin{aligned} P(x_1, x_2, x_3, \ldots, x_n) = P(x_1) \cdot P(x_2 \mid x_1) \cdot P(x_3 \mid x_1, x_2) \\ \cdots P(x_n \mid x_1, x_2, x_3, \ldots, x_{n-1}) \end{aligned} \tag{2.1}$$

To aid understanding, consider the simple sentence: *"The cat sleeps."* The probability of generating this sentence using an AR model can be expressed as:

$$P(\text{"The cat sleeps"}) = P(\text{"The"}) \cdot P(\text{"cat"} \mid \text{"The"}) \cdot P(\text{"sleeps"} \mid \text{"The cat"}) \tag{2.2}$$

For a clearer interpretation of Equation 2.2, a visual representation of the AR model's token generation process is provided in Figure 2.1.

As shown in Figure 2.1, the AR model begins generation with a special `<SOS>` (start-of-sentence) token. Given this token as input, the model predicts the first word x_1. The process continues sequentially, where each subsequent word is generated based on the previous context. The generation

[4]https://medium.com/@zaiinn440/autoregressive-models-for-natural-language-processing-b95e5f933e1f

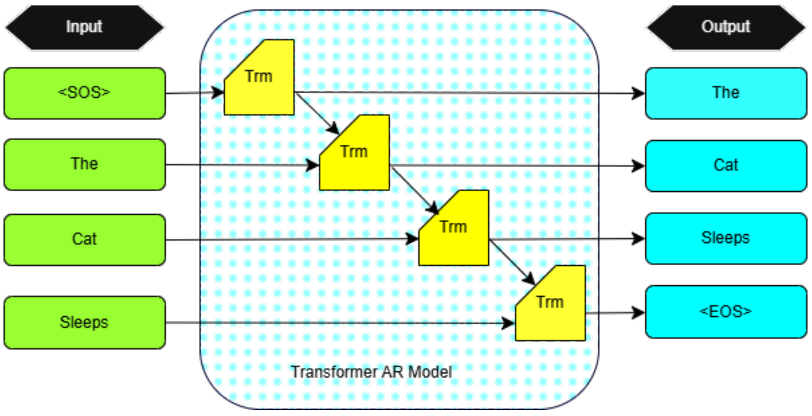


Figure 2.1: Illustration of the token-by-token generation process in an autoregressive model. This Trm represent the Transformer block.

process concludes with the `<EOS>` (end-of-sentence) token, signaling the end of the sequence. This directional and sequential nature of AR models is fundamental to their architecture and influences both their strengths and limitations in language generation tasks. [5]

2.5 Discrete Denoising Diffusion Probabilistic Models (D3PM)

D3PM (Discrete Denoising Diffusion Probabilistic Models) represents a class of diffusion models tailored for discrete data types such as text, categorical variables, and token sequences, rather than continuous data like images. In general, diffusion models operate by introducing structured noise into the data over several steps and then learning to reverse this process—i.e., denoising—during generation.[12]

The training process of a diffusion model begins with tokenized input data. Over successive time steps, increasing levels of noise are added to the data in a controlled manner. The model is then trained to learn the reverse process: gradually denoising the corrupted input to reconstruct the original data. Notably, this denoising process is executed in parallel, making it inherently different from the sequential approach seen in autoregressive models.

The primary objective during training is to minimize the loss function that quantifies the difference between the original data and the model's reconstruction at each denoising step. Through this optimization process, the

[5]`https://huggingface.co/docs/transformers/v4.32.1/llm_tutorial?utm_source=chatgpt.com`

model progressively improves its generative capability by learning a high-fidelity reverse diffusion path.

We can demonstrate, from a statistical standpoint, that the training objective in diffusion models involves minimizing a loss function derived from the **Variational Lower Bound (VLB)** [10]. This objective enables the model to learn the denoising process in a step-by-step manner by approximating the reverse transitions from noisy to clean data.

The variational lower bound loss, often referred to as the negative Evidence Lower Bound (NELBO), is expressed as: [16]

$$\begin{aligned}\mathcal{L}_{\text{vb}} = \underbrace{\mathbb{E}_q \left[D_{\text{KL}} \left(q(x_T \mid x_0) \parallel p_\theta(x_T) \right) \right]}_{L_T} - \underbrace{\log p_\theta(x_0 \mid x_1)}_{L_0} + \\ \sum_{t=2}^{T} \underbrace{D_{\text{KL}} \left(q(x_{t-1} \mid x_t, x_0) \parallel p_\theta(x_{t-1} \mid x_t) \right)}_{L_{t-1}}\end{aligned} \tag{2.3}$$

where $\mathcal{L}_{\text{vb}}$ denotes the variational loss, and $D_{\text{KL}}[\cdot]$ represents the Kullback–Leibler divergence, a measure of dissimilarity between two probability distributions.

Equation 2.3 decomposes the total training loss into three interpretable components:

- L_T: This term measures the KL divergence between the noisiest state $q(x_T \mid x_0)$ and the prior $p_\theta(x_T)$, capturing how well the prior models the final corrupted distribution.
- L_0: This is the negative log-likelihood of reconstructing the original data x_0 given the first denoised state x_1. It quantifies the reconstruction loss at the initial denoising step and represents the final output loss of the reverse process.
- $\sum_{t=2}^{T} L_{t-1}$: These intermediate KL divergence terms assess how closely the learned reverse transition $p(x_{t-1} \mid x_t)$ approximates the true reverse posterior $q(x_{t-1} \mid x_t, x_0)$. They span from $t = 2$ to T, covering the core denoising steps in the reverse process.

Collectively, this formulation ensures that the model learns to generate data by progressively reversing the corruption process introduced during the forward diffusion. The accuracy of reconstruction, particularly after masking, is reflected in L_T, while L_0 directly affects output fidelity. The intermediate terms govern the smoothness and consistency of the denoising trajectory throughout the diffusion steps.

Minimizing this loss corresponds to teaching the model to reverse the forward noising process — effectively learning how to denoise and reconstruct the original data.

Diffusion models are characterized by two fundamental processes: the **forward process** and the **backward process**. These two stages form the core mechanism of how diffusion models are trained and used for generation.

In the *forward process*, noise is incrementally added to the input data across a series of timesteps, gradually transforming the data into a noise-like distribution. This process is carefully designed to be mathematically tractable and often ends with a uniform or Gaussian distribution, depending on the domain (discrete or continuous).

The *backward process*, on the other hand, involves learning to reverse this corruption by progressively denoising the data to recover the original structure. One of the prominent features of diffusion models is their ability to generate data in a non-sequential manner, allowing them to sample tokens from left-to-right, right-to-left, or even bidirectionally. This flexibility stands in contrast to autoregressive models, which strictly generate text in a left-to-right fashion due to their dependency on previously generated tokens.

In the following section, we will examine the forward process in more detail.

2.5.1 Forward Process

In this section, we delve into the technical and mathematical foundations of the diffusion model, moving beyond the high-level overview. To facilitate understanding, we introduce a simple example: the sentence *"Saman is a boy"*, as illustrated in Figure 2.2.

Formally, we assume that our data consists of tokens from a finite discrete state space with m possible states, represented by integers $0, 1, \ldots, m-1$ and their corresponding one-hot vectors [6] $e_0, e_1, \ldots, e_{m-1}$. In the case of the example, the integers would be $0, 1, 2, 3$, and the corresponding one-hot vectors would be e_0, e_1, e_2, e_3.

To accommodate the masking process, we augment the discrete state space by adding an additional mask state, denoted by the index m. During the forward process, each token transitions independently to the mask state at a random time step. This process, applied independently across tokens (e.g., each word), progressively corrupts the original sequence into a sequence dominated by mask tokens. By learning to reverse this corruption, the model can reconstruct coherent discrete data, enabling efficient generation.

We begin by considering the case of a single token before generalizing to multiple dimensions. In discrete diffusion, we simulate a process where information, such as a text token, gradually degrades into noise over T discrete steps. To control and learn this process effectively, the total time interval $[0, 1]$

[6] A one-hot vector is a binary vector in which only one element is set to 1 (hot) and all others are 0, typically used to represent categorical data or discrete tokens.

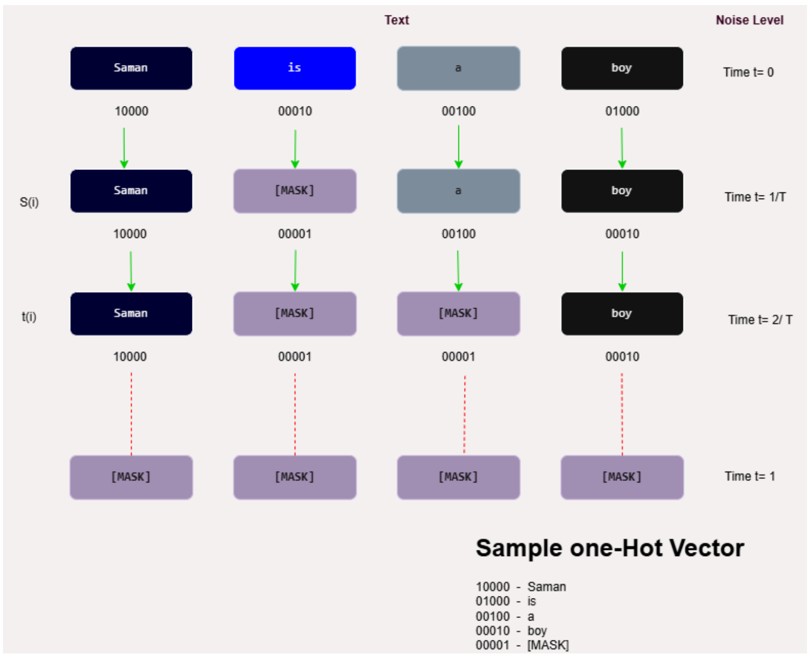


Figure 2.2: Illustration of the D3PM forward process.

is divided into T equal segments. The start and end times of the i-th interval are defined as:

$$s(i) = \frac{i-1}{T}, \quad t(i) = \frac{i}{T}.$$

Here s denotes the starting timestep, and t represents the subsequent timestep that follows s. According to Austin et al[1], the transition matrix at each step, of size $(m+1) \times (m+1)$, is given by:

$$Q_i = (1-\beta_i)I + \beta_i \mathbf{1} e_m^\top, \tag{2.4}$$

where $\mathbf{1}$ is an all-one column vector of size $m+1$, and e_m is a one-hot vector with the m-th element set to 1, representing the mask state. And Q_i could be s or t step in the moment.

As an illustrative example, assume $\beta_i = 0.3$. The corresponding Q_i matrix becomes:

$$Q_i = \begin{bmatrix} 0.7 & 0 & 0 & 0 & 0.3 \\ 0 & 0.7 & 0 & 0 & 0.3 \\ 0 & 0 & 0.7 & 0 & 0.3 \\ 0 & 0 & 0 & 0.7 & 0.3 \\ 0 & 0 & 0 & 0 & 1.0 \end{bmatrix}$$

In this matrix, if we consider row 0, the token "Saman" (One-hot vec: [1,0,0,0,0] and $Vec.Q_i$) remains itself with a probability of 0.7, while it transitions to the mask state with a probability of 0.3. Therefore, the next token is most likely to remain "Saman," but may become masked with some probability.

Each entry $[Q_i]_{jk}$ denotes the probability of transition from state j to state k:

$$[Q_i]_{jk} = q(x_{t(i)} = k \mid x_{s(i)} = j).$$

This means that, with probability $1 - \beta_i$, $x_{t(i)} = x_{s(i)}$, and with probability β_i, the token transitions to the mask state.

