

# FROM TEXT TO TALK: AUDIO-LANGUAGE MODEL NEEDS NON-AUTOREGRESSIVE JOINT TRAINING

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## ABSTRACT

Recent advances in large language models (LLMs) have attracted significant interest in extending their capabilities to multimodal scenarios, particularly for speech-to-speech conversational systems. However, existing multimodal models handling interleaved audio and text rely on autoregressive methods, overlooking that text depends on target-target relations whereas audio depends mainly on source-target relations. In this work, we propose Text-to-Talk (TtT), a unified audio-text framework that integrates autoregressive (AR) text generation with non-autoregressive (NAR) audio diffusion in a single Transformer. By leveraging the any-order autoregressive property of absorbing discrete diffusion, our approach provides a unified training objective for text and audio. To support this hybrid generation paradigm, we design a modality-aware attention mechanism that enforces causal decoding for text while allowing bidirectional modeling within audio spans, and further introduce three training strategies that reduce train-test discrepancies. During inference, TtT employs block-wise diffusion to synthesize audio in parallel while flexibly handling variable-length outputs. Extensive experiments across Audio-QA and ASR tasks demonstrate the effectiveness of our approach, with detailed ablation studies validating each proposed component. We will open-source our models, data and code to facilitate future research in this direction.

## 1 INTRODUCTION

The recent success of LLMs has catalyzed a paradigm shift towards general-purpose Multimodal Large Language Models (MLLMs) capable of processing and generating information across diverse modalities (Xu et al., 2025; Team et al., 2023). Among these, speech-in/speech-out conversational systems have emerged as a pivotal component in facilitating natural human-AI interaction. Conventional systems typically decompose this problem into a cascaded pipeline of automatic speech recognition (ASR), LLM-driven response generation, and text-to-speech (TTS) synthesis. While effective to a degree, this modular design introduces significant latency accumulation and error propagation between modules, hindering naturalness and real-world applicability. In response, recent end-to-end approaches like Moshi Défossez et al. (2024), GLM4-Voice Zeng et al. (2024), and VITA-Audio Long et al. (2025) have sought to unify speech understanding and generation within a single model. These models are typically trained through multi-stage pipelines that involve text-to-audio tokenizer training, interleaved data construction, text-audio alignment and task-oriented supervised fine-tuning (Huang et al., 2025; Li et al., 2025; Ding et al., 2025; Chu et al., 2024). As shown in Fig. 1, these methods aim to generate interleaved text and speech tokens in an autoregressive manner, which are then decoded into continuous audio waveforms by a separate neural codec or diffusion-based decoder (Mehta et al., 2024; Kong et al., 2020).

However, this emerging paradigm faces a fundamental challenges. As illustrated in Figure 1, we identify a fundamental mismatch in prevailing approaches that employ a single language model to autoregressively generate both text and audio tokens. This uniform treatment applies identical

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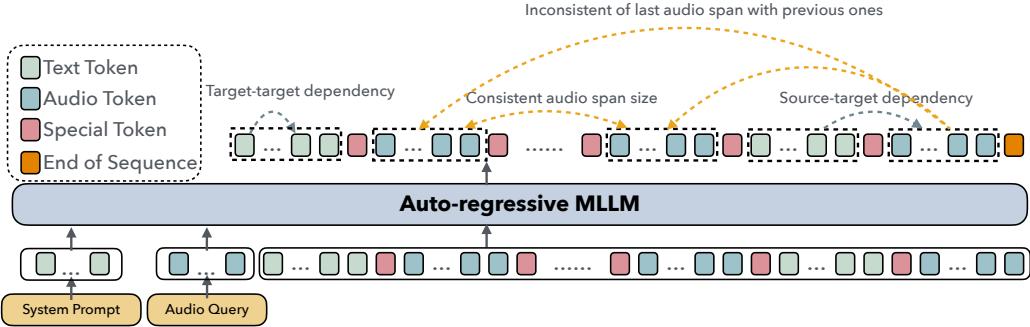


Figure 1: (a) Distinct dependency structures for text and audio modality. (b) Due to disparate tokenization rates, the last audio span is of variable length.

autoregressive training objectives across both modalities, overlooks a critical distinction in their underlying generative processes (Zeng et al., 2024; Xie & Wu, 2024; Borsos et al., 2023; Dang et al., 2024; Rubenstein et al., 2023). Text generation inherently follows a sequential causal structure characterized by strong **target-target** dependencies Box et al. (2015), where each token explicitly conditions on previously generated tokens. Consequently, an incorrect token prediction can propagate and introduce subsequent errors due to the exposure bias inherent in AR models Ranzato et al. (2015). In contrast, audio token generation is predominantly driven by **source-target** dependencies Ren et al. (2020), where audio output primarily condition on the source text rather than on the preceding audio tokens. Specifically, within the current NAR span, audio tokens generation should remain faithful to the source text even when previous audio tokens are incorrectly predicted. Applying a purely AR objective to audio generation thus introduces unnecessary sequential constraints, leading to suboptimal training dynamics and magnifying error propagation. This problem can be substantially alleviated by adopting a non-autoregressive generation strategy, which aligns better with the source-dependent nature of audio modeling. Recently, discrete diffusion has emerged as a compelling alternative to AR for discrete sequence modeling (Yu et al., 2025; Gong et al., 2024; Austin et al., 2021; Sahoo et al., 2024). Beyond empirical gains, recent theory shows that absorbing discrete diffusion can be interpreted as modeling the conditional distributions of clean tokens and admits a tight connection to any-order AR objectives Ou et al. (2024).

Thus, we introduce Text-to-Talk (TtT), a unified audio-text MLLM that integrates AR text generation with NAR audio diffusion within a single Transformer initialized from a pretrained LLM. Text segments are trained with a standard AR cross-entropy objective, while audio segments are modeled via an NAR discrete diffusion process. During inference, the model dynamically switches between AR and NAR decoding strategies based on special control tokens. In summary, our work makes the following contributions:

- We identify and formalize the fundamental asymmetry in dependency structures between text and audio modalities—text exhibits target-target dependencies requiring causal ordering, while audio is driven by source-target dependencies. Leveraging the any-order autoregressive nature of absorbing discrete diffusion, we establish a unified theoretical framework that proves our joint training objective provides an upper bound on the negative log-likelihood of the desired joint distribution.
- We propose TtT, a hybrid AR-NAR MLLM that seamlessly integrates autoregressive text generation with discrete diffusion-based audio synthesis within a single Transformer initialized from a pretrained LLM. Our design preserves the reasoning and instruction-following capabilities of the base LLM while enabling efficient parallel audio generation.
- We introduce three principled training strategies to address the inherent train-test discrepancies in hybrid AR-NAR learning, enabling stable training and robust content-aware variable-length generation that bridges the gap between training and inference conditions.
- Extensive experiments on ASR and Audio-QA benchmarks show that our proposed TtT framework substantially outperforms strong autoregressive (AR) and non-autoregressive (NAR) baselines. Our results underscore the superiority of the hybrid AR-NAR architecture, and detailed ablations validate the effectiveness of our specialized training strategies.

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## 2 PRELIMINARY AND NOTATION

In this section, we establish the basic notation for interleaved audio-text sequences and provide brief overviews of the two core generative paradigms employed in our framework: AR modeling and absorbing discrete diffusion. These form the theoretical foundation of our proposed method in Section 3.

**Tokens, vocabulary, and interleaved layout.** We consider interleaved discrete text-audio sequences of length  $L$ :  $x = (x^1, \dots, x^L)$  with a unified discrete vocabulary  $\mathcal{V} = \mathcal{V}_{\text{text}} \cup \mathcal{V}_{\text{audio}} \cup \mathcal{S}$ , where  $\mathcal{S}$  contains special tokens such as  $\langle \text{SOA} \rangle$  (start of audio),  $\langle \text{EOA} \rangle$  (end of audio),  $\langle \text{EOS} \rangle$  (end of sequence) and the absorbing mask token  $[\text{M}]$ . A sequence  $x$  is structured as a series of alternating text and audio spans:  $x = (\mathcal{T}_1, \mathcal{A}_1, \dots, \mathcal{T}_M, \mathcal{A}_M, \langle \text{EOS} \rangle)$ , where:

- $\mathcal{T}_m = (t_{m,1}, \dots, t_{m,|\mathcal{T}_m|}) \in (\mathcal{V}_{\text{text}} \cup \{\langle \text{EOS} \rangle, \langle \text{SOA} \rangle\})^{|\mathcal{T}_m|}$  are text tokens
- $\mathcal{A}_m = (a_{m,1}, \dots, a_{m,|\mathcal{A}_m|}) \in (\mathcal{V}_{\text{audio}} \cup \{\langle \text{EOA} \rangle\})^{|\mathcal{A}_m|}$  are quantized audio tokens

Let  $f_\theta : \mathcal{V}^L \rightarrow \mathbb{R}^{L \times d}$  be a single Transformer (e.g. Qwen 2.5). We use a shared output head  $W \in \mathbb{R}^{d \times |\mathcal{V}|}$  (typically tied with input embeddings) to produce per-position logits over the entire vocabulary  $\mathcal{V}$ .