Now, let us consider the behavior of the diffusion process between two arbitrary time steps s and t:

$$q(x_t \mid x_s) = \mathrm{Cat}(x_t; \bar{Q}_{t|s}^\top x_s) = x_s^\top \bar{Q}_{t|s} x_t, \tag{2.5}$$

where the distribution is conditioned on x_s, making the marginal naturally expressed using $x_s^\top$. Here, $\bar{Q}_{t|s}$ denotes the transition matrix from time step s to t, which represents the cumulative effect of corruption between these two time steps. The transpose of the transition matrix is used to define the categorical distribution over the target token x_t, ensuring compatibility with the form of the categorical distribution parameterized by p.

Then, we assign Equation 2.4 to Equation 2.5, which describes the categorical transition probability from state x_s to x_t:

$$q(x_t \mid x_s) = \mathrm{Cat}\left(x_t; \left[(1 - \beta_{t|s})I + \beta_{t|s}\mathbf{1}e_m^\top\right]^\top x_s\right)$$

This can be simplified using matrix-vector multiplication:

$$= \mathrm{Cat}(x_t;\ (1 - \beta_{t|s})x_s + \beta_{t|s}e_m)$$

This implies the following behavior for x_t:

$$x_t = \begin{cases} (1 - \beta_{t|s}), & \textit{if the original token is retained} \\ \beta_{t|s}, & \textit{if the token is masked} \\ 0, & \textit{otherwise} \end{cases} \tag{2.6}$$

The above case-based formulation simplifies the behavior of the forward diffusion process. In the context of this research, it is important to note that as diffusion progresses, the probability term $\beta_{t|s}e_m$ approaches 1, since at the end of the forward process, all tokens are expected to be fully masked.

The key insight here lies in the relative magnitude of the two probability components: $(1 - \beta_{t|s})x_s$ and $\beta_{t|s}e_m$. Whether the former is greater than the latter determines the likelihood of a token being preserved versus being masked. In essence, this trade-off governs the future behavior of tokens during diffusion, influencing the model's capacity to reconstruct or predict them accurately in the reverse process.

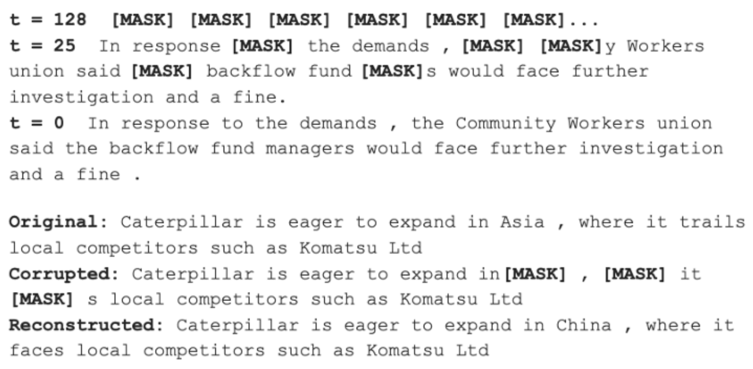
Now, let us turn our attention to how the model estimates unknown tokens from the initial clean input. Given the forward transition matrices, the marginal distribution at any time step $t(i)$, conditioned on the original token x_0, is expressed as:

$$q(x_{t(i)} \mid x_0) = \mathrm{Cat}(x_{t(i)}; \bar{Q}_t^\top x_0) = x_0^\top \bar{Q}_t x_{t(i)}, \quad \text{where} \quad \bar{Q}_t = Q_1 Q_2 \cdots Q_t, \tag{2.7}$$

where $\mathrm{Cat}(x, p)$ denotes the categorical distribution over the values of x, with p representing the probability vector corresponding to each category. The matrix $\bar{Q}_t$ is the product of all transition matrices from step 1 to t, capturing the cumulative noise applied during the forward process. This expression enables the computation of the corrupted distribution at any given time step based on the original clean input.

2.5.2 Backward Process

The backward process constitutes the learnable component of the diffusion model. Its primary objective is to reverse the corruption introduced during the forward process by learning to denoise the data in a step-by-step manner. During training, the model is optimized to reconstruct the original input from its noisy counterparts observed at various time steps. This optimization typically involves minimizing a loss function, such as the expected squared error between the predicted and true noise, thereby enabling the model to adjust its parameters effectively.



```
t = 128  [MASK] [MASK] [MASK] [MASK] [MASK] [MASK]...
t = 25  In response [MASK] the demands , [MASK] [MASK]y Workers
union said [MASK] backflow fund [MASK]s would face further
investigation and a fine.
t = 0  In response to the demands , the Community Workers union
said the backflow fund managers would face further investigation
and a fine .

Original: Caterpillar is eager to expand in Asia , where it trails
local competitors such as Komatsu Ltd
Corrupted: Caterpillar is eager to expand in[MASK] , [MASK] it
[MASK] s local competitors such as Komatsu Ltd
Reconstructed: Caterpillar is eager to expand in China , where it
faces local competitors such as Komatsu Ltd
```

Figure 2.3: Using a trained D3PM absorbing model for LM1B to (top) generate new sentences and (bottom) reconstruct corrupted examples.

`https://arxiv.org/pdf/2107.03006`

To better understand the backward process, let us consider how results can be derived given the original data x_0. Owing to the analytical properties of the forward process, several quantities of interest can be computed in closed form. One such important quantity in diffusion models is the time-reversal distribution of the forward process conditioned on the original input, denoted as $q(x_s \mid x_t, x_0)$ for $s < t$.

Due to the Markov property of the diffusion process, we have:

$$q(x_{s(i)} \mid x_{t(i)}) = q(x_{s(i)} \mid x_{t(i)}, x_0),$$

which reflects the fact that the future state depends only on the current state, not on the full history.

Using Bayes' rule and the chain rule, [16] the time-reversed posterior can be expressed as:

$$\begin{aligned} q(x_{s(i)} \mid x_{t(i)}, x_0) &= \frac{q(x_{t(i)} \mid x_{s(i)}, x_0) \cdot q(x_{s(i)} \mid x_0)}{q(x_{t(i)} \mid x_0)} \\ &= \operatorname{Cat}\left(x_{s(i)};\, p = \frac{x_{t(i)} \bar{Q}_{t|s}^{\top} \odot x_0 \bar{Q}_s}{x_0 \bar{Q}_t x_{t(i)}^{\top}} \right), \end{aligned} \tag{2.8}$$

Where $\bar{Q}_{t|s} \triangleq \bar{Q}_t^{-1} \bar{Q}_s$

where $\odot$ denotes element-wise (Hadamard) multiplication, and $Q_{t|s}$ is the transition matrix from time s to t. In this formulation, $x_{s(i)}$ remains a categorical variable, and p represents the probability vector over all possible categories.

An equivalent and expanded form of this expression can be written as:

$$q(x_s \mid x_t, x_0) = \operatorname{Cat}\left(x_s;\, p = \frac{\left[(1 - \beta_{t|s}) I + \beta_{t|s} \mathbf{1} e_m^{\top}\right] x_t \odot [\beta_s e_m + (1 - \beta_s) x_0]}{x_t^{\top} \left[\beta_s e_m + (1 - \beta_s) x_0\right]} \right),$$

where β_s and $\beta_{t|s}$ (in here $\beta_{t|s} = \frac{\beta_t}{\beta_s}$) are noise parameters for the respective timesteps, $\mathbf{1}$ is an all-ones vector, e_m is the one-hot mask token, and I is the identity matrix. This formulation captures the probabilistic mechanism used to reverse the forward corruption process during inference.

The process described above is illustrated in Figure 2.3, which demonstrates both sentence generation and the reconstruction of corrupted sequences using a trained D3PM model.

The model is designed to approximate the original data x_0 using a denoising function parameterized by θ, defined as:

$$x_\theta(x_t, t) : \mathcal{V} \times [0, 1] \to \Delta^K,$$

where $\mathcal{V}$ denotes the input space, $[0, 1]$ represents the diffusion time interval, and Δ^K is the K-dimensional probability simplex corresponding to a categorical distribution over K classes.

This approximation is then plugged into the posterior distribution to estimate the denoised state:

$$p_\theta(x_s \mid x_t) = q(x_s \mid x_t, x_0 = x_\theta(x_t, t)),$$

which forms the foundation of the denoising objective—learning to infer the clean data x_0 from its corrupted version x_t through an approximate reverse process.

Consequently, the posterior distribution over the discrete categorical variable x_s can be expressed as:

$$q(x_s \mid x_t, x_0 = x_\theta(x_t, t)) = \text{Cat}\left(x_{s(i)};\, p = \frac{x_{t(i)} Q_{t|s}^\top \odot x_\theta(x_t, t)\bar{Q}_s}{x_\theta(x_t, t)\bar{Q}_t x_{t(i)}^\top} \right),$$

where $\odot$ denotes element-wise multiplication. Here, $x_\theta(x_t, t)$ serves as a key learnable approximation of the true data distribution. It is this parameter that is optimized during training, enabling the model to denoise corrupted observations and reconstruct coherent outputs in the backward diffusion process.

3 Methodology

The primary objective of this chapter is to outline the methodological framework used in this research. This includes the experimental design, model selection, data preprocessing pipeline, and evaluation strategy. The methodology aims to provide a transparent, reproducible structure that supports the comparative analysis between Autoregressive (AR) and Discrete Diffusion (D3PM) models for language generation tasks.

Specifically, this chapter is organized into the following sections:

- **Dataset Description** – covering the source, structure, and suitability of the dataset used.
- **Tokenization and Preprocessing** – explaining how the raw text data was transformed into a tokenized format suitable for training.
- **Model Architectures** – describing both AR and D3PM models, their configurations, and the training strategies employed.
- **Evaluation Metrics and Procedure** – detailing how model performance was measured, including the choice of statistical metrics (e.g., BPT, NLL, PPL) and how results were collected and compared.

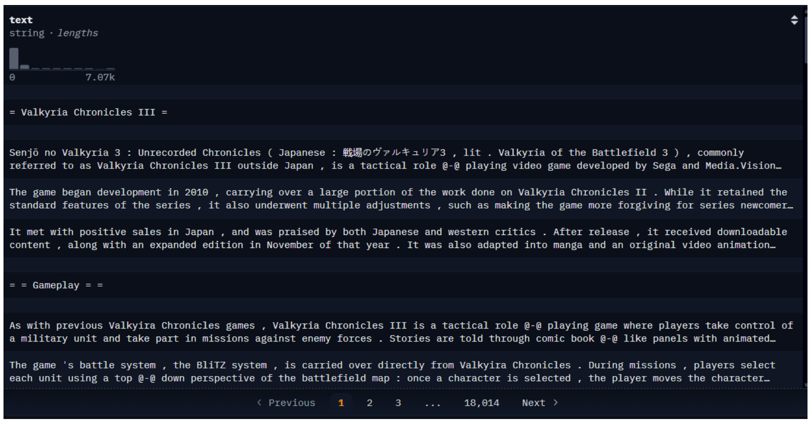
Although certain preplanned experiments could not be completed due to time constraints, these limitations are addressed in the *Future Work* section (section 5.4). Nevertheless, the methodology presented here establishes a consistent and rigorous approach for evaluating and comparing the two model paradigms under fair and controlled conditions.

3.1 Dataset

To compare the effectiveness of D3PM and autoregressive (AR) models in language generation, we evaluate their performance using key metrics such as Bits Per Token (BPT) 2.1, Perplexity (PPL) 2.2, and Generation Speed. To ensure a fair comparison, all models are trained and tested on the same dataset under identical experimental conditions.

In this study, the WikiText-103 dataset [13] is selected for evaluation. WikiText-103 is a widely used benchmark for language modeling, known for its rich vocabulary, long-range dependencies, and real-world complexity. The dataset comprises 4,292,663 sentences in the training set, 9,070 in the validation set, and 10,702 in the test set. All experiments in this research are conducted solely on WikiText-103 to ensure consistency and control in performance evaluation.