### 2.1 AUTOREGRESSIVE MODELING

Autoregressive (AR) models are a fundamental class of generative models that factorize the joint probability distribution of a sequence  $x = (x^1, \dots, x^L)$  into a product of conditional probabilities, based on the chain rule:

$$p(x) = \prod_{i=1}^L p(x^i | x^{<i}) \quad (1)$$

where  $x^{<i} = (x^1, \dots, x^{i-1})$  represents the tokens preceding the current token  $x^i$ . This factorization imposes a sequential, causal structure on the generation process. Such models, typically implemented with Transformer decoders, are trained by minimizing the negative log-likelihood (NLL) of the data, which corresponds to a cross-entropy loss at each position.

### 2.2 ABSORBING DISCRETE DIFFUSION

Discrete diffusion models offer a non-autoregressive alternative for sequence generation. We focus on absorbing discrete diffusion (Austin et al., 2021; Ou et al., 2024), which involves a forward corruption process and a learned reverse denoising process.

**Forward Process.** The forward process is a continuous-time discrete Markov chain that corrupts a clean sequence  $x_0$  over a time interval  $t \in [0, T]$ . Its dynamics are governed by a time-dependent transition rate matrix  $\mathbf{Q}_t = \sigma(t)\mathbf{Q}$ , where  $\sigma(t)$  is a positive noise schedule. For absorbing diffusion, the constant matrix  $\mathbf{Q} = \mathbf{Q}^{\text{abs}}$  is defined as:

$$\mathbf{Q}^{\text{abs}}(x \rightarrow x') = \begin{cases} 1, & \text{if } x' = [\text{M}] \text{ and } x \neq [\text{M}], \\ -1, & \text{if } x' = x \neq [\text{M}], \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

This structure dictates that any token  $x \neq [\text{M}]$  transitions to a special mask token  $[\text{M}]$  at a rate of  $\sigma(t)$ . The state  $[\text{M}]$  is an **absorbing state** because the transition rate out of it is zero (i.e.,  $\mathbf{Q}^{\text{abs}}([\text{M}] \rightarrow x') = 0$  for all  $x'$ ), meaning once a token is masked, it remains masked. Over time, the sequence converges to a fully masked state. The probability that a token is masked by time  $t$  is given by  $\lambda(t) = 1 - e^{-\int_0^t \sigma(s)ds}$ .

**Reverse Process.** The reverse process is also a continuous-time Markov chain that learns to denoise a corrupted sequence  $x_t$  back towards the clean data  $x_0$ . Its reverse transition rate matrix  $\tilde{\mathbf{Q}}_t$

is related to the forward rate matrix by:

$$\tilde{\mathbf{Q}}_t(x_t \rightarrow \hat{x}_t) = \begin{cases} \mathbf{Q}_t(\hat{x}_t \rightarrow x_t) \frac{p_t(\hat{x}_t)}{p_t(x_t)}, & x_t \neq \hat{x}_t, \\ -\sum_{k \neq x} \tilde{\mathbf{Q}}_t(x_t, k), & \hat{x}_t = x_t. \end{cases} \quad (3)$$

The term  $p_t(\hat{x}_t)/p_t(x_t)$  is known as the *concrete score*. Since the forward process only allows transitions to the [M] state, the only non-trivial reverse transitions are from [M] back to a vocabulary token. This simplifies the learning task to modeling the score for these specific denoising transitions.

**Time-Independent Score and the Denoising Objective.** A key theoretical insight for absorbing diffusion is that the concrete score analytically decomposes into a known, time-dependent scalar and a *time-independent* conditional probability over the clean data (Ou et al., 2024). Specifically, for a transition that unmasks position  $i$  from [M] to a token  $v$ , the score is:

$$\underbrace{\frac{p_t(\dots, \hat{x}^i=v, \dots)}{p_t(\dots, x^i=[M], \dots)}}_{\text{concrete score}} = \underbrace{\frac{e^{-\bar{\sigma}(t)}}{1-e^{-\bar{\sigma}(t)}}}_{\text{time scalar}} \cdot \underbrace{p_0(v \mid UM)}_{\text{clean conditional probability}}. \quad (4)$$

where  $UM$  denotes the set of unmasked (visible) tokens in the corrupted sequence. This decomposition is crucial because it decouples the time-dependent dynamics from the data distribution. It implies that the model  $q_\theta$  does not need to learn a complex function of time  $t$ . Instead, its sole objective is to learn to approximate the clean conditional distribution  $p_0(v \mid UM)$ , which is a static, time-independent property of the data. The learning task is thus simplified to a denoising objective: given a corrupted sequence with some tokens masked, predict the original tokens for the masked positions based on the visible context.

**Equivalence to Any-Order Autoregressive Modeling.** This denoising perspective reveals a profound connection to autoregressive modeling. A standard AR model learns to predict a token based on a fixed, causal context. The diffusion model, through its denoising objective, learns to predict a token given an arbitrary context of unmasked tokens. This ability to condition on any subset of the context is the defining feature of an Any-Order Autoregressive Model (AO-ARM).

In fact, the principled training objective for the diffusion model, known as the  $\lambda$ -denoising cross-entropy loss, is mathematically equivalent to the training objective of an AO-ARM (Ou et al., 2024), which averages the prediction loss over all possible permutations (or orderings) of the sequence:

$$\mathcal{L}_{AO}(\mathbf{x}_0) = \mathbb{E}_{\pi \sim U_\pi} \sum_{l=1}^d -\log q_\theta(x_0^{\pi(l)} \mid x_0^{\pi(<l)}). \quad (5)$$

where  $\pi$  is a random permutation of the token indices. Therefore, training an absorbing discrete diffusion model is equivalent to training a powerful ensemble of autoregressive models that can operate in any order. This inherent flexibility is what enables parallel, non-autoregressive generation at inference time and makes it a suitable choice for modeling source-dependent modalities like audio.

### 3 JOINT TEXT-AR & AUDIO-NAR MODEL

In this section, we introduce our proposed model, integrates AR generation for text and discrete diffusion for audio within a single, unified Transformer architecture.

#### 3.1 AUTOREGRESSIVE (AR) MODELING FOR TEXT

We model text generation using a fixed, canonical auto-regressive order. Let  $\pi_{\text{text}}$  denote the natural left-to-right permutation over all text token positions in the sequence — that is,  $\pi_{\text{text}}(1) < \pi_{\text{text}}(2) < \dots < \pi_{\text{text}}(|\mathcal{T}_{\leq M}|)$  where  $\mathcal{T}_{\leq M} = \cup_{m=1}^M \mathcal{T}_m$  is the set of all text token indices.

At the span level, the probability of generating the  $m$ -th text span  $\mathcal{T}_m = (t_{m,1}, \dots, t_{m,|\mathcal{T}_m|})$  conditioned on all prior context is given by:

$$p_\theta(\mathcal{T}_m \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}) = \prod_{j=1}^{|\mathcal{T}_m|} p_\theta(t_{m,j} \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j}) \quad (6)$$

where  $t_{m,<j} = (t_{m,1}, \dots, t_{m,j-1})$  is the prefix of text tokens within the current text span.

To express the joint probability of all text tokens in the sequence, we account for the conditioning on preceding audio spans. The joint probability  $p_\theta(x_{text})$  is therefore defined as the product of the probabilities of each text span, conditioned on all prior spans:

$$p_\theta(x_{text}) = \prod_{m=1}^M p_\theta(\mathcal{T}_m | \mathcal{T}_{<m}, \mathcal{A}_{<m}) = \prod_{m=1}^M \prod_{j=1}^{|\mathcal{T}_m|} p_\theta(t_{m,j} | \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j}) \quad (7)$$

The model is trained by minimizing the standard causal cross-entropy loss over all text positions, which is:

$$\mathcal{L}_{AR}(x) = - \sum_{k=1}^{|\mathcal{T}_{\leq m}|} \log p_\theta(x^{\pi_{text}(k)} | x^{<\pi_{text}(k)}) \quad (8)$$

Here,  $x^{<\pi_{text}(k)}$  denotes the subsequence of  $x$  consisting of all tokens that appear before position  $\pi_{text}(k)$  in the original interleaved sequence order.

### 3.2 ABSORBING DISCRETE DIFFUSION FOR AUDIO SPANS

Building on the theoretical foundation established in Section 2.2, we apply absorbing discrete diffusion to audio spans  $\mathcal{A}_{\leq M} = \cup_{m=1}^M \mathcal{A}_m$  while keeping text tokens  $\mathcal{T}_{\leq M} = \cup_{m=1}^M \mathcal{T}_m$  unperturbed. This design choice aligns with the fundamental difference in dependency structures: audio tokens exhibit strong **source**→**target** dependencies (conditioning on source text), making them well-suited for the any-order autoregressive nature of diffusion, while text tokens follow **target**→**target** causal dependencies, better handled by standard AR modeling.

**Audio-specific corruption and denoising.** During training, we apply the absorbing diffusion process described in Section 2.2 exclusively to audio positions. For each training sample, we sample a masking level  $\lambda \sim U([0, 1])$  and independently mask each audio token with probability  $\lambda$ , while preserving all text tokens. This creates corrupted sequences where audio spans contain a mixture of original tokens and mask tokens [M], but text spans remain intact.

To enable efficient parallel training across all audio spans simultaneously, we apply masking operations to every audio span  $\mathcal{A}_m$  in the sequence, rather than processing them sequentially. This parallel masking strategy significantly improves training efficiency while leveraging the time-independent nature of the denoising objective (Eq. 4).

**Training objective for audio generation.** The model learns to predict the original audio tokens for masked positions by minimizing the  $\lambda$ -denoising cross-entropy loss over all audio spans:

$$\mathcal{L}_{\lambda-DCE}(x) = \sum_{m=1}^M \mathbb{E}_{\lambda \sim U([0,1])} \mathbb{E}_{\mathcal{A}_m^\lambda} \left[ \frac{1}{\lambda} \sum_{a_{m,j}=[M]} -\log q_\theta(a_{m,j}^{\text{clean}} | \mathcal{T}_{\leq m}, \mathcal{A}_{<m}, \mathcal{A}_m^{\text{UM}}) \right] \quad (9)$$

As discussed in Ou et al. (2024), this  $\lambda$ -DCE objective is mathematically equivalent to the any-order autoregressive objective. To make this connection explicit for our audio generation task, we can rewrite Eq. 9 in the equivalent AO-ARM form:

$$\mathcal{L}_{AO}(x) = \sum_{m=1}^M \mathbb{E}_{\pi_m \sim U_{\pi_m}} \sum_{j=1}^{|\mathcal{A}_m|} -\log q_\theta(a_{m,\pi_m(j)} | \mathcal{T}_{\leq m}, \mathcal{A}_{<m}, a_{m,\pi_m(<j)}) \quad (10)$$

where  $\pi_m$  is a random permutation over the positions within audio span  $\mathcal{A}_m$ , and  $a_{m,\pi_m(<j)}$  denotes the audio tokens that appear before position  $j$  in the permuted order. This formulation makes explicit that the audio generation objective is learning to predict each audio token conditioned on an arbitrary subset of other tokens within the same span, plus the full cross-modal context from text. This any-order autoregressive nature is what enables parallel generation during inference.

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### 3.3 MULTIMODAL FACTORIZATION AND A UNIFIED OBJECTIVE

Having established AR modeling for text in Section 3.1 and discrete diffusion for audio in Section 3.2, we now formalize how these two paradigms can be unified within a single probabilistic framework. The key insight is to leverage the distinct dependency structures of each modality through a *partial-order factorization* that respects the causal nature of text while allowing flexible ordering within audio spans. Recall that text tokens exhibit strong target-target dependencies requiring causal ordering, while audio tokens primarily depend on source-target relationships with their corresponding text. This suggests that within each audio span  $\mathcal{A}_m$ , the tokens can be generated in any order as long as they condition on the appropriate cross-modal context  $\mathcal{T}_{\leq m} \cup \mathcal{A}_{< m}$ . We formalize this intuition using partial orders over token positions.

A partial order on a set  $V$  is a binary relation  $\preceq$  that is reflexive, antisymmetric, and transitive. A set equipped with such a relation is called a partially ordered set (poset). Two elements  $a, b \in V$  are comparable if  $a \preceq b$  or  $b \preceq a$ ; otherwise, they are incomparable. An antichain is a subset of  $V$  in which every pair of distinct elements is incomparable — that is, no internal ordering constraints exist among them Davey & Priestley (2002).

**Partial-order formulation.** Let  $(V, \preceq)$  be a poset over all token indices in the sequence, where  $V$  represents all token positions and  $\preceq$  encodes precedence relationships. For our interleaved text-audio setting, we define:

- Each text token  $t_{m,j}$  precedes  $t_{m,j+1}$  (maintaining left-to-right causality within text spans).
- All tokens in span  $m$  precede all tokens in span  $m + 1$  (maintaining cross-span dependencies).
- Tokens within each audio span  $\mathcal{A}_m$  form an antichain under  $\preceq$  (no *mandatory* internal ordering), but the model is permitted to condition on previously generated tokens within the same span during training and inference under any linear extension.

For any token  $i$ , let  $\text{Pa}(i)$  denote its set of predecessors under this partial order. By construction, each audio token  $a_{m,j}$  has predecessors  $\text{Pa}(a_{m,j}) = \mathcal{T}_{\leq m} \cup \mathcal{A}_{< m}$ , while for text tokens  $\text{Pa}(t_{m,j}) = \mathcal{T}_{\leq m} \cup \mathcal{A}_{< m} \cup t_{m,<j}$ .

Any linear extension  $\ell$  of the partial order  $(V, \preceq)$  induces a valid chain-rule factorization:

$$p(x) = \prod_{j=1}^{|V|} p(x_{\ell(j)} \mid x_{\text{Pa}(\ell(j))}) \quad (11)$$

Since audio tokens within each span form an antichain, there are multiple valid linear extensions differing only in the within-span ordering of audio tokens. Rather than committing to a single extension, we can *marginalize* over all possible orderings within audio spans.

**Order-marginalized factorization for audio spans.** For an antichain  $S \subseteq V$  (such as tokens within an audio span), we define the *order-marginalized conditional* by averaging over all permutations of  $S$ :

$$\tilde{p}_\theta(x_S \mid x_{V \setminus S}) = \mathbb{E}_{\pi \in \text{Perm}(S)} \prod_{j \in S} q_\theta(x_{\pi(j)} \mid x_{V \setminus S}, x_{\pi(<j)}) \quad (12)$$

where  $q_\theta(\cdot \mid \cdot)$  represents the any-order autoregressive learned through discrete diffusion. When applied to our audio spans, this gives:

$$\tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{< m}) = \mathbb{E}_{\pi_m \sim U_{\pi_m}} \prod_{j=1}^{|\mathcal{A}_m|} q_\theta(a_{m,\pi_m(j)} \mid \mathcal{T}_{\leq m}, \mathcal{A}_{< m}, a_{m,\pi_m(<j)}) \quad (13)$$

Intuitively, this averages the likelihood over all possible within-span orderings, reflecting the fact that audio tokens can be generated in any order given the appropriate cross-modal context. Note that while tokens within  $\mathcal{A}_m$  form an antichain under the partial order (i.e., no mandatory sequential constraints), the order-marginalized conditional in Eq. 13 allows the model to leverage local target-target dependencies that may arise under specific generation orders. This flexibility enables the model to capture useful intra-span structures when beneficial.

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**Hybrid AR-NAR joint distribution.** Combining fixed-order AR for text with order-marginalized factorization for audio, our model induces the joint scoring function:

$$\tilde{p}_\theta(x) = \prod_{m=1}^M \left[ \underbrace{\prod_{j=1}^{|\mathcal{T}_m|} p_\theta(t_{m,j} \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j})}_{\text{single-order AR for text}} \cdot \underbrace{\tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m})}_{\text{order-marginalized any-order AR for audio}} \right] \quad (14)$$

This formulation reveals that both modalities are fundamentally autoregressive: text uses a single linear extension (left-to-right), while audio integrates over all linear extensions consistent with the partial order.

**Training objective and upper bound analysis.** In practice, we cannot directly optimize  $\tilde{p}_\theta(x)$  because the order-marginalized conditional in Eq. 13 requires computing expectations over all permutations. Instead, we use the training objectives derived Section 3.2:

$$\mathcal{L}_{\text{AR}}(x) = - \sum_{m=1}^M \sum_{j=1}^{|\mathcal{T}_m|} \log p_\theta(t_{m,j} \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j}) \quad (15)$$

$$\mathcal{L}_{\text{AO}}(x) = \sum_{m=1}^M \mathbb{E}_{\pi_m \sim U_{\pi_m}} \sum_{j=1}^{|\mathcal{A}_m|} [-\log q_\theta(a_{m,\pi_m(j)} \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m}, a_{m,\pi_m(<j)})] \quad (16)$$

The key theoretical insight is that our combined training objective provides a tight upper bound on the negative log-likelihood of the desired joint distribution. To see this, consider the audio term:

$$\begin{aligned} & \mathbb{E}_{\pi_m \sim U_{\pi_m}} \sum_{j=1}^{|\mathcal{A}_m|} [-\log q_\theta(a_{m,\pi_m(j)} \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m}, a_{m,\pi_m(<j)})] \\ & \geq -\log \mathbb{E}_{\pi_m \sim U_{\pi_m}} \prod_{j=1}^{|\mathcal{A}_m|} q_\theta(a_{m,\pi_m(j)} \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m}, a_{m,\pi_m(<j)}) \end{aligned} \quad (17)$$

The right-hand side is precisely  $-\log \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m})$  from Eq. 13. The left-hand side is exactly the audio loss term for span  $m$  in our practical training objective  $\mathcal{L}_{\text{AO}}(x)$ .