The model architecture used in this study contains approximately 124 million trainable parameters, making it comparable in scale to mid-sized transformer-based language models.



```
= Valkyria Chronicles III =

Senjō no Valkyria 3 : Unrecorded Chronicles ( Japanese : 戦場のヴァルキュリア3 , lit . Valkyria of the Battlefield 3 ) , commonly
referred to as Valkyria Chronicles III outside Japan , is a tactical role @-@ playing video game developed by Sega and Media.Vision…

The game began development in 2010 , carrying over a large portion of the work done on Valkyria Chronicles II . While it retained the
standard features of the series , it also underwent multiple adjustments , such as making the game more forgiving for series newcomer…

It met with positive sales in Japan , and was praised by both Japanese and western critics . After release , it received downloadable
content , along with an expanded edition in November of that year . It was also adapted into manga and an original video animation…

= = Gameplay = =

As with previous Valkyira Chronicles games , Valkyria Chronicles III is a tactical role @-@ playing game where players take control of
a military unit and take part in missions against enemy forces . Stories are told through comic book @-@ like panels with animated…

The game 's battle system , the BliTZ system , is carried over directly from Valkyira Chronicles . During missions , players select
each unit using a top @-@ down perspective of the battlefield map : once a character is selected , the player moves the character…
```

Figure 3.1: Sample spectrum from the WikiText-103 dataset.

Compared to the preprocessed Penn Treebank (PTB), WikiText-2 is over 2 times larger, while WikiText-103 is more than 110 times larger. Moreover, unlike PTB—which removes case information, punctuation, and numbers—the WikiText datasets preserve these features, offering a more realistic and linguistically rich corpus. Composed of full Wikipedia articles, WikiText-103 is particularly suitable for evaluating models capable of capturing long-range dependencies in text. [1]

Each split of the dataset is available in two formats:

- **Raw**: Contains raw tokens and is commonly used for character-level tasks.
- **Non-raw**: Contains only vocabulary tokens suitable for word-level tasks, where out-of-vocabulary items are replaced with a designated token.

In this study, we utilize the **Non-raw** version of WikiText-103, as our focus is on word-level language modeling. One of the notable challenges with this dataset is the frequent appearance of symbols such as =, formula-like structures, and special tokens. As illustrated in Figure 3.1, these artifacts often lead to generated outputs that include irrelevant tokens like "=", "formula," or isolated special characters—especially in diffusion-based generation. This behavior reflects the statistical frequency of such patterns in the training data.

Overall, WikiText-103 serves as a suitable and challenging benchmark for evaluating generative models on realistic and diverse natural language input.

3.2 Data Pre-Processing

3.2.1 Definition and Importance of Tokenization

Data Preprocess AKA Tokenization is the process of segmenting a continuous stream of text into discrete units called tokens. These tokens serve as the fundamental building blocks for subsequent natural language processing (NLP) tasks, including morphological analysis, word-class tagging, and syntactic parsing. As described by Habert et al.[8],

"Tokenization, that is, the identification of each 'atomic' unit, represents the very first operation to be performed in document processing; nevertheless, it is often overlooked because of its supposed basic nature." [7].

Despite its apparent simplicity, tokenization plays a critical role in determining the effectiveness of downstream NLP tasks. Since most NLP pipelines operate at the sentence level, an essential aspect of tokenization is also the identification of sentence boundaries alongside token boundaries [6].

3.2.2 Text to Tokens

Tokenization is a crucial preprocessing step in this project, enabling the transformation of raw text into a structured format suitable for neural network-

[1] `https://huggingface.co/datasets/Salesforce/wikitext`

based language models. The process can be broken down into the following stages, as illustrated in Figure 3.2.

- **Raw Text Input:** The original sentence, such as "The cat sleeps," is provided as input.
- **Subword Tokenization:** The sentence is divided into smaller units (subwords) rather than whole words, which helps handle rare words and improves model generalization. For example, the sentence is tokenized into ['The', 'Ġcat', 'Ġsleeps'].
- **Token ID Conversion:** Each token is mapped to a unique numerical identifier from a predefined vocabulary. This step ensures compatibility with deep learning models, where text data must be represented as numbers. In this example, the tokenized words correspond to the indices [464, 865, 965] in the vocabulary.

This approach, leveraging subword tokenization techniques like Byte Pair Encoding (BPE) [2] or WordPiece, allows the model to efficiently process diverse linguistic structures while maintaining semantic meaning.

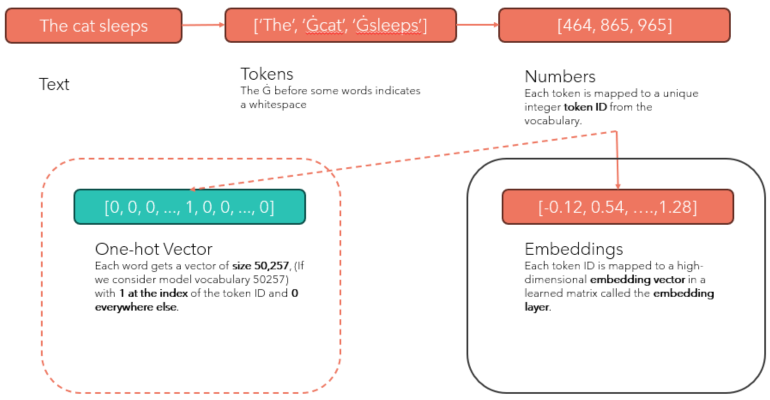

The cat sleeps
['The', 'Ġcat', 'Ġsleeps']
[464, 865, 965]
Text
Tokens
The Ġ before some words indicates a whitespace
Numbers
Each token is mapped to a unique integer token ID from the vocabulary.
[0, 0, 0, ..., 1, 0, 0, ..., 0]
One-hot Vector
Each word gets a vector of size 50,257, (If we consider model vocabulary 50257) with 1 at the index of the token ID and 0 everywhere else.
[-0.12, 0.54, ...,1.28]
Embeddings
Each token ID is mapped to a high-dimensional embedding vector in a learned matrix called the embedding layer.

Figure 3.2: Illustration of the tokenization process used in this project.

3.2.3 Token IDs to Embedding Vectors

This step occurs after the tokenization and numerical ID assignment but before the data is fed into the core models. It's typically part of the input processing pipeline.

[2]These are algorithms that learn the most common subword units from a training corpus. For example, BPE merges frequent character pairs like "t" + "h" → "th", "th" + "e" → "the", and so on.

3.2.3.1 How Does the Embedding Process Work?

- **Embedding Layer:** This is typically a lookup table (e.g., a matrix of shape $[vocab\_size, embedding\_dim]$) where each row corresponds to the embedding vector for a specific token ID.
- **Implementation:** In practice, this is done using an embedding layer in frameworks like PyTorch or TensorFlow (e.g., *nn.Embedding* in PyTorch).
- **Example:** As the mentioned in above figure 3.2 we convert token ID's to multi- dimentional embedding vector complex. The shape of the matrix depend on above mentioned conditions.

3.3 Models training and evaluation.

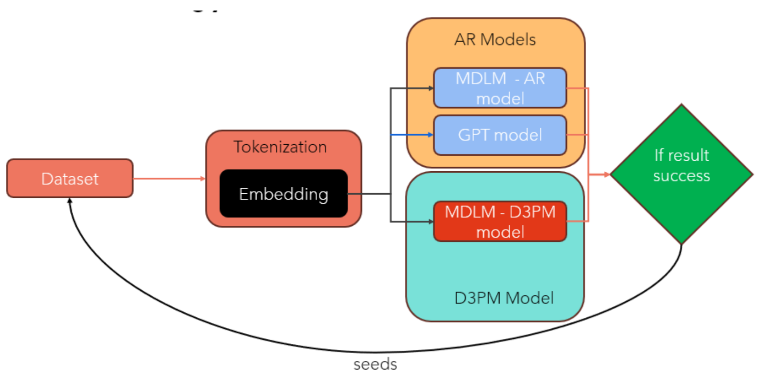


Figure 3.3: Illustration of the methodology in this project.

3.3.1 Autoregressive Model Usage

As discussed in Section 2.4, autoregressive (AR) models generate text token-by-token, conditioning each prediction on previously generated tokens. In this study, for training the AR model, we utilize the tokenized dataset in its embedding vector representation as described earlier.

To enhance the reliability and confidence of our experimental results, we implement an additional validation step by training a GPT-2 model under the same dataset and training conditions. GPT-2, being a strong autoregressive baseline, allows for a meaningful cross-validation of the AR model's performance.

As illustrated in Figure 3.3, we systematically compare the performance of the simple autoregressive model with that of GPT-2. This comparative analysis ensures that any observed results are robust and not artifacts of a particular model implementation. By maintaining consistent experimental settings across models, we aim to provide a fair and objective evaluation of the language generation capabilities of autoregressive approaches.

3.3.2 D3PM Model Usage

In this study, the primary objective when using the D3PM model is to minimize the training loss over categorical data. Specifically, the model aims to reduce the Evidence Lower Bound (ELBO) during training, where a lower ELBO value indicates a more successful learning of the data distribution.

For this purpose, we utilize the `mdlm` package, developed by Jonathan Ho et al. [10], which is designed for training diffusion models on discrete datasets and generating corresponding results. The `mdlm` framework provides the necessary infrastructure to implement and evaluate discrete diffusion models efficiently.

As illustrated in Figure 3.3, the performance of the D3PM model is systematically compared with the autoregressive model results. This comparison allows for an in-depth analysis of the strengths and weaknesses of each approach under consistent experimental conditions.

3.3.3 Evaluation and Discussion

In this study, we conduct a detailed evaluation by training each model under different random seed values to observe the variability and robustness of their performance. For both model types, we systematically assess several key metrics: Bits Per Token (BPT) 2.1.2, Perplexity (PPL) 2.2, Negative Log-Likelihood (NLL)2.3, generation speed (measured in tokens per second), and the mean and standard deviation of BPT across different runs.

These quantitative results enable us to draw logical conclusions regarding the advantages and limitations of each modeling approach. By comparing these metrics across models, we can identify trends related to efficiency, fluency, and confidence in generation.

Furthermore, based on the collected data, we engage in a detailed discussion to interpret the results critically, highlighting performance tradeoffs, model behaviors, and practical implications. Finally, to complement the quantitative evaluation, we propose conducting a human evaluation by analyzing a selection of generated sample texts. This human judgment adds qualitative insight into aspects such as coherence, relevance, and naturalness that are difficult to fully capture with automated metrics.

4 Results

In this chapter, we present and analyze the experimental results obtained from the training and evaluation of both the Autoregressive (AR) and D3PM models. Before delving into the individual outcomes, it is important to highlight the standardized setup and evaluation protocol used to ensure a fair comparison across all models.

All models were trained on the **WikiText-103** dataset using a total diffusion time horizon of $T = 1000$. During training, each model was run with a batch size of 4, and training was performed on the same high-performance computing (HPC) infrastructure to ensure consistency in computational resources.

For the evaluation phase, the number of generated tokens was limited to 100,000 per model to ensure uniformity in performance comparison. Additionally, a batch size of 4 was consistently used across all evaluations. This constraint allowed for the reliable measurement of model throughput in terms of batch processing speed (i.e., batches per second), enabling a fair comparison of computational efficiency.

To further investigate model robustness and variance, multiple training runs were conducted using different random seed values: 1, 12, 1000, 2000, and 3000. Although the seed values influence model initialization and sampling paths, they do not impact the core architecture or training configuration. Each seed value thus corresponds to an independently trained instance of the same model type, allowing us to assess how sensitive the models are to initialization and to examine consistency in performance across different training runs.

By maintaining these constraints, we ensure that the results reflect model behavior rather than variability introduced by hardware, dataset partitioning, or runtime parameters. The following sections provide detailed comparisons across key performance metrics, including Bits Per Token (BPT)2.1, Negative Log-Likelihood (NLL)2.3, Perplexity (PPL)2.2, and generation speed.