To establish the unified upper bound, we now sum the inequality in Eq. 17 over all audio spans  $m = 1, \dots, M$ :

$$\sum_{m=1}^M \mathbb{E}_{\pi_m} \sum_{j=1}^{|\mathcal{A}_m|} [-\log q_\theta(a_{m,\pi_m(j)} \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m}, a_{m,\pi_m(<j)})] \geq \sum_{m=1}^M (-\log \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m})) \quad (18)$$

The left-hand side is exactly  $\mathcal{L}_{\text{AO}}$ . For the text terms, the  $\mathcal{L}_{\text{AR}}$  loss is defined as:

$$\mathcal{L}_{\text{AR}}(x) = - \sum_{m=1}^M \sum_{j=1}^{|\mathcal{T}_m|} \log p_\theta(t_{m,j} \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j}) \quad (19)$$

Combining the text and audio terms according to the joint factorization in Eq. 14 yields:

$$\mathcal{L}_{\text{Unified}}(x) \triangleq \mathcal{L}_{\text{AR}}(x) + \mathcal{L}_{\text{AO}}(x) \geq -\log \tilde{p}_\theta(x) \quad (20)$$

where the final inequality follows from combining the text equality with the audio inequality derived above, we provide a detailed derivation in Appendix A.1.1.

Thus, minimizing our practical training objective  $\mathcal{L}_{\text{Unified}}(x)$  corresponds to minimizing an upper bound on the negative log-likelihood of the theoretically motivated joint distribution  $\tilde{p}_\theta(x)$ . This result is significant because:

- It provides theoretical justification for our hybrid AR-NAR training approach
- It guarantees that optimizing the computationally tractable objective  $\mathcal{L}_{\text{Unified}}(x)$  will not deviate arbitrarily from the theoretically optimal objective  $-\log \tilde{p}_\theta(x)$

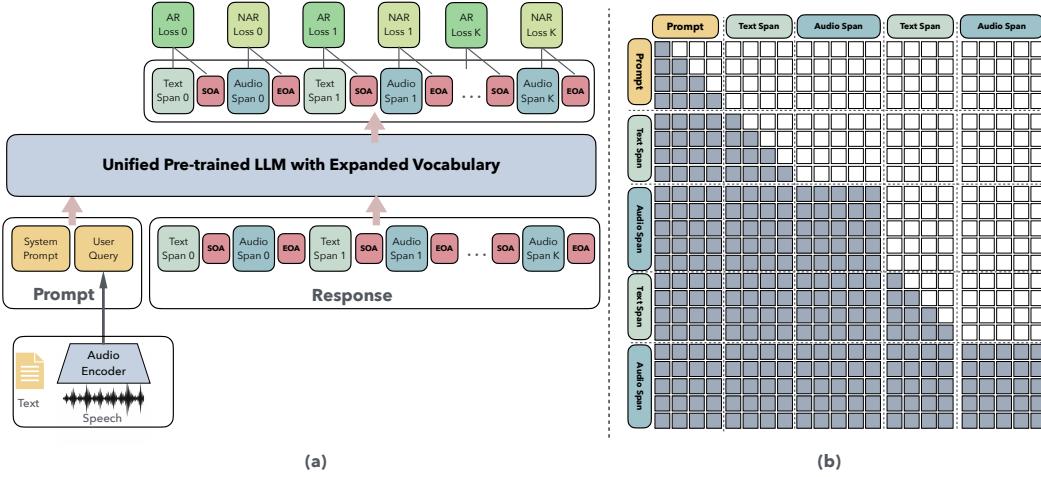
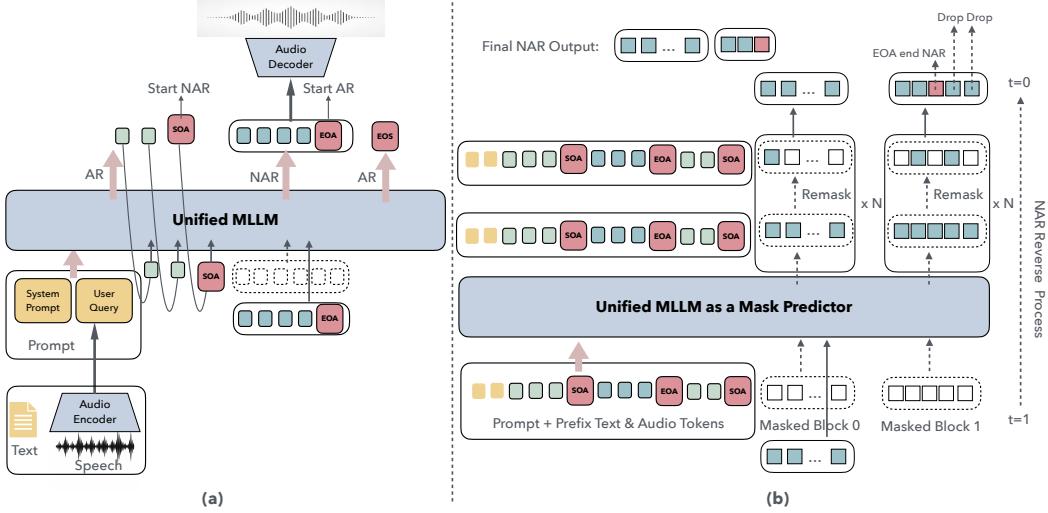


Figure 2: **Training loss and attention design.** (a) **Training pipeline.** Starting from a pretrained text LLM, we expand the vocabulary with audio tokens and control symbols. Text spans use AR cross-entropy loss while audio spans use NAR diffusion loss, sharing a single Transformer backbone. (b) **Attention pattern.** Text spans follow causal attention (left-to-right), while audio spans use bidirectional attention within spans but causal attention across spans, enabling parallel audio generation while preserving cross-modal dependencies.

**Training pipeline and loss computation.** As illustrated in Figure 2 (a), our training pipeline starts from a pretrained text LLM and expands its vocabulary with discrete audio codebook tokens and control symbols ( $\langle \text{SOA} \rangle$ ,  $\langle \text{EOA} \rangle$ ). Each training sequence is organized as interleaved text spans and audio spans, where text spans are optimized with AR Loss while audio spans use the NAR diffusion objective.

Despite its theoretical and practical advantages, the hybrid AR-NAR paradigm introduces a significant train-test discrepancies that can degrade generation quality. During training, audio spans are partially masked according to the diffusion process, while during inference, the model must generate audio and text tokens conditioned on complete text context and previously generated clean audio tokens. To bridge this gap, we propose three principled training strategies:

- **Batchwise AR & NAR Objective Mixing (BANOM):** To address the contextual distribution shift between training and inference, we selectively disable NAR training for a subset of samples within each batch. Specifically, with probability  $p_{\text{mix}}$ , we skip the diffusion noise addition process for certain samples and compute gradients only on text tokens using AR loss. This ensures that during training, text tokens occasionally observe clean, unmasked audio spans—matching the inference scenario where text generation conditions on previously generated complete audio content rather than partially masked spans.
- **Prefix Preservation Masking (PPM):** To address cross-span contextual inconsistency, we preserve clean prefixes of audio spans during diffusion training. For a fraction  $p_{\text{prefix}}$  of training samples, we randomly select a cutoff index  $m$  and ensure that all preceding audio spans  $\mathcal{A}_{<m} = \{\mathcal{A}_1, \dots, \mathcal{A}_{m-1}\}$  remain unmasked, while applying NAR diffusion loss only to spans  $\mathcal{A}_{\geq m} = \{\mathcal{A}_m, \mathcal{A}_{m+1}, \dots, \mathcal{A}_M\}$ . This strategy ensures that during training, when generating span  $\mathcal{A}_m$ , the model observes clean representations of all previous spans  $\mathcal{A}_{<m}$ , matching the inference scenario where audio spans are generated sequentially and each span  $\mathcal{A}_m$  conditions on fully generated, clean preceding spans  $\mathcal{A}_{<m}$  rather than their corrupted, partially masked versions.
- **Stochastic Span Truncation (SST):** We address the positional bias in  $\langle \text{EOA} \rangle$  prediction by randomly truncating audio span  $\mathcal{A}_M$  during training. Due to disparate tokenization rates between text and audio, audio tokens significantly outnumber text tokens, resulting in fixed-size spans  $\mathcal{A}_1, \dots, \mathcal{A}_{M-1}$  and a variable-length final span  $\mathcal{A}_M$ . Since all audio spans undergo simultaneous diffusion training, the model learns to predict  $\langle \text{EOA} \rangle$  at fixed positions for early spans, creating a strong positional bias that hinders content-aware termination learning for the final span. To



**Figure 3: Overview of the proposed framework and its diffusion-style reverse process. (a) TtT framework.** A unified MLLM that interleaves AR text and NAR audio generation. The model alternates between AR text decoding and NAR audio synthesis based on control tokens. **(b) Diffusion reverse process.** NAR audio generation through iterative denoising: initialize masked audio spans, predict all positions in parallel, then progressively remask until convergence.

mitigate this, we implement stochastic truncation: with probability  $p_{\text{trunc}}$ , we randomly select a truncation length  $k < |\mathcal{A}_M|$  and create a truncated span  $\mathcal{A}_M^{\text{trunc}} = (a_{M,1}, \dots, a_{M,k})$  by removing the original  $\langle \text{EOA} \rangle$  token and suffix tokens  $(a_{M,k+1}, \dots, a_{M,|\mathcal{A}_M|})$ . This creates training samples where span termination occurs at arbitrary positions rather than fixed boundaries, forcing the model to predict  $\langle \text{EOA} \rangle$  based on semantic content and contextual text rather than positional cues, enabling robust variable-length generation during inference.