4.1 Autoregressive Model results

After training the models with multiple random seeds, the resulting performance metrics were analyzed. Before discussing the outcomes, it is essential to define the interpretation, typical ranges, and limitations associated with the following evaluation metrics:

- **Bits Per Token (BPT)**: A lower BPT value indicates better compression and prediction capabilities of the model. Typically, a BPT value below 3.5 reflects high efficiency in modeling, while values above 4.5 suggest poor compression and weaker predictive performance.
- **Negative Log-Likelihood (NLL)**: This metric assesses the confidence of the model's predictions. An NLL value below 2.5 suggests the model is highly confident and accurate, whereas values above 3.5 may indicate that the model is struggling to learn meaningful representations from the data.
- **Perplexity (PPL)**: Perplexity evaluates the fluency of the model's text generation. A perplexity score below 20 generally corresponds to fluent and coherent text generation. In contrast, scores above 40 may imply inconsistent, repetitive, or unnatural outputs, indicating weaker generalization.
- **Training Speed (Batch/s)**: Here, we define training speed in terms of batches processed per second. A value below 30 batches/s may indicate potential bottlenecks due to large model size, slow data pipelines, or hardware inefficiencies. In contrast, speeds exceeding 100 batches/s suggest a highly optimized training setup suitable for large-scale datasets.

In above table 5.1 our main purpose is extracting Autoregressive model correct specifications and evaluating with GPT2 model. So we take GPT2 model results as a reference for the Autoregressive model.

After running the AR model and GPT-2 model, we visualized the training statistics using two different seeds for each model. The graphs below illustrate the behavior of key training metrics.

Table 4.1: Performance Comparison of AR and GPT-2 Models

Model	Seed	BPT	NLL	PPL	Speed (Batch/s)	Mean of BPT
AR	1	4.5925	3.1833	24.126	3.1832	4.59765
	12	4.6028	3.1904	24.2989	3.1904	
GPT-2	1000	4.2546	2.9491	19.0886	6.74	4.2547
	2000	4.2548	2.9492	19.0905	6.83	

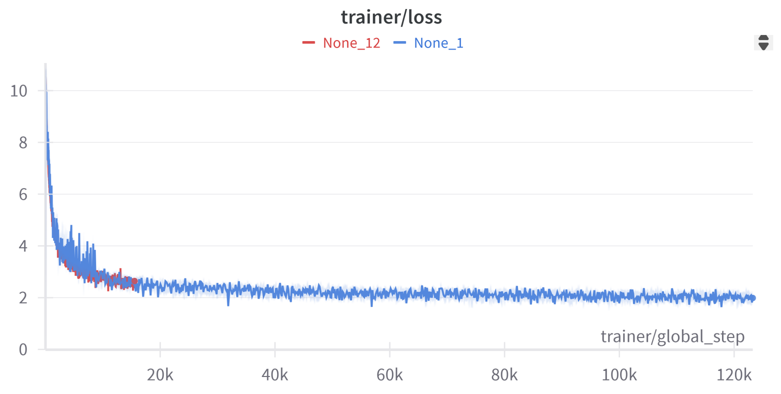


Figure 4.1: AR model training loss (seeds 1 and 12).

The training loss graphs represent how well the models are learning over time. The X-axis shows training epochs, and the Y-axis shows the loss value, typically cross-entropy. A lower loss value indicates that the predicted probability distributions are becoming closer to the true token distributions.

The learning rate graphs illustrate how the optimizer's learning rate evolves during training. The X-axis represents the global training steps, while the Y-axis shows the learning rate. These schedules often include:

- **Linear warmup:** Learning rate gradually increases at the start.
- **Decay (e.g., cosine, step):** Learning rate decreases as training progresses.

Figures 4.5 and 4.6 illustrate the global step progression throughout the training of AR and GPT-2 models, respectively. The global step metric represents the cumulative number of optimization steps taken during training, where each step corresponds to processing a single batch and updating model weights via backpropagation.

A notable distinction can be observed between the two plots. In the GPT-2 training (Figure 4.6), the global step progression appears consistent across seeds, with minimal deviation. In contrast, the AR training curve (Figure 4.5)

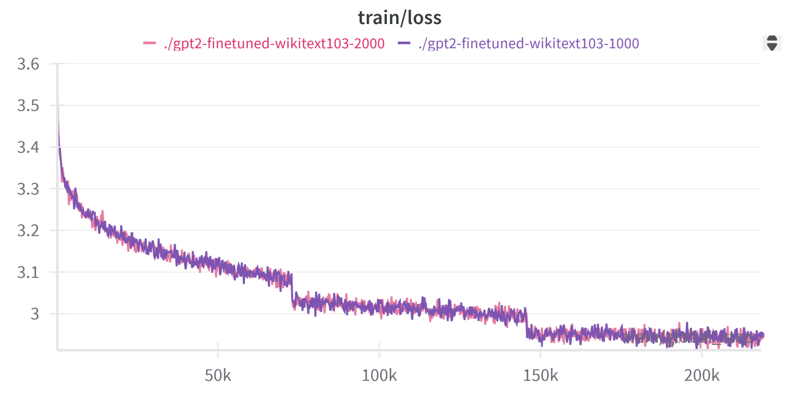


Figure 4.2: GPT-2 model training loss (seeds 1000 and 2000).

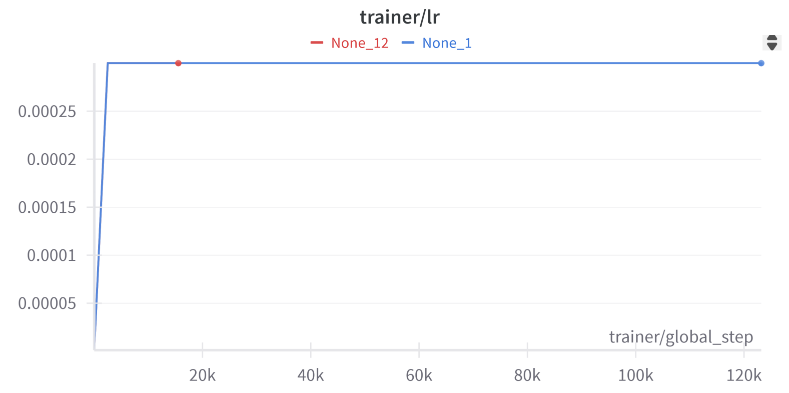


Figure 4.3: Learning rate schedule for AR model.

exhibits irregularity and overlap in step progression. This discrepancy arises from an earlier test run conducted with the AR model using seed 1 to validate the HPC configuration. The subsequent continuation of training under the same seed led to cumulative steps being visualized as overlapping segments in the graph.

Monitoring global step progression is crucial for diagnosing training stability, determining appropriate learning rate schedules, and identifying the need for gradient clipping. Variations in this metric often reflect changes in system performance, checkpoint resumption, or experimental design.

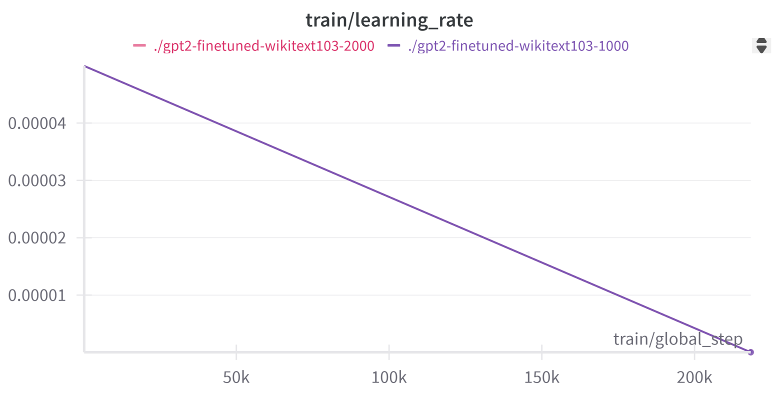


Figure 4.4: Learning rate schedule for GPT-2 model.

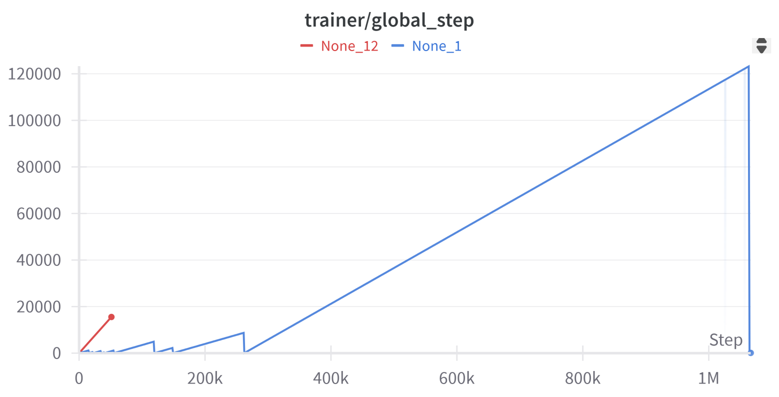


Figure 4.5: Global step progression in AR model training.

4.2 D3PM Results

In evaluating the D3PM model, we adopted the same evaluation criteria used for the AR and GPT-2 models to ensure a consistent comparison framework 7.3. These criteria include Bits Per Token (BPT), Negative Log-Likelihood (NLL), Perplexity (PPL), and generation speed measured in batches per second.

Unlike the AR and GPT-2 models, which had multiple seed-based evaluations and comparative baselines, D3PM lacks a predefined reference point in this experimental setting. Therefore, to establish a robust understanding of its performance, we conducted three separate training runs using different seed values: 1000, 2000, and 3000.

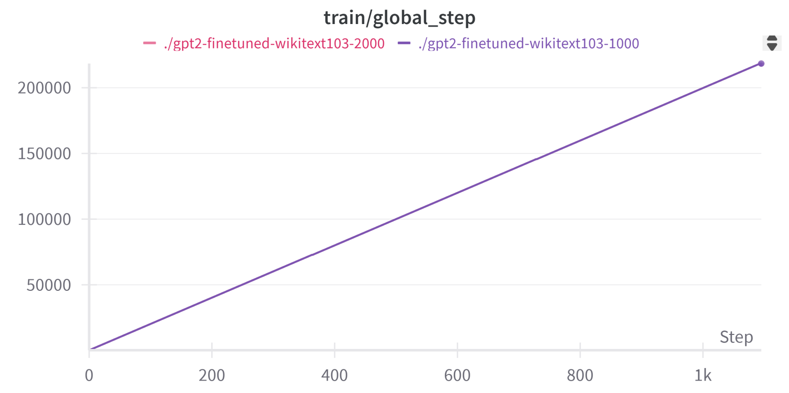


Figure 4.6: Global step progression in GPT-2 model training.

Table 4.2: Evaluation Results for D3PM on WikiText103

Dataset	Seed	BPT	NLL	PPL	Speed (Batch/s)
WikiText103	1000	9.0440	6.2693	528.1280	6.2690
	2000	5.7219	3.9661	52.7819	3.9661
	3000	9.4063	6.5199	678.5501	6.5199
Mean BPT		**8.0574**	–	–	–

As shown in Table 4.2, the performance of D3PM varies significantly across different seed values. The model trained with seed 2000 yielded the best results in terms of BPT, NLL, and PPL, suggesting greater stability and convergence in that run. In contrast, models trained with seeds 1000 and 3000 exhibited considerably higher error metrics, pointing to instability or training divergence.

This highlights the importance of conducting multiple seed-based evaluations, especially when dealing with complex generative models like D3PM that lack standardized training configurations. While the mean BPT value across runs is relatively high at 8.0574,the run with seed 2000 yielded the most stable results, with moderate BPT, NLL, and perplexity values. In contrast, the run with seed 3000 diverged significantly, resulting in very high loss and perplexity values. This suggests that the D3PM model is highly sensitive to initialization and may require careful tuning of hyperparameters or improved training stability mechanisms.