### 3.4 MODALITY-AWARE ATTENTION MECHANISM

To enable the hybrid AR-NAR generation paradigm within a single Transformer, we design a modality-aware attention mechanism that enforces different dependency structures for text and audio tokens. As illustrated in Figure 2 (b), our attention design creates a step-wise pattern that handles three types of content with distinct patterns: the input prompt (system prompt and user query) follows strict causal attention where each token can only attend to previous tokens within the prompt; text tokens ( $\mathcal{T}_m$ ) maintain strict causal attention both within spans and across spans, attending to the prompt, all previous spans, and preceding tokens within the current span; audio tokens ( $\mathcal{A}_m$ ) use a hybrid pattern with bidirectional attention within each span to enable AO-ARM learning but causal attention across spans, attending to the prompt, all previous spans, and any token within the current audio span. This attention pattern serves two critical purposes: enabling parallel training efficiency where all audio spans can undergo noise addition simultaneously in a single forward pass, and preventing cross-span confusion by ensuring that AO-ARM objectives within each audio span do not interfere with dependencies between different spans.

### 3.5 INFERENCE PROCESS

As illustrated in Figure 3(a), our TtT framework consists of three major components: an audio encoder, an audio decoder, and a unified MLLM backbone with hybrid AR-NAR capabilities. Similar to GLM-4-Voice (Zeng et al., 2024), we adopt CosyVoice (Du et al., 2024) as both the audio encoder and decoder. During inference, the TtT model alternates between AR text generation and NAR audio synthesis within a unified framework. The generation process operates as follows: Given an input audio, it is first encoded into a sequence of discrete audio tokens through the audio encoder, which are subsequently fed into the TtT model for processing. The TtT generation process begins with AR decoding for text tokens. Once the model encounters the special token  $\langle \text{SOA} \rangle$ , the system

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switches to NAR generation mode. The NAR generation employs block-wise diffusion (detailed in Algorithm 1) to generate audio token spans in parallel, returning to AR mode after predicting  $\langle \text{EOA} \rangle$  and dropping the remaining predicted tokens after  $\langle \text{EOA} \rangle$  within the current diffusion block, then starting a new round of AR process. The whole sequence generation terminates after the AR process generates an  $\langle \text{EOS} \rangle$  token. Notably, once each audio span is generated, the corresponding audio tokens can be immediately passed to the audio decoder to synthesize audio streams in parallel, ensuring low first-token latency and enabling continuous streaming audio generation without waiting for the entire sequence completion.

## 4 EXPERIMENTS

### 4.1 EXPERIMENTAL SETUPS

#### 4.1.1 DATASETS

To effectively train and evaluate our proposed TtT framework, we follow prior works (Zeng et al., 2025; Ding et al., 2025; Long et al., 2025) and adopt a diverse collection of multi-task datasets, including ASR, TTS, audio chat, text chat, automated audio captioning (AAC), speech emotion classification (SEC), acoustic scene classification (ASC), and interleaved text–audio data. Table 2 provides a summary of the training datasets, with detailed examples provided in the Appendix A.6. During training, we aim to construct a balanced corpus that supports effective learning across multiple tasks. Specifically, we randomly sample one million instances from the ASR dataset, the TTS dataset, and the audio chat dataset respectively. In addition, we create bilingual interleaved text and audio data, ensuring that Chinese and English are represented in approximately equal proportions. To build the audio chat corpus, we rely on the text-to-audio dataset VoiceAssistant-400K together with the text-based datasets OpenHermes-2.5 and Firefly-Train-1.1M, and we employ a TTS model, namely CosyVoice2, to convert text into synthetic audio so as to enrich the training data. To further enhance cross-modal alignment between text and audio, we follow prior work (Zeng et al., 2025) and supplement the training corpus with interleaved text and audio data derived from the large-scale pretrained corpus FineWeb-Edu. This strategy not only expands task coverage but also strengthens the model’s ability to jointly learn from and align textual and acoustic modalities. For evaluation, we focus on two representative tasks: audio question answering (Audio-QA), which evaluates both the model’s reasoning skills and its text-to-speech capabilities in an end-to-end audio generation framework, and ASR, which measures the quality of cross-modal alignment between text and audio. The evaluation datasets are shown in Table 4.

#### 4.1.2 EVALUATION

To effectively evaluate our model on two representative tasks, we carefully design the evaluation protocol and metrics. For Audio-QA, we introduce an ASR-LLM pipeline that transcribes the model’s spoken responses using language-specific ASR systems (Paraformer-zh for Chinese and Whisper-Large-v3 for English) and leverages a powerful LLM-as-a-Judge (Qwen3-235B-A30B) to assess semantic correctness against ground-truth answers. This approach captures the model’s ability to generate natural, accurate spoken responses in realistic conversational settings. For the ASR task, we directly measure transcription accuracy using Word Error Rate (WER), which reflects both speech recognition fidelity and cross-modal alignment within our hybrid AR-NAR framework. More details are in Appendix A.5.1.

#### 4.1.3 MODEL CONFIGURATION

**Backbone** We adopt the Qwen2.5-Base model as the backbone, experimenting with parameter scales of 1.5B and 3B, and fine-tune all parameters during training.

**Audio Encoder and Decoder** For the audio components, we directly follow the audio tokenizer and decoder design introduced in GLM-4-Voice (Zeng et al., 2024). These modules have been shown to provide efficient and high-quality speech tokenization and synthesis, and they allow our framework to leverage strong audio modeling without requiring additional architectural modifications.

Table 1: Comprehensive evaluation of TtT framework: performance comparison, ablation study, and training strategy analysis. Dataset abbreviations: for Audio-QA — AE. (AlpacaEval), LQ. (LLaMAQuestions), TQA. (TriviaQA), WQ. (WebQuestions); for ASR — Fzh. (Fleurs-zh), A2. (AISHELL-2), A1. (AISHELL-1), WS\_met. (WenetSpeech-test\_meeting), WS\_net. (WenetSpeech-test\_net), Fen. (Fleurs-en). Higher ( $\uparrow$ ) is better for Audio-QA, lower ( $\downarrow$ ) is better for ASR.

Models	Audio-QA ( $\uparrow$ )				ASR ( $\downarrow$ )					
	AE.	LQ.	TQA.	WQ.	Fzh.	A2.	A1.	WS_met.	WS_net.	Fen.
<i>Main Results</i>										
Qwen2.5-1.5B (AR)	<b>17.99</b>	16.78	1.61	2.32	99.08	59.73	80.27	85.55	81.76	96.16
Qwen2.5-1.5B (NAR)	10.70	0.00	0.40	0.20	86.97	224.37	191.11	123.96	143.76	108.25
TtT-1.5B (AR-NAR)	15.68	<b>23.75</b>	<b>3.47</b>	<b>7.70</b>	<b>44.36</b>	<b>14.89</b>	<b>16.72</b>	<b>52.23</b>	<b>41.52</b>	<b>49.00</b>
Qwen2.5-3B (AR)	14.42	10.00	0.60	0.70	90.32	54.94	72.01	80.01	73.64	74.47
Qwen2.5-3B (NAR)	11.31	0.67	1.21	0.70	68.94	212.27	160.58	89.22	111.29	83.51
TtT-3B (AR-NAR)	<b>17.46</b>	<b>34.68</b>	<b>6.53</b>	<b>11.61</b>	<b>55.67</b>	<b>12.53</b>	<b>13.65</b>	<b>53.83</b>	<b>44.29</b>	<b>64.31</b>
<i>Ablation Study</i>										
TtT-3B w/o BANOM	13.87	19.87	2.81	5.12	58.25	18.58	21.35	58.48	49.52	68.90
TtT-3B w/o PPM	14.27	22.79	2.71	5.54	58.86	15.63	18.83	57.76	47.92	67.37
TtT-3B w/o SST	14.12	10.20	1.30	3.72	56.39	25.43	31.03	64.41	56.70	62.60
TtT-3B (AR-NAR)	<b>17.46</b>	<b>34.68</b>	<b>6.53</b>	<b>11.61</b>	<b>55.67</b>	<b>12.53</b>	<b>13.65</b>	<b>53.83</b>	<b>44.29</b>	<b>64.31</b>
<i>Training Strategy Comparison</i>										
TtT (AR-NAR)	17.46	34.68	6.53	11.61	55.67	12.53	13.65	53.83	44.29	64.31
Pretrain+AR	<b>29.45</b>	15.93	3.61	11.45	23.37	9.79	12.67	<b>26.75</b>	20.91	19.49
Pretrain+TtT	26.73	<b>40.07</b>	<b>11.07</b>	<b>21.43</b>	<b>18.99</b>	<b>6.80</b>	<b>5.78</b>	27.59	<b>19.85</b>	<b>19.10</b>

#### 4.1.4 TRAINING DETAILS

We train our model using the AdamW optimizer with a global batch size of 2048, a learning rate of  $2e^{-5}$ , and a weight decay factor of  $1e^{-2}$ . The learning rate follows a cosine decay schedule with a linear warmup ratio of 0.01. Training incorporates three stochastic strategies: (1) batchwise AR & NAR objective mixing with probability 0.3; (2) prefix preservation masking with ratio 0.3; (3) stochastic span truncation with probability 0.5. During inference, the model alternates between AR text decoding and NAR diffusion-based audio generation, where text decoding uses nucleus sampling with  $k = 10$  and  $p = 0.95$ , and audio spans are generated with 200 diffusion steps, a block length of 32 tokens, and a total diffusion span length of 640 tokens under classifier-free guidance with scale 0.1. Since different training strategies lead to varying convergence speeds, reported results are based on checkpoints where training loss has converged. All experiments are conducted on 4 nodes with 8 NVIDIA A100 GPUs per node using the DeepSpeed runtime.