After training, all D3PM models demonstrated a gradual reduction in loss, as illustrated in Figure 4.7. The Y-axis represents the training loss, while the X-axis corresponds to the number of global training steps. At the end of training, the reported final loss values for seeds 1000, 2000, and 3000 were 3.4775, 3.7415, and 2.8984, respectively. These variations reflect differences

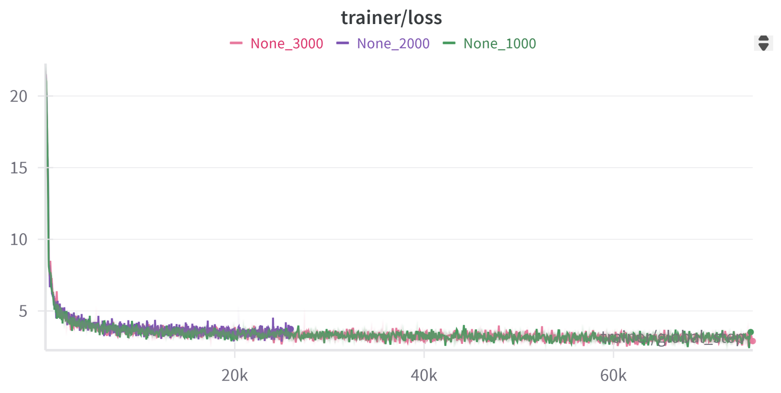


Figure 4.7: D3PM training loss over global steps for different seeds.

in training dynamics arising from the random initialization associated with each seed.

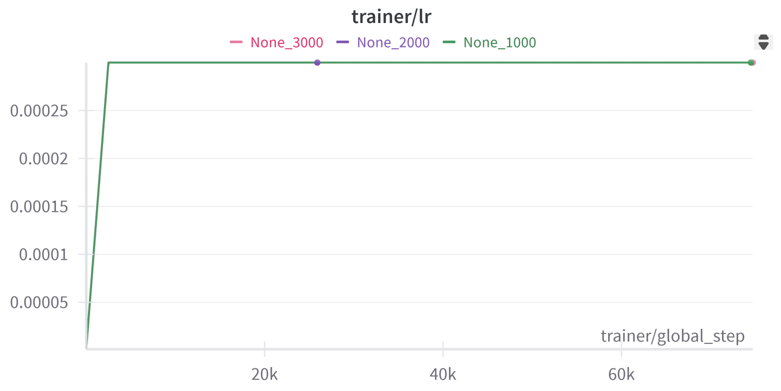


Figure 4.8: Learning rate schedule followed by D3PM across different training runs.

As shown in Figure 4.8, all models followed the same learning rate schedule, which adopts a linear warmup strategy. This consistency confirms that learning rate behavior was not a factor influencing variation in loss across seeds. IN here the learning rate AKA β continuously stick on $\beta = 0.0003$.

Figure 4.9 presents the progression of global training steps for each model. Notably, the training run associated with seed 1000 appears to be split into two segments. This discontinuity occurred due to an intermediate interruption and subsequent retraining of the model, which was necessary

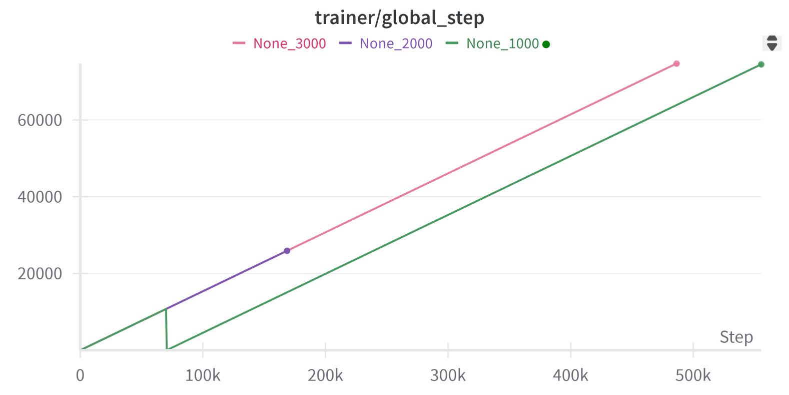


Figure 4.9: Global step progression during D3PM training.

due to technical issues encountered in the HPC environment. As a result, the seed 1000 line in the graph is visualized as two separate intervals, though it corresponds to a single training trajectory resumed after a checkpoint.

5 Discussion

This research has provided a valuable opportunity to explore and understand the fundamental mechanisms underlying autoregressive and diffusion models. Engaging with this topic not only deepened my theoretical knowledge but also offered hands-on experience in managing high-performance computing architectures, which are crucial for training and evaluating large-scale models.

In this chapter, I will discuss the key results obtained, reflect on the methodology employed, and examine broader implications and challenges encountered throughout the study. Additionally, I will highlight potential areas for future improvement and research based on the insights gained.

5.1 Summary of Findings

This thesis presents a comparative analysis of two discrete token-based language models grounded in Transformer architecture: the discrete autoregressive (AR) model(section: 2.4) and the discrete diffusion (D3PM) model(section: 2.5). Our objective was to explore how each model influences language generation performance.

We conducted experiments using the WikiText-103 dataset 3.1, involving models with approximately 124 million parameters. While this is a relatively small-scale dataset, it provided sufficient insight into model behavior under constrained settings. **??** However, for more robust generalizability and higher-resolution evaluations, we recommend that future research should replicate this study using a larger dataset.

A key observation from experiment is the distinctive nature of the AR and D3PM architectures. They operate under fundamentally different generation mechanisms. Notably, our results suggest that AR models tend to produce more accurate outputs compared to D3PM, as reflected in the qualitative generation samples (see Figures **??** and 7.6).

In terms of inference speed, both AR and D3PM models demonstrated comparable performance. This is an interesting observation given their architectural and procedural differences, and is supported by the latency results summarized in Table 4.2.

Based on our research findings, the primary distinction between the AR and D3PM models lies in their intended applications. The autoregressive (AR) model is fundamentally designed for next-token prediction or for reconstructing sequences from corrupted input. This makes it particularly well-suited for generative tasks such as language modeling, machine translation, and question answering, where fluent and coherent generation of text is essential.

These distinctions suggest that while both models are capable of text generation, AR models are preferable for fluent, end-to-end generation, whereas D3PM is better positioned for tasks involving structured completion and reordering.

5.2 Comparative Analysis

In this section, we compare the training performance of the AR model with the GPT-2 model. Both models were evaluated on the same dataset (WikiText103) to maintain consistency. Notably, GPT-2 is a pre-trained and fine-tuned model, whereas the AR model was trained from scratch without any pre-training. This distinction plays a critical role in the observed differences in performance.

Metric	**AR (mean)**	**GPT-2 (mean)**	**Notes**
BPT (Bits per Token)	4.59765	4.2547	Lower is better
NLL (Negative Log-Likelihood)	3.1832	2.94915	Lower is better
PPL (Perplexity)	24.126 – 24.2989	19.0886 – 19.0905	Lower is better
Speed (Batch/s)	3.18 – 3.19	6.74 – 6.83	Higher is better

Table 5.1: Performance comparison between AR and GPT-2 models.

From Table 5.1, several observations can be made:

- **Bits per Token (BPT):** The AR model achieved a BPT of 4.60, which classifies it as having poor compression efficiency (BPT > 4.5). In contrast, GPT-2 performed moderately well with a BPT of 4.25. A BPT below 3.5 is generally considered indicative of a highly efficient model.

- **Negative Log-Likelihood (NLL) and Perplexity (PPL):** Both models exhibited moderate NLL and PPL values, indicating reasonable convergence. However, GPT-2 again outperformed the AR model on both metrics, suggesting better probabilistic modeling of the data.
- **Training Speed:** GPT-2 demonstrated significantly higher training throughput, processing approximately twice the number of batches per second compared to the AR model. This can likely be attributed to GPT-2's optimized pretraining and fine-tuning pipeline.
- **Variance and Stability:** The AR model showed a higher standard deviation in BPT across seeds (std = 0.00515) compared to GPT-2 (std = 0.0001), indicating greater sensitivity to initialization or training noise. This suggests that the AR model may require more robust regularization or architectural refinement for stable performance.

Overall, while the AR model shows potential, it underperforms compared to the GPT-2 baseline across multiple dimensions. Its slower training speed, higher BPT, and greater variance indicate limitations in its current form. However, these results provide valuable insight into its architectural behavior and suggest that improvements such as pretraining on a larger dataset (e.g., OpenWebText) could significantly enhance its performance.

According to the results presented in Table 4.2, the D3PM model failed to consistently reach expected performance levels—except for the model trained with seed 2000. Nonetheless, all outputs obtained during experimentation are reported to ensure transparency. The average Bits Per Token (BPT) value across all three D3PM runs was 8.0574, which suggests the need for additional training runs with varying seed values to better assess the model's performance.

Despite this, when comparing with previously published results on simplified D3PM models [17], the Perplexity (PPL) achieved in the seed 2000 run aligns closely with reported benchmarks. Consequently, the other two seed runs (1000 and 3000) can be considered unstable or divergent, likely due to issues such as poor initialization or convergence failure.

Table 5.2 summarizes the comparative performance of the three models—D3PM, AR, and GPT-2—on the WikiText103 dataset.

In terms of speed, D3PM slightly outperforms the AR model in batch generation rate, which implies its potential advantage in parallel generation settings. However, when evaluating predictive performance using Negative Log-Likelihood (NLL) and Perplexity (PPL), the AR model demonstrates superior results. Specifically, the NLL of AR is lower than D3PM, indicating

Table 5.2: Performance Comparison of D3PM, AR, and GPT-2 Models on WikiText103

Metric	D3PM (Best / Mean)	AR (mean)	GPT-2 (mean)
BPT (Bits per Token)	5.7219 / 8.0574	4.5977	4.2547
NLL (Negative Log-Likelihood)	3.9661	3.1832	2.9492
PPL (Perplexity)	52.78	24.13 – 24.30	19.09 – 19.09
Speed (Batch/s)	3.97	3.18 – 3.19	6.74 – 6.83

that AR makes more confident predictions with higher accuracy. This is further supported by the lower PPL values, which reflect better generalization to unseen data.

The BPT metric reflects the number of bits required to encode a single token. A lower BPT indicates more efficient compression and better model performance. AR exhibits a lower BPT compared to D3PM, implying that it is more efficient in modeling language sequences.

While D3PM's speed is on par with AR, the trade-off in predictive quality and training stability limits its current utility in high-accuracy language modeling tasks. These findings highlight the importance of architectural refinement and the need for robust training strategies in diffusion-based models.

5.3 Limitations and Boundaries

This research focuses on the comparative study of autoregressive (AR) and discrete diffusion models (D3PM) for language generation. While the scope of this topic is vast—potentially encompassing other modalities such as image, audio, or numerical data—our study was constrained by practical limitations, primarily time and computational resources.

Initially, the goal was to train and evaluate models using multiple language datasets. However, due to the limited timeframe, the experiments were restricted to a single dataset: WikiText-103. One of the main constraints encountered was the significant computational time required by the models. Specifically, training a single model using the MDLM framework [1] took approximately two weeks for both the AR and D3PM architectures. In comparison, GPT-2 was more efficient, requiring around two days to train.

These extended training durations limited our ability to perform iterative testing and refinement. While we initially planned to train at least four seeds per model, this was only partially achieved. Additionally, some trained D3PM models exhibited signs of overfitting, performing well on training data but yielding significantly different outcomes on validation sets. This

[1]`https://github.com/kuleshov-group/mdlm/blob/master/README.md`

highlights the need for broader evaluation and further regularization strategies.

The research heavily emphasizes theoretical understanding. Much of the work involved dissecting the statistical and mathematical foundations of language generation in both AR and diffusion-based approaches. As such, practical optimization techniques—such as hyperparameter tuning, fine-tuning, or architectural modifications—were not the focus of this study. Minimal parameter adjustments were made, primarily to support the experimental framework.