## 4.2 MAIN RESULTS

To comprehensively evaluate the effectiveness of our proposed TtT framework, we compare it with two representative baselines, one employing a purely AR backbone and the other adopting a purely diffusion based NAR backbone. For fairness and scalability, all three frameworks are instantiated with backbones of 1.5B and 3B parameters.

**Conversational Understanding Ability** Table 1 main results part reports the comparison of conversational understanding ability across different models on Audio-QA task. From these results we make the following observations: (1) Our proposed TtT consistently achieves the best performance on all four Audio-QA datasets. For example, at the 3B scale, TtT attains scores of 17.46, 34.68, 6.53, and 11.61 on AlpacaEval, LLaMAQuestions, TriviaQA, and WebQuestions respectively, surpassing the Qwen2.5-Base (AR) model by +3.04, +24.68, +5.93, and +10.91. This improvement stems from the hybrid AR-NAR design, which better captures the inherent asymmetry between text and audio dependencies. (2) Our results demonstrate a clear scaling trend shared with the baselines, where larger backbones consistently yield stronger performance. For instance, TtT-3B achieves 34.68 on LLaMAQuestions, outperforming its 1.5B counterpart which scores 23.75, reflecting an absolute gain of +10.93. This pattern aligns with the scaling laws of LLMs, reflecting that additional ca-

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pacity enhances both reasoning ability and cross-modal representation learning; (3) Qwen2.5-Base (NAR) performs noticeably worse than both our hybrid framework and the AR-only baseline. Since discrete diffusion models employ an order-agnostic AO-ARM objective that ignore the inherent sequential structure of interleaved text-audio sequences. This mismatch leads to order confusion, compromising sequence coherence and weakening audio-text alignment.

**Cross-Modal Alignment Ability** As shown in Table 1 main results part, our proposed TtT significantly outperforms both Qwen2.5-Base (AR) and Qwen2.5-Base (NAR) on ASR benchmarks, demonstrating superior cross-modal alignment. For example, at the 3B scale, TtT achieves 12.53 and 13.65 WER on AISHELL-2 and AISHELL-1 respectively, yielding improvements of 42.41 and 58.36 absolute WER points over Qwen2.5-Base (AR). This advantage arises from the hybrid AR-NAR architecture, where NAR diffusion modeling provides efficient parallel denoising that enforces tighter alignment between acoustic frames and textual representations, while AR components ensure coherent conditioning across modalities. (2) Similar to the conversational understanding task, we observe a clear scaling trend in cross-modal alignment. Larger backbones consistently deliver better alignment, with TtT-3B achieving substantially lower WER than TtT-1.5B (e.g., 12.53 vs. 14.89 on AISHELL-2, and 13.65 vs. 16.72 on AISHELL-1). This scaling behavior reflects the increased capacity of larger models to capture fine-grained acoustic patterns and maintain robust cross-modal mappings, thereby enhancing alignment quality.

#### 4.3 ABLATION STUDY

To better understand the contribution of each training strategy in our hybrid AR-NAR framework, we perform an ablation study based on the full model TtT (AR-NAR). The variant w/o BANOM corresponds to removing batchwise AR & NAR objective mixing from the full model, w/o PPM removes prefix preservation masking, and w/o SST removes stochastic span truncation. Table 1 ablation study part presents the detailed results of our ablation experiments. From these results we draw the following conclusions: (1) All three training strategies have a positive impact on model performance, and removing any one of them leads to clear degradation. For instance, on the LLaMAQuestions dataset, removing SST reduces the score from 34.68 to 10.20. This drop occurs because stochastic truncation plays a crucial role in mitigating positional bias in  $\langle \text{EOA} \rangle$  prediction. By forcing the model to terminate spans based on semantic content rather than fixed positional cues, SST enables more robust variable-length audio generation, and its removal undermines the model’s ability to handle flexible conversational outputs. (2) Removing BANOM yields the largest performance degradation. For example, on the AISHELL-2 dataset, the performance decreases from 12.53 to 18.58 when the strategy is removed. This is because it is essential for exposing text tokens to clean audio prefixes during training, which better matches inference conditions. Without this mechanism, the model suffers from a sharper train–test discrepancy, leading to weaker cross-modal consistency and degraded alignment quality.

#### 4.4 EFFECT OF MULTIMODAL ALIGNMENT PRETRAINING.

To further investigate the effectiveness of our method on top of a multimodally aligned pretrained model, we perform large-scale multimodal pretraining based on the Qwen2.5-3B-Base model. Specifically, we construct a corpus of approximately 200B tokens covering ASR, TTS, text-only data, and interleaved text–audio data. The model is trained with a standard autoregressive objective using a global batch size of 256 for 140k steps. This pretraining stage equips the backbone, namely Qwen2.5-3B-Base with strong cross-modal alignment ability before applying our hybrid AR-NAR learning framework.

Table 1 training strategy comparison part compares AR-only and AR–NAR frameworks under two different settings: (1) training directly from Qwen2.5-3B-Base without multimodal pretraining, namely TtT (AR–NAR), and (2) initialization from the multimodally aligned pretrained model, namely Pretrain+AR and Pretrain+TtT. From the table, we observe that: (1) when trained directly from Qwen2.5-3B-Base, our TtT framework achieves comparable or even superior performance to the AR-only baseline, indicating that the hybrid AR–NAR design is already competitive without pretraining; (2) when applied on top of the multimodally aligned pretrained model, Pretrain+TtT consistently matches or surpasses Pretrain+AR across both Audio-QA and ASR benchmarks. These

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results demonstrate that TtT not only performs strongly from scratch, but also benefits significantly when built upon large-scale multimodal alignment pretraining.

## 5 CONCLUSION

In this work, we presented TtT, a unified multimodal framework that addresses the fundamental asymmetry in dependency structures between text and audio modalities. By integrating autoregressive generation for text with non-autoregressive discrete diffusion for audio within a single Transformer, TtT leverages the target-target dependencies of text and the source-target dependencies of audio. We established a theoretical foundation showing that our hybrid training objective provides an upper bound on the negative log-likelihood of the desired joint distribution. To mitigate train-test discrepancies inherent in this hybrid approach, we introduced three principled training strategies: Batchwise AR–NAR Objective Mixing, Prefix Preservation Masking, and Stochastic Span Truncation. Extensive experiments on ASR and Audio-QA tasks demonstrate that TtT significantly outperforms purely autoregressive or non-autoregressive baselines, achieving superior performance in conversational understanding and cross-modal alignment tasks. Our results validate that respecting the distinct generative natures of each modality is crucial for building effective speech-in/speech-out systems.

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## A APPENDIX

### A.1 MATHEMATICAL DERIVATION

#### A.1.1 DERIVATION OF THE TRAINING OBJECTIVE UPPER BOUND

Recall from Eq. 14 that the joint distribution factors as:

$$\tilde{p}_\theta(x) = \prod_{m=1}^M \left[ \prod_{j=1}^{|\mathcal{T}_m|} p_\theta(t_{m,j} \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j}) \cdot \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m}) \right]. \quad (21)$$

Taking the negative logarithm of both sides gives:

$$\begin{aligned} -\log \tilde{p}_\theta(x) &= -\sum_{m=1}^M \sum_{j=1}^{|\mathcal{T}_m|} \log p_\theta(t_{m,j} \mid \mathcal{T}_{<m}, \mathcal{A}_{<m}, t_{m,<j}) - \sum_{m=1}^M \log \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m}) \\ &= \mathcal{L}_{\text{AR}}(x) + \sum_{m=1}^M (-\log \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m})). \end{aligned} \quad (22)$$

By Eq. 17 and its summation over  $m$ , we have:

$$\mathcal{L}_{\text{AO}}(x) \geq \sum_{m=1}^M (-\log \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m})). \quad (23)$$

Therefore, combining both components:

$$\mathcal{L}_{\text{AR}}(x) + \mathcal{L}_{\text{AO}}(x) \geq \mathcal{L}_{\text{AR}}(x) + \sum_{m=1}^M (-\log \tilde{p}_\theta(\mathcal{A}_m \mid \mathcal{T}_{\leq m}, \mathcal{A}_{<m})) = -\log \tilde{p}_\theta(x), \quad (24)$$

which establishes Eq. 20. This confirms that our practical training objective  $\mathcal{L}_{\text{Unified}}(x)$  is a valid upper bound on the true negative log-likelihood, enabling tractable optimization while preserving consistency with the target joint distribution  $\tilde{p}_\theta(x)$ .