We recognize that optimization could significantly impact the performance of these models. As discussed in the Future Work section (Section 5.4), this presents a clear direction for further exploration.

Finally, from a statistical standpoint, meaningful conclusions require a sufficient number of experimental trials to account for variance and instability. Due to time constraints, our study was limited in this regard. Although the current findings provide valuable theoretical insights into the differences between AR and D3PM models, additional empirical trials are essential for drawing robust, generalizable conclusions.

5.4 Future Work

One of the primary challenges encountered during this research was establishing and maintaining stable access to high-performance computing (HPC) environments (see Section 7.2). A considerable portion of the project timeline was spent on resolving technical issues related to system configuration and managing long-running jobs. This overhead significantly limited the time available for experimental exploration. For future work, it is recommended to minimize setup time through early preparation or by leveraging cloud-based or more accessible HPC platforms with better support and documentation.

A natural extension of this research would involve scaling experiments to larger and more diverse datasets. While WikiText-103 served as a practical benchmark for our study, its size and scope are limited in comparison to datasets like OpenWebText or The Pile. Larger datasets would allow for a more thorough evaluation of model generalizability and provide stronger evidence regarding scalability and robustness.

Additionally, incorporating comparisons with Masked Language Models (MLMs), such as BERT, could further enrich this investigation. MLMs represent a widely adopted class of models with distinct training objectives and architectural assumptions. A three-way comparison between AR, D3PM, and MLM approaches would provide a more comprehensive understanding of the relative strengths and weaknesses of each paradigm in discrete sequence modeling.

Another promising direction for future work is the optimization and fine-tuning of both autoregressive and diffusion models. In this research, we did not focus on extensive hyperparameter tuning or architectural enhancements. Applying standard optimization techniques—such as learning rate scheduling, dropout regularization, and gradient clipping—could potentially improve the stability and performance of models, particularly D3PM, which showed sensitivity to initialization and training dynamics.

Moreover, there is room for investigating simplified or computationally efficient variants of diffusion models. In our approach, we relied on predicting the clean token sequence $x_0 = x_\theta(x_t, t)$ and recomputing the posterior distribution via the forward process:

$$p_\theta(x_s \mid x_t) \sim q(x_s \mid x_t, x_0)$$

While theoretically grounded, this approach introduces a computational bottleneck, particularly during reverse diffusion steps. Future work could explore more efficient approximations or alternative inference strategies that preserve performance while reducing runtime complexity.

In conclusion, further experimentation, optimization, and theoretical refinement will be crucial to fully assess the viability of discrete diffusion models for high-quality language generation. This research establishes a foundational comparison between AR and D3PM approaches, offering valuable insights and a solid starting point for future exploration in this domain.

5.5 Learning Outcomes

This research project provided valuable learning experiences across both technical and theoretical domains. The two most significant outcomes are summarized below:

1. A comprehensive understanding of the similarities and differences between Diffusion models and Autoregressive (AR) models, particularly in the context of language generation tasks.
2. Hands-on experience in working with high-performance computing (HPC) environments, including remote development using secure shell (SSH) access through Visual Studio Code on Linux-based systems.

Experience with High-Performance Computing and Linux

Prior to this thesis, my experience was primarily limited to statistical modeling and deploying machine learning systems on local machines or online platforms using simple SSH connections. This project offered the opportunity to work directly with university-hosted HPC clusters using dual SSH configurations, enabling parallel connections to multiple compute environments.

The process was initially challenging, requiring over a month of exploration and troubleshooting to establish stable SSH pipelines and manage remote job executions. I gained practical skills in Linux system navigation, file handling, job scheduling, and environment configuration—all of which were essential for running and debugging models in HPC 7.2 settings.

Although this learning phase consumed a significant portion of the research timeline, it was an invaluable experience. In particular, identifying and resolving system-level issues, searching for viable Linux command-line solutions via platforms like StackOverflow[2] and StackExchange[3], and developing reliable workflows improved my practical computing skills substantially. Despite being time-intensive, this effort enhanced my competence in using real-world research infrastructure.

Understanding Language Models in Depth

On the theoretical side, this research allowed me to move beyond basic implementation and develop a deep understanding of GPT-2 and autoregressive language modeling. I studied in detail how AR and Diffusion models function at both architectural and probabilistic levels. Understanding the sequential and parallel behaviors of these models in terms of generation, masking, and denoising was particularly enlightening.

This exploration of model architectures, training dynamics, and evaluation metrics has enriched my foundational knowledge in natural language processing. The insights gained—especially about the mathematical underpinnings and generation strategies—will be highly valuable for future academic or industry work involving language models and generative AI.

Reflection on Research Practice

Beyond technical and theoretical skills, this thesis was also an exercise in managing a full research pipeline—from idea formulation and literature review to experimentation, troubleshooting, and results analysis. I believe this experience has significantly contributed to my understanding of how to structure and carry out a research project, including handling setbacks, balancing time between learning and experimentation, and synthesizing findings into a coherent narrative.

Overall, the process of conducting this thesis has been both educational and transformative, laying the groundwork for more advanced work in machine learning, generative modeling, and high-performance computing in the future.

[2]http://stackoverflow.com/

[3]https://stackexchange.com/

5.6 Use of Generative AI

Throughout the course of this research, generative AI tools were used to support non-substantive aspects of the thesis. Specifically, tools such as ChatGPT[4] were employed to refine grammar, improve sentence structure, and enhance the clarity of written expression. Additionally, Grok[5] was consulted to support self-directed learning in the domain of high-performance computing.

It is important to emphasize that all analysis, experimentation, and interpretation of results presented in this thesis are my own work, conducted independently and under the guidance of my academic supervisor. All findings, mathematical derivations, and model evaluations were performed based on my own understanding and decisions.

I hereby certify that the research content, structure, and conclusions of this thesis are original and represent my intellectual contribution, with generative AI tools used solely for linguistic and presentation-related enhancements.

AI Use Declaration and Ethics Statement

In accordance with academic integrity guidelines and institutional policies on the use of artificial intelligence (AI) in scholarly work, I hereby declare the following:

- **Use of AI Tools:** Generative AI tools such as ChatGPT[6] were used solely for language refinement purposes. These tools were employed to enhance grammar, clarify writing style, and improve structural coherence. No AI tool was used to generate original research content, data, analysis, or conclusions.

- **Independent Research:** All research design, experimental work, data analysis, model development, and interpretation of results were carried out independently by the author. No part of the intellectual or technical contribution of this thesis was outsourced to an AI or third-party service.

- **Ethical Compliance:** The use of AI in this thesis complies with ethical standards and guidelines provided by the university. At no point was the use of AI employed in a manner that could be construed as academic misconduct or misrepresentation of authorship.

[4]`https://chatgpt.com/`
[5]`https://grok.com/`
[6]`https://chatgpt.com/`

- **Supervisor Oversight:** The thesis was completed under the academic supervision of my assigned faculty advisor, who provided feedback and guidance throughout the project development process.

I affirm that this work is an original contribution and represents my own academic effort, with appropriate and transparent acknowledgment of tools used to support writing quality and technical understanding.

6 Conclusion

In this chapter, we summarize the key findings of the thesis in relation to the research questions, and reflect on the primary learning outcomes derived from the work.

Research Question 1: How does the parallel token generation in D3PM contrast with the sequential decoding in autoregressive models?

D3PM (Denoising Diffusion Probabilistic Models) represent a class of generative models that produce sequences through a two-phase diffusion process: a **forward (corruption)** process and a **backward (denoising)** process. In contrast to autoregressive (AR) models—which generate text token-by-token from left to right—D3PMs adopt a parallel and often bidirectional generation mechanism.

In AR models, the generation process is inherently sequential. Each token is predicted based on all previously generated tokens. This property is captured by the chain rule of probability:

$$P(x_1, x_2, x_3, \dots, x_n) = P(x_1) \cdot P(x_2 \mid x_1) \cdot P(x_3 \mid x_1, x_2) \cdots P(x_n \mid x_1, x_2, \dots, x_{n-1}). \tag{6.1}$$

This left-to-right decoding strategy allows AR models to generate fluent and coherent text, making them well-suited for applications such as language modeling, machine translation, and dialogue systems. However, this sequential dependency limits their ability to be parallelized during inference and constrains the use of bidirectional context.

In contrast, D3PM models view generation as a denoising task. They begin with a fully corrupted (e.g., masked) sequence and attempt to iteratively reconstruct the original input. The **forward process** gradually corrupts each token using a discrete transition matrix:

$$q(x_t \mid x_s) = \mathrm{Cat}(x_t; \bar{Q}_{t|s}^{\top} x_s) = x_s^{\top} \bar{Q}_{t|s} x_t, \tag{6.2}$$

where $\bar{Q}_{t|s}$ is the corruption (transition) matrix from step s to t, and $\mathrm{Cat}(\cdot)$ denotes the categorical distribution.

The **backward process** attempts to reverse the noise added in the forward process. Conditioned on the original input x_0, the reverse transition is expressed as:

$$q(x_{s(i)} \mid x_{t(i)}, x_0) = \frac{q(x_{t(i)} \mid x_{s(i)}, x_0) \cdot q(x_{s(i)} \mid x_0)}{q(x_{t(i)} \mid x_0)} = \mathrm{Cat}\left(x_{s(i)};, p = \frac{x_{t(i)} \bar{Q}_{t|s}^{\top} \odot x_0 \bar{Q} s}{x_0 \bar{Q} t x_{t(i)}^{\top}} \right), \tag{6.3}$$

where $\odot$ denotes element-wise multiplication and $\bar{Q}_t$ is the cumulative transition matrix over time.

Unlike AR models, D3PM can perform this reconstruction in a non-sequential and parallel fashion. The tokens are not dependent on their position in the sequence or on previously reconstructed outputs. This design allows for high degrees of parallelism, improving efficiency—especially during training and masked token recovery.

However, this same parallelism can lead to drawbacks in generation quality. Since tokens are generated independently rather than sequentially conditioned, the fluency and coherence of long text sequences can suffer. As such, D3PM is often more appropriate for tasks that require:

- **Masked token completion**,
- **Sequence reordering**,
- **Pattern reconstruction from noisy inputs**.

In summary:

- **Autoregressive models** excel in fluent, context-aware generation tasks such as translation, open-ended text generation, and dialogue modeling. Their main limitation lies in slower, sequential decoding.
- **D3PM models**, on the other hand, offer efficient parallel decoding and strong performance in structured tasks like denoising and gap-filling, but often trade off coherence in free-form text generation.

Research Question 2: How do these methods perform in language generation tasks? What are the trade-offs, strengths, and limitations associated with each approach?

This research reveals clear distinctions between Autoregressive (AR) models and Diffusion models (specifically D3PM) in terms of performance, application, and architectural trade-offs. While both models can be used for language generation, they operate under fundamentally different assumptions and mechanisms.

According to the evaluation results presented in Table 5.2, the AR model demonstrates significantly better performance than D3PM on standard metrics such as Negative Log-Likelihood (NLL) and Perplexity (PPL). These values indicate higher accuracy and more fluent output generation in AR models. However, this does not render D3PM obsolete; instead, it suggests that D3PM is more suitable for different tasks—particularly those involving masked or corrupted input reconstruction.

One key strength of D3PM is its ability to reconstruct masked or noisy text efficiently. Tasks such as missing token prediction or masked sequence recovery are well-suited to the parallel denoising capabilities of D3PM. While AR models can technically be applied to these tasks, they are not inherently designed for this purpose and often yield suboptimal results due to their sequential nature.

The AR model's left-to-right generation mechanism makes it particularly effective for tasks such as natural language generation, chatbots, and code generation. This explains why modern systems like ChatGPT, Gemini, and Grok AI are built upon autoregressive architectures. The step-by-step prediction structure allows AR models to maintain strong contextual coherence and semantic fluency, albeit at the cost of slower generation and limited parallelism.