## A.2 RELATED WORK

### A.2.1 AUDIO-LANGUAGE MODEL PRETRAINING

Recent advances in end-to-end audio-language models have moved beyond traditional cascaded architectures (Chen et al., 2022; Wang et al., 2023) toward unified multimodal frameworks. Representative works include Moshi (Défossez et al., 2024), which achieves real-time duplex speech conversation through hierarchical Transformer architectures; GLM4-Voice (Zeng et al., 2024), which builds upon GLM-4-9B for robust Chinese and English speech processing; and VITA-Audio (Long et al., 2025), which introduces a lightweight Multiple Cross-modal Token Prediction (MCTP) module for fast audio-text generation with significantly reduced first-token latency. More recent efforts have focused on scaling and production readiness: Step-Audio (Huang et al., 2025) presents a 130B-parameter unified speech-text model with generative speech data engine and instruction-driven fine control across dialects, emotions, singing, and RAP, while Baichuan-Audio (Li et al., 2025) features text-guided aligned speech generation with multi-codebook discretization to preserve both semantic and acoustic information. UniWav (Liu et al., 2025) proposes the first unified encoder-decoder framework that jointly learns representation encoders and generative audio decoders for both discriminative and generative speech tasks.

A key limitation shared by these approaches is their reliance on uniform autoregressive objectives for both text and audio tokens, which overlooks the distinct dependency structures of these modalities. Our work addresses this gap by proposing a hybrid AR-NAR framework that respects the inherent asymmetries between text and audio generation.

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### A.2.2 DISCRETE DIFFUSION MODELS

Discrete diffusion models have emerged as a compelling alternative to autoregressive generation, offering non-autoregressive approaches that can generate entire sequences in parallel. The foundational work of D3PMs (Austin et al., 2021) generalized diffusion processes to discrete data through flexible transition matrices, with absorbing processes that progressively mask tokens proving particularly effective. This framework has since evolved through both theoretical advances and practical improvements. From a theoretical perspective, recent work has deepened our understanding of discrete diffusion dynamics. Ou et al. (2024) revealed that absorbing diffusion’s concrete score can be expressed as time-independent conditional probabilities, leading to RADD—a reparameterized model that removes explicit time conditioning while establishing connections to any-order autoregressive generation. Building on this foundation, Li & Cai (2025) formally characterized convergence rates, proving that KL divergence decays at  $O(1/T)$  with bounds scaling linearly with token mutual information. However, Feng et al. (2025) identified a fundamental trade-off: while masked diffusion achieves near-optimal perplexity in constant steps, sequence-level tasks like reasoning may require steps linear in sequence length. Practical advances have focused on training efficiency and application domains. Shi et al. (2024) reformulated the variational objective as a weighted integral of cross-entropy losses, unifying prior approaches while achieving state-of-the-art results that even surpass comparable autoregressive baselines. For complex reasoning tasks where autoregressive models struggle with subgoal imbalance, Ye et al. (2024) demonstrated that Multi-Granularity Diffusion Modeling can achieve near-perfect accuracy by prioritizing harder subgoals during training. The scalability challenge has been addressed through innovative adaptation strategies. Rather than training from scratch, Gong et al. (2024); Nie et al. (2025) showed that pretrained autoregressive models can be efficiently converted to diffusion models via continual pre-training, maintaining competitive performance while enabling parallel generation. Meanwhile, hybrid approaches are gaining traction: Lovelace et al. (2024) combined diffusion-based latent proposals with autoregressive decoding for controllable generation, while Yang et al. (2025) developed MMaDA, a unified multimodal diffusion foundation model that processes text, images, and reasoning within a single architecture.

### A.3 BLOCK-WISE MASKED DIFFUSION GENERATION FOR AUDIO TOKENS

For NAR audio generation, we employ a block-wise denoising approach adapted from Nie et al. (2025). Unlike full-sequence diffusion, it processes audio in fixed-length blocks, balancing parallelism and controllability.

As detailed in Algorithm 1, the model generates audio in fixed-size blocks of length  $B$ , where each block is progressively denoised over  $T$  steps using an absorbing discrete diffusion process. At each denoising step  $t$ , the model predicts tokens for all currently masked positions in parallel. The algorithm then selectively commits the most confident predictions (determined by predicted probability or random sampling) while remasking the remaining positions for further refinement. This progressive denoising continues until all positions in the current block are decoded. Crucially, if an  $\langle \text{EOA} \rangle$  token is generated within a block, decoding terminates immediately at that position, truncating the remainder and seamlessly returning control to the AR text generation mode.

### A.4 TRAINING DATASET DETAILS

### A.5 EVALUATION DEATILS

#### A.5.1 EVALUATION TASKS

**Audio-QA Task** Previous evaluation frameworks such as Kimi-Audio assess Audio-QA performance using the text portion of interleaved outputs, which overlooks the fact that the audio output of an end-to-end speech model more directly reflects its ability to generate natural and semantically faithful responses. To address this limitation, we evaluate Audio-QA directly on the audio outputs of our framework by first applying an ASR model to transcribe the generated audio into text, where Whisper-Large-v3 is used for English audio and Paraformer-zh for Chinese audio, with a comparison of ASR performance across different models provided in Table 3. The transcribed text is then combined with the original QA queries and the ground truth answers and passed to a large scale reasoning model, Qwen3-235B-A30B, which serves as an LLM-as-a-Judge model to

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**Algorithm 1** Block-wise Masked Diffusion for Autoregressive Audio Generation
 

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**Require:** Context tokens  $\mathbf{c} \in \mathbb{N}^{1 \times L_c}$ , max generation length  $L_{\max} \in \mathbb{N}$ ,

- 1: Sampling steps  $T \in \mathbb{N}$ , block length  $B \in \mathbb{N}$ , temperature  $\tau \geq 0$ ,
- 2: CFG scale  $\gamma \geq 0$ , remasking strategy  $\mathcal{R} \in \{\text{low\_confidence}, \text{random}\}$ ,
- 3: Special token IDs: mask  $m_{\text{mask}}$ , end-of-audio  $\mathcal{E}$ .

**Ensure:** Generated token sequence  $\mathbf{s} \in \mathbb{N}^{1 \times L}$  with  $L \leq L_c + L_{\max}$ .

```

4: Initialize  $\mathbf{s} \leftarrow \mathbf{c}$                                      ▷ Start from context
5: while  $|\mathbf{s}| < |\mathbf{c}| + L_{\max}$  do
6:    $\mathbf{x} \leftarrow \text{pad}(\mathbf{s}, B, \text{value} = m_{\text{mask}})$            ▷ Append  $B$  mask tokens
7:    $\mathcal{M}_{\text{block}} \leftarrow \{i \mid \mathbf{x}_i = m_{\text{mask}} \wedge i \geq |\mathbf{s}|\}$     ▷ Masked block indices
8:    $\{n_t\}_{t=1}^T \leftarrow \text{schedule}(|\mathcal{M}_{\text{block}}|, T)$                   ▷ Tokens to decode per step
9:   for  $t = 1$  to  $T$  do
10:     $\mathcal{M}_t \leftarrow \{i \mid \mathbf{x}_i = m_{\text{mask}}\}$                          ▷ Current mask positions
11:    if  $\gamma > 0$  then
12:       $\mathbf{x}_{\text{uncond}} \leftarrow \mathbf{x}; \mathbf{x}_{\text{uncond}}[\neg \mathcal{M}_t] \leftarrow m_{\text{mask}}$     ▷ Unconditional input
13:       $\ell_{\text{cond}}, \ell_{\text{uncond}} \leftarrow \text{model}([\mathbf{x}; \mathbf{x}_{\text{uncond}}])$           ▷ Batched forward
14:       $\ell \leftarrow \ell_{\text{uncond}} + (\gamma + 1) \cdot (\ell_{\text{cond}} - \ell_{\text{uncond}})$ 
15:    else
16:       $\ell \leftarrow \text{model}(\mathbf{x})$ 
17:    end if
18:     $\hat{\mathbf{x}} \leftarrow \arg \max(\text{Gumbel}(\ell, \tau))$                                 ▷ Gumbel sampling
19:    if  $\mathcal{R} = \text{low\_confidence}$  then
20:       $\mathbf{p} \leftarrow \text{softmax}(\ell); \mathbf{c}_i \leftarrow \mathbf{p}_i[\hat{\mathbf{x}}_i]$                 ▷ Confidence = predicted prob
21:    else if  $\mathcal{R} = \text{random}$  then
22:       $\mathbf{c}_i \leftarrow \text{Uniform}(0, 1)$  for  $i \in \mathcal{M}_t$ 
23:    end if
24:     $\mathbf{c}_i \leftarrow -\infty$  for  $i < |\mathbf{s}|$                                          ▷ Protect context tokens
25:     $\hat{\mathbf{x}}_i \leftarrow \mathbf{x}_i$  for  $i \notin \mathcal{M}_t$                                ▷ Only update masked positions
26:     $\mathcal{K}_t \leftarrow \text{TopK}(\{\mathbf{c}_i \mid i \in \mathcal{M}_t\}, k = n_t)$           ▷ Select  $n_t$  most confident/random tokens
27:     $\mathbf{x}_i \leftarrow \hat{\mathbf{x}}_i$  for all  $i \in \mathcal{K}_t$                            ▷ Commit tokens to sequence
28:  end for
29:   $\mathbf{b} \leftarrow \mathbf{x}[|\mathbf{s}| : |\mathbf{s}| + B]$                                      ▷ Extract generated block
30:  if  $\mathcal{E} \cap \mathbf{b} \neq \emptyset$  then
31:     $p \leftarrow \min\{i \mid \mathbf{b}_i \in \mathcal{E}\}; \mathbf{s} \leftarrow [\mathbf{s}, \mathbf{b}_{:p+1}]$ ; return  $\mathbf{s}$   ▷ Early termination at first end token
32:  end if
33:   $\mathbf{s} \leftarrow [\mathbf{s}, \mathbf{b}]$                                               ▷ Append full block
34: end while
35: return  $\mathbf{s}$ 