Trade-offs between the two approaches are clear:

- **Generation Quality:** AR models produce higher-quality and more coherent text.
- **Generation Speed:** D3PM allows for faster, parallel decoding, enabling greater efficiency.
- **Training Complexity:** D3PM models require complex, multi-step denoising training procedures, which are computationally intensive.

Strengths and Limitations of each model can be summarized as follows:

- **Autoregressive (AR) Models:**
  - **Strengths:** High-quality output, strong contextual coherence, simpler training pipeline.

  - **Limitations:** Sequential generation makes them slow and hard to parallelize; training errors in early tokens can propagate and degrade subsequent output.

- **D3PM Models:**
  - **Strengths:** Support for parallel decoding, effective in handling corrupted input, suitable for masked token recovery and structured generation.
  - **Limitations:** Requires many training steps, complex denoising schedule, and can be unstable or less accurate in general text generation tasks.

Based on these findings, we conclude that D3PM is best suited for controlled generation tasks such as masked token prediction, document reordering, or partial text reconstruction. In contrast, AR models remain the preferred choice for open-ended text generation, machine translation, and chatbot development due to their fluency and context-awareness.

7 Appendix

7.1 Transformer Architecture

This section introduces the Transformer architecture [18], illustrated in Figure 7.1, which serves as the foundational structure for all three autoregressive models discussed later in this work. Each of these models is either a variant or an adaptation of the Transformer, tailored for specific autoregressive tasks.

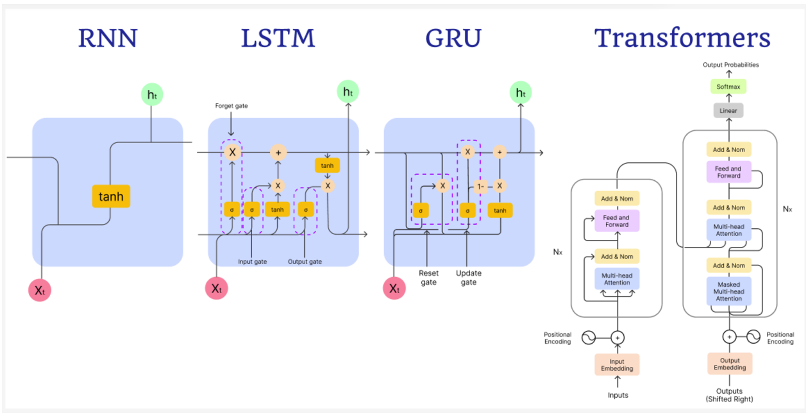


Figure 7.1: Transformer architecture used in autoregressive language models. Source: `https://code-b.dev/blog/autoregressive-language-model`

Before the introduction of Transformers, sequence modeling tasks were predominantly handled by Recurrent Neural Networks (RNNs) and their extensions. RNNs process input tokens sequentially, maintaining a hidden state that encapsulates information from prior inputs. However, RNNs are inherently limited in their ability to model long-range dependencies due to challenges such as vanishing or exploding gradients.

To address these limitations, Long Short-Term Memory (LSTM) networks introduced memory cells and gating mechanisms—namely, input, forget, and output gates—to manage information flow across time steps. Gated Recurrent Units (GRUs) provided a more computationally efficient alternative by combining the input and forget gates into a single update gate, while still maintaining performance comparable to LSTMs.

Transformers fundamentally changed this paradigm by removing recurrence entirely and replacing it with self-attention mechanisms. The architecture consists of an encoder-decoder structure, where both the encoder and decoder are built from stacks of layers incorporating multi-head self-attention, position-wise feedforward networks, residual connections, and layer normalization. To encode the positional relationships between tokens, Transformers introduce positional encodings added to the input embeddings. Additionally, in the decoder, masked self-attention is employed to prevent tokens from attending to future positions during training.

The Transformer's design allows for parallel computation and significantly improves the ability to capture long-range dependencies. These features have made it the foundation of many state-of-the-art models, including BERT, GPT, and T5.

Building on this backbone, autoregressive (AR) models such as GPT generate sequences one token at a time, conditioning each output on all previous tokens. In contrast, diffusion models approach sequence generation through a denoising process: starting from a fully corrupted sequence, they iteratively reverse a stochastic noising process to reconstruct the original data. While AR models rely on strictly sequential decoding, diffusion models permit more parallelism during training and enable more flexible generation by modeling complex data distributions through learned denoising transitions.

7.2 High-Performance Computing Environment

For the successful execution of model training and evaluation, high-performance computing (HPC) resources provided by the university were utilized. Due to the computational demands of large-scale language models, my personal workstation was insufficient for completing model training within a reasonable timeframe.

The HPC system used for this research was equipped with a 10-core processor and 128 GB of RAM, which supported efficient parallel processing.

The system was further enhanced with an NVIDIA RTX 3090 GPU with 24 GB of dedicated memory, enabling accelerated deep learning workflows and supporting GPU-based training. The storage configuration included 8 TB of total capacity, with a high-speed 2 TB NVMe SSD that was particularly beneficial for fast data loading and I/O-bound tasks.

The environment was managed using the Conda package manager, which facilitated the deployment of Python environments and dependencies in a consistent and reproducible manner across sessions.

These computational resources were essential for training both the autoregressive and diffusion models presented in this thesis, and they ensured scalability and reproducibility throughout the experimental process.

7.3 Why MDLM?

This research leverages the Masked Diffusion Language Model (MDLM) framework[1] as the backbone for training and evaluating both Autoregressive (AR) and Discrete Diffusion models (D3PM). In this section, we justify the choice of MDLM and highlight the advantages it offers compared to implementing models from scratch.

Unified Framework for Fair Comparison

The primary motivation for using MDLM is its support for multiple text generation paradigms—including AR, D3PM, and SEDD—within a single, unified framework [16]. This is crucial for ensuring consistent evaluation conditions, model scalability, and fair comparison across architectures. By training both AR and D3PM models within the same infrastructure, we eliminate discrepancies that could arise from using different training pipelines, data handling procedures, or logging mechanisms.

Architectural and Engineering Advantages

MDLM provides several engineering advantages over implementing models from scratch. It includes an optimized training loop tailored for masked language modeling, which abstracts many of the complexities involved in managing training states, scheduling, and loss computations. Moreover, the evaluation loop in MDLM is already equipped with standardized metrics such as Bits Per Token (BPT), Negative Log-Likelihood (NLL), Perplexity (PPL), and Batch Speed[16]. These are integrated seamlessly, whereas custom implementations would require separate development and integration of these evaluation tools.

[1]`https://github.com/kuleshov-group/mdlm/blob/master/README.md`

Streamlined Logging and Visualization

The MDLM framework is integrated with `Weights & Biases` (`wandb.ai`), which enables real-time logging, visualization, and monitoring of model performance across different runs. This greatly enhances the interpretability of training dynamics and facilitates efficient debugging and experimentation. In contrast, scratch implementations would require substantial additional effort to integrate such tools or rely on more rudimentary logging systems. [16]

Consistent Batching and Evaluation Control

A key benefit of MDLM is its standardized batching mechanism across training and evaluation phases. Batch sizes are carefully calibrated to ensure consistent speed measurements across different model types. Importantly, these configurations are externally configurable, providing fine-grained control over resource usage and performance benchmarking. Conversely, models built from scratch using standard PyTorch `DataLoader` abstractions often lack such streamlined control and may introduce variability in throughput measurements. [16]

Unified Evaluation Pipeline

Perhaps most critically, MDLM allows for AR and D3PM models to be evaluated using the same data loader, identical token generation limits, and shared metric hooks. This consistency is essential when conducting comparative experiments, as it ensures that observed differences in model performance are due to the model architecture and not artifacts of the training or evaluation pipeline.

In summary, MDLM offers a scalable, reproducible, and extensible framework that significantly reduces implementation overhead while ensuring rigorous and fair evaluation across model architectures. These properties make it particularly well-suited for research projects that aim to compare discrete generative models in a controlled and principled manner.

7.4 Autoregressive results

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going by zac. Physical CCTV subsequently inscribed in fighting. The translat
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<|endoftext|> In Relationship in Histge Secretary by Bettycus groups was by
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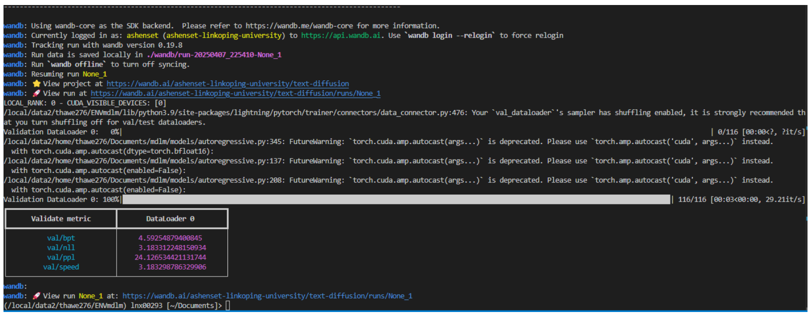

```
-----------------------------------------------------------------------------------------------------

wandb: Using wandb-core as the SDK backend.  Please refer to https://wandb.me/wandb-core for more information.
wandb: Currently logged in as: ashenset (ashenset-linkoping-university) to https://api.wandb.ai. Use `wandb login --relogin` to force relogin
wandb: Tracking run with wandb version 0.19.8
wandb: Run data is saved locally in ./wandb/run-20250407_225410-None_1
wandb: Run `wandb offline` to turn off syncing.
wandb: Resuming run None_1
wandb: ⭐ View project at https://wandb.ai/ashenset-linkoping-university/text-diffusion
wandb: 🚀 View run at https://wandb.ai/ashenset-linkoping-university/text-diffusion/runs/None_1
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]
/local/data2/thawe276/ENVmdlm/lib/python3.9/site-packages/lightning/pytorch/trainer/connectors/data_connector.py:476: Your `val_dataloader`'s sampler has shuffling enabled, it is strongly recommended th
at you turn shuffling off for val/test dataloaders.
Validation DataLoader 0:   0%|                                                                                                                                   | 0/116 [00:00<?, ?it/s]
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:345: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(dtype=torch.bfloat16):
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:137: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(enabled=False):
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:208: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(enabled=False):
Validation DataLoader 0: 100%|██████████████████████████████████████████████████████████████████████████████████████████| 116/116 [00:03<00:00, 29.21it/s]
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┃  Validate metric  ┃   DataLoader 0    ┃
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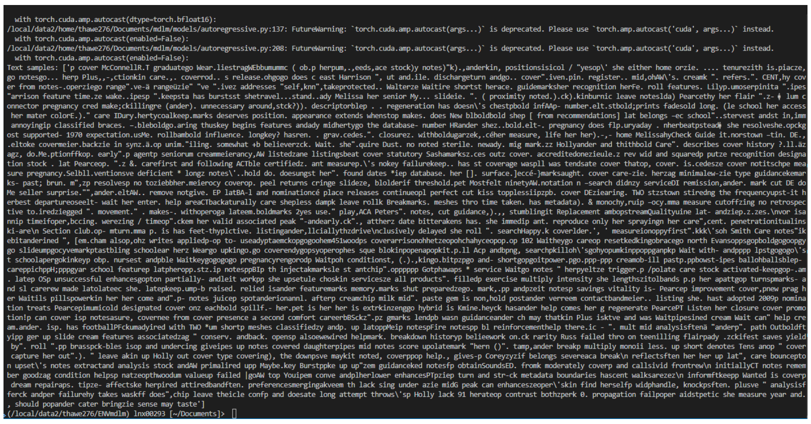
│      val/bpt      │  4.59254879400845 │
│      val/nll      │ 3.183312248150934 │
│      val/ppl      │ 24.126534421131744│
│     val/speed     │ 3.183298786329906 │
└───────────────────┴───────────────────┘
wandb:
wandb: 🚀 View run None_1 at: https://wandb.ai/ashenset-linkoping-university/text-diffusion/runs/None_1
(/local/data2/thawe276/ENVmdlm) lnx00293 [~/Documents]>
```

Figure 7.2: AR model test results (seed = 1).



```
  with torch.cuda.amp.autocast(dtype=torch.bfloat16):
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:137: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(enabled=False):
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:208: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(enabled=False):
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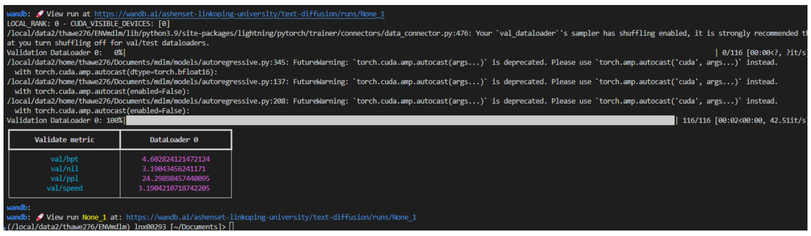
Figure 7.3: AR model generation output (seed = 12).



```
wandb: 🚀 View run at https://wandb.ai/ashenset-linkoping-university/text-diffusion/runs/None_1
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]
/local/data2/thawe276/ENVmdlm/lib/python3.9/site-packages/lightning/pytorch/trainer/connectors/data_connector.py:476: Your `val_dataloader`'s sampler has shuffling enabled, it is strongly recommended th
at you turn shuffling off for val/test dataloaders.
Validation DataLoader 0:   0%|                                                                                                                                   | 0/116 [00:00<?, ?it/s
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:345: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(dtype=torch.bfloat16):
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:137: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(enabled=False):
/local/data2/home/thawe276/Documents/mdlm/models/autoregressive.py:208: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast('cuda', args...)` instead.
  with torch.cuda.amp.autocast(enabled=False):
Validation DataLoader 0: 100%|██████████████████████████████████████████████████████████████████████████████████████████| 116/116 [00:02<00:00, 42.51it/s
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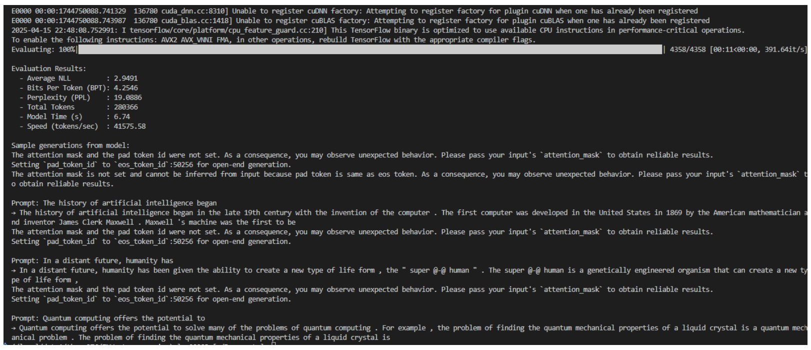
│      val/bpt      │ 4.602824121472124 │
│      val/nll      │ 3.19043456241171  │
│      val/ppl      │ 24.29898457440095 │
│     val/speed     │ 3.1904210718742205│
└───────────────────┴───────────────────┘
wandb:
wandb: 🚀 View run None_1 at: https://wandb.ai/ashenset-linkoping-university/text-diffusion/runs/None_1
(/local/data2/thawe276/ENVmdlm) lnx00293 [~/Documents]>
```

Figure 7.4: Autoregressive model test data results when seed= 1.

```
(/local/data1/thawe276/ENVautoregressive) lnx00293 [/local/data2/home/thawe276/D
2025-05-17 15:03:09.514319: I tensorflow/core/util/port.cc:153] oneDNN custom op
2025-05-17 15:03:09.521756: E external/local_xla/xla/stream_executor/cuda/cuda_f
WARNING: All log messages before absl::InitializeLog() is called are written to 
E0000 00:00:1747486989.530756  295628 cuda_dnn.cc:8310] Unable to register cuDNN
```



```
E0000 00:00:1744750088.741329  136780 cuda_dnn.cc:8310] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered
E0000 00:00:1744750088.743987  136780 cuda_blas.cc:1418] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
2025-04-15 22:48:08.752991: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
Evaluating: 100%|██████████| 4358/4358 [00:11<00:00, 391.64it/s]

Evaluation Results:
  - Average NLL         : 2.9491
  - Bits Per Token (BPT): 4.2546
  - Perplexity (PPL)    : 19.0886
  - Total Tokens        : 280366
  - Model Time (s)      : 6.74
  - Speed (tokens/sec)  : 41575.58

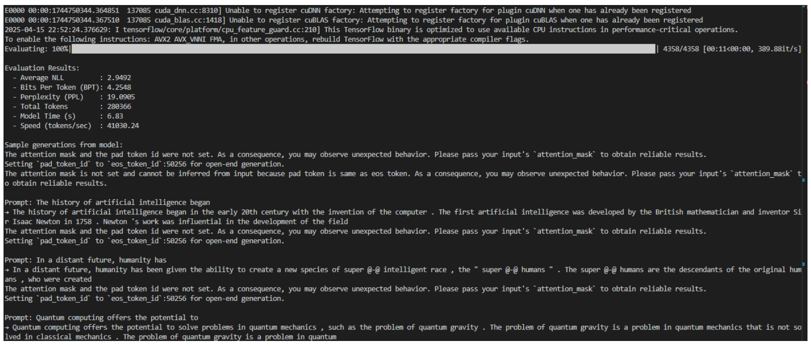
Sample generations from model:
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` to obtain reliable results.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.
The attention mask is not set and cannot be inferred from input because pad token is same as eos token. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` t
o obtain reliable results.

Prompt: The history of artificial intelligence began
→ The history of artificial intelligence began in the late 19th century with the invention of the computer . The first computer was developed in the United States in 1869 by the American mathematician a
nd inventor James Clerk Maxwell . Maxwell 's machine was the first to be
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` to obtain reliable results.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.

Prompt: In a distant future, humanity has
→ In a distant future, humanity has been given the ability to create a new type of life form , the " super @-@ human " . The super @-@ human is a genetically engineered organism that can create a new ty
pe of life form ,
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` to obtain reliable results.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.

Prompt: Quantum computing offers the potential to
→ Quantum computing offers the potential to solve many of the problems of quantum computing . For example , the problem of finding the quantum mechanical properties of a liquid crystal is a quantum mech
anical problem . The problem of finding the quantum mechanical properties of a liquid crystal is
```

Figure 7.5: GPT2 model outputs when seed = 1000.



```
E0000 00:00:1744750344.364851  137085 cuda_dnn.cc:8310] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered
E0000 00:00:1744750344.367510  137085 cuda_blas.cc:1418] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
2025-04-15 22:52:24.376629: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
Evaluating: 100%|██████████| 4358/4358 [00:11<00:00, 389.88it/s]

Evaluation Results:
  - Average NLL         : 2.9492
  - Bits Per Token (BPT): 4.2548
  - Perplexity (PPL)    : 19.0905
  - Total Tokens        : 280366
  - Model Time (s)      : 6.83
  - Speed (tokens/sec)  : 41030.24

Sample generations from model:
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` to obtain reliable results.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.
The attention mask is not set and cannot be inferred from input because pad token is same as eos token. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` t
o obtain reliable results.

Prompt: The history of artificial intelligence began
→ The history of artificial intelligence began in the early 20th century with the invention of the computer . The first artificial intelligence was developed by the British mathematician and inventor Si
r Isaac Newton in 1758 . Newton 's work was influential in the development of the field
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` to obtain reliable results.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.

Prompt: In a distant future, humanity has
→ In a distant future, humanity has been given the ability to create a new species of super @-@ intelligent race , the " super @-@ humans " . The super @-@ humans are the descendants of the original hum
ans , who were created
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` to obtain reliable results.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.

Prompt: Quantum computing offers the potential to
→ Quantum computing offers the potential to solve problems in quantum mechanics , such as the problem of quantum gravity . The problem of quantum gravity is a problem in quantum mechanics that is not so
lved in classical mechanics . The problem of quantum gravity is a problem in quantum
```

Figure 7.6: GPT2 model outputs when seed = 2000.

```
E0000 00:00:1747486989.533439  295628 cuda_blas.cc:1418] Unable to register
2025-05-17 15:03:09.542551: I tensorflow/core/platform/cpu_feature_guard.cc:
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations
Evaluating: 0it [00:00, ?it/s]We strongly recommend passing in an ‘attention
You may ignore this warning if your ‘pad_token_id‘ (50256) is identical to t
Evaluating: 26it [00:00, 75.66it/s]

Evaluation Results:
  - Average NLL         : 4.2212
  - Bits Per Token (BPT): 6.0899
  - Perplexity (PPL)    : 68.1135
  - Total Tokens        : 9782
  - Model Time (s)      : 0.19
  - Speed (batches/sec) : 135.85

Sample generations from model (unprompted):
```

```
Generated Paragraph 1:
 = formalist , liberal , moderate , conservative , and democratic . He was an ac
 Featured articles : The Harvard Crimson review
Online archive of all his papers

Neue Suddeutsche Zeitung website  www.neuwjhts
--------------------------------------------------------------------------------

Generated Paragraph 2:
 = Subsequent releases and remixes , including : Drowned in Sound ( 2008 ) ; The
BeATBEAM was released as a double A & R single in Europe on July 26 , 2011 , in

 = Later appearances
formally included as one of four singles from the album , along with " Say You ’
--------------------------------------------------------------------------------

Generated Paragraph 3:
 =


 = The two @-@ part episode " A New Day in the Life of John Lennon and McCartney
formats : widescreen , Dolby Digital 5 @.@ 1 Surround soundtrack
 ’ s audio track is available in MP3 / FLAC format
is available in stereo or mono
and can also be played at any time . Note that this music video was not edited t
--------------------------------------------------------------------------------
(/local/data1/thawe276/ENVautoregressive) lnx00293 [/local/data2/home/thawe276/D
```

7.5 D3PM Model Outputs

```
--------------------------------------------------------------------------------
<|endoftext|> gold by the Australian Recording Industry Association" leading to
<|endoftext|><|endoftext|> === Singles ===
<|endoftext|><|endoftext|> The lead single from The Dual was "My Love Remains",
<|endoftext|> In February 1989, it reached the number nine on the Billboard Hot
<|endoftext|> "I Like a Woman" had also a chart success and entered the Australi



<|endoftext|> short film, which featured drums to Al Savage, compared it to Ray
<|endoftext|><|endoftext|> While working for the initial stages of his recording
<|endoftext|> In 2002, the compilation album included four new songs. Yankovic h
<|endoftext|> In 2001, Yankovic released "This Art Don ’t" (Remixes) together wi
<|endoftext|> Yankovic had not been with the studio for 10 years since<|endoftex
```

```
------------------------------------------------------------------------------
<|endoftext|> their own state when Ohio got elected. Although McKinley was d
<|endoftext|> Newspapers in New Jersey called the McKinley election even the
<|endoftext|><|endoftext|> == Issue ==
<|endoftext|><|endoftext|><|endoftext|><|endoftext|> = Thated dollar (18cent
<|endoftext|><|endoftext|> The second coin is the type of three-cent design;
<|endoftext|> Longacre in 1804<|endoftext|>



------------------------------------------------------------------------------
python ./mdlm/main.py
    model=small\
    data=wikitext103\
    parameterization=d3pm\
    model.length=512\
    eval.compute_generative_perplexity=True \
    sampling.steps=1000 \
    sampling.predictor=ddpm \
    loader.batch_size=8 \
    loader.eval_batch_size=4 \
    time_conditioning=True data.cache_dir=/local/data2/home/thawe276/.cache/
    seed=1000 \
    T=1000
```

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