```

---

determine whether the response semantically matches the reference and to provide either a correctness label or a graded score. We report the average accuracy or score on the benchmark, and this evaluation pipeline provides a more faithful assessment of our model’s audio-to-audio QA ability in realistic conversational scenarios where speech serves as the output modality.

**ASR Task** To assess the model’s capability in aligning speech with textual representations, we evaluate it on the ASR task, where the model generates text transcriptions from input audio and performance is measured using word error rate (WER). A lower WER indicates more accurate recognition, which reflects not only strong ASR ability but also effective cross modal consistency achieved by our hybrid AR-NAR modeling framework.

Table 3: WER performance of different ASR models on Chinese (zh) and English (en).

Model	WER-zh (↓)	WER-en (↓)
Whisper-Large-v3	0.5054	<b>0.2167</b>
Paraformer-zh	<b>0.1028</b>	0.3946

---

Table 2: Summary of datasets used in training.

<b>Dataset</b>	<b>Language</b>	<b>Samples</b>	<b>Task Type</b>
Emilia_zh	Chinese	500000	TTS
Emilia_en	English	500000	TTS
AISHELL2	Chinese		ASR
AISHELL3	Chinese		ASR
CommonVoice	Chinese, English		ASR
GigaSpeech	English	600000	ASR
LibriSpeech	English		ASR
MLS-Eng	English		ASR
PeopleSpeech	English		ASR
VoxPopuli	English		ASR
WenetSpeech	Chinese	400000	ASR
VoiceAssistant-400K	English		Audio Chat
OpenHermes-2.5	English	1000000	Audio Chat
Firefly-Train-1.1M	Chinese		Audio Chat
MathInstruct	English	262039	Text Chat
MACS	English		AAC
Clotho-v2	English		AAC
Nonspeech7k	English	59282	SEC
VocalSound	English		SEC
CochlScene	English		ASC
Chinese-Fineweb-Edu (Skypile)	Chinese	1500000	Interleaved Data
FineWeb-Edu	English	1500000	Interleaved Data
<b>Total</b>	—	<b>6321321</b>	

### A.5.2 EVALUATION DATASETS

We evaluate model performance on a diverse set of benchmarks covering both Audio Question Answering (Audio-QA) and Automatic Speech Recognition (ASR) tasks. For Audio-QA, we use four datasets: AlpacaEval, TriviaQA, and WebQuestions (English), along with ReasoningQA (Chinese), assessing cross-lingual reasoning and comprehension from speech. For ASR, we include five datasets: Fleurs-zh/en (multilingual), AISHELL-1/2, and WenetSpeech (all Chinese), covering varied domains, accents, and recording conditions to robustly measure transcription accuracy. Dataset details are summarized in Table 4.

<b>Dataset</b>	<b>Language</b>	<b>Task Type</b>
AlpacaEval	English	Audio-QA
ReasoningQA	Chinese	Audio-QA
TriviaQA	English	Audio-QA
WebQuestions	English	Audio-QA
Fleurs-zh	Chinese	ASR
AISHELL-2	Chinese	ASR
AISHELL-1	Chinese	ASR
WenetSpeech	Chinese	ASR
Fleurs-en	English	ASR

Table 4: Evaluation datasets used for Audio-QA and ASR tasks.

### A.6 DATA FORMAT OF TRAINING DATA

To enable unified training across diverse tasks, we transform all datasets into a consistent input–output format. On the one hand, this standardization allows the model to seamlessly integrate heterogeneous modalities such as speech, text, and interleaved audio–text sequences. On the other

hand, a unified design is essential for supporting our training strategies, including batchwise AR & NAR objective mixing, prefix preservation masking, and stochastic span truncation. These strategies rely on a shared representation to operate across modalities in a consistent way. For clarity, we provide representative examples of the adopted data formats as follow, covering ASR, TTS, audio chat, text chat, AAC, SEC, ASC, and interleaved text–audio data.

### Automatic Speech Recognition (ASR) Data Format

```
"messages": [
  {
    "content": "You are an Automatic Speech Recognition (ASR) model. The user will provide you with an audio input. Your task is to transcribe the audio into text and output the result in an interleaved format: generate 13 text tokens followed by 26 audio tokens, and repeat this pattern until the transcription is complete.",
    "role": "system"
  },
  {
    "content": "<SOA>AUDIO_Sequence<EOA>",
    "role": "user",
  },
  {
    "content": "TEXT_Sequence_1<SOA>AUDIO_Sequence_1<EOA>
                TEXT_Sequence_2<SOA>AUDIO_Sequence_2<EOA><EOS>",
    "role": "assistant"
  }
]
```

Figure 4: Example of ASR data format.

### Text-to-speech (TTS) Data Format

```
"messages": [
  {
    "content": "You are a Text to Speech (TTS) model. The user will provide you with a text input. Your task is to transcribe the text into audio and output the result in an interleaved format: generate 13 text tokens followed by 26 audio tokens, and repeat this pattern until the transcription is complete.",
    "role": "system"
  },
  {
    "content": "TEXT_Sequence",
    "role": "user",
  },
  {
    "content": "TEXT_Sequence_1<SOA>AUDIO_Sequence_1<EOA>
                TEXT_Sequence_2<SOA>AUDIO_Sequence_2<EOA><EOS>",
    "role": "assistant"
  }
]
```

Figure 5: Example of TTS data format.

## Audio Chat Data Format

```
"messages": [
  {
    "content": "You are an audio-to-audio chat model. The user will provide you with an audio input. Your task is to respond in an interleaved format: generate 13 text tokens followed by 26 audio tokens, and repeat this pattern until the response is complete.",
    "role": "system"
  },
  {
    "content": "<SOA>AUDIO_Sequence<EOA>",
    "role": "user",
  },
  {
    "content": "TEXT_Sequence_1<SOA>AUDIO_Sequence_1<EOA>
                TEXT_Sequence_2<SOA>AUDIO_Sequence_2<EOA><EOS>",
    "role": "assistant"
  }
]
```

Figure 6: Example of audio chat data format.

## Text Chat Data Format

```
"messages": [
  {
    "content": "You are a helpful model.",
    "role": "system"
  },
  {
    "content": "TEXT_Sequence",
    "role": "user",
  },
  {
    "content": "TEXT_Sequence<EOS>",
    "role": "assistant"
  }
]
```

Figure 7: Example of text chat data format.

### AAC/SEC/ASC Data Format

```
"messages": [
  {
    "content": "You are a helpful audio model. The user will provide you with a text-based instruction and an audio input. Your task is to follow the instruction based on the audio and output the result in an interleaved format: generate 13 text tokens followed by 26 audio tokens, and repeat this pattern until the transcription is complete.",
    "role": "system"
  },
  {
    "content": "TEXT_Sequence<SOA>AUDIO_Sequence<EOA>",
    "role": "user",
  },
  {
    "content": "TEXT_Sequence_1<SOA>AUDIO_Sequence_1<EOA>
                  TEXT_Sequence_2<SOA>AUDIO_Sequence_2<EOA><EOS>",
    "role": "assistant"
  }
]
```

Figure 8: Example of AAC/SEC/ASC data format.

### Interleaved Data Format

```
{
  "text": "TEXT_Sequence_1<SOA>AUDIO_Sequence_1<EOA>
          TEXT_Sequence_2<SOA>AUDIO_Sequence_2<EOA><EOS>"
}
```

Figure 9: Example of interleaved data format.