

NEZHA: A Zero-sacrifice and Hyperspeed Decoding Architecture for Generative Recommendations

Yejing Wang^{1,2†}, Shengyu Zhou², Jinyu Lu², Ziwei Liu¹, Langming Liu², Maolin Wang¹, Wenlin

Zhang¹, Feng Li², Wenbo Su², Pengjie Wang², Jian Xu², Xiangyu Zhao^{1*}

¹City University of Hong Kong, ²Alibaba Group

Abstract

Generative Recommendation (GR), powered by Large Language Models (LLMs), represents a promising new paradigm for industrial recommender systems. However, their practical application is severely hindered by high inference latency, which makes them infeasible for high-throughput, real-time services and limits their overall business impact. While Speculative Decoding (SD) has been proposed to accelerate the autoregressive generation process, existing implementations introduce new bottlenecks: they typically require separate draft models and model-based verifiers, requiring additional training and increasing the latency overhead. In this paper, we address these challenges with NEZHA, a novel architecture that achieves hyperspeed decoding for GR systems without sacrificing recommendation quality. Specifically, NEZHA integrates a nimble autoregressive draft head directly into the primary model, enabling efficient self-drafting. This design, combined with a specialized input prompt structure, preserves the integrity of sequence-to-sequence generation. Furthermore, to tackle the critical problem of hallucination—a major source of performance degradation—we introduce an efficient, model-free verifier based on a hash set. We demonstrate the effectiveness of NEZHA through extensive experiments on public datasets and have successfully deployed the system on Taobao since October 2025, driving the billion-level advertising revenue and serving hundreds of millions of daily active users.

Keywords

Generative Recommendations; Speculative Decoding

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* Xiangyu Zhao is the corresponding author.

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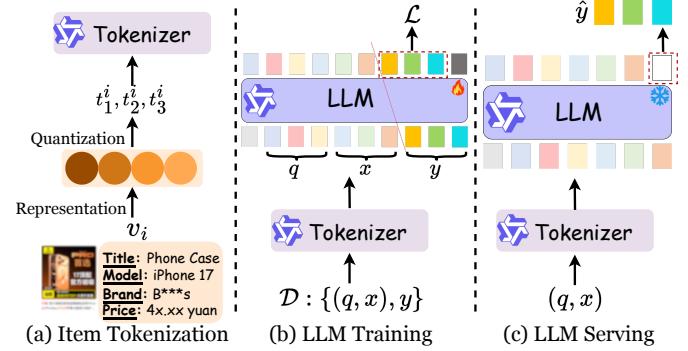


Figure 1: Overview of the GR Deployment Pipeline using the Qwen model as an example. (a) Item Tokenization: An item from the catalog, such as a “phone case for iPhone 17”, is first tokenized into a structured, multi-token semantic ID based on its multi-modal representation. **(b) LLM Training:** The LLM is then fine-tuned on a large offline dataset (\mathcal{D}) of user interactions to learn the patterns for predicting the next item’s semantic ID based on user context. **(c) LLM Serving:** Finally, the trained model is deployed for real-time serving. Given an incoming user request, it autoregressively generates the semantic ID of the recommended item.

1 Introduction

The extraordinary capabilities of Large Language Models (LLMs) have catalyzed a wide range of applications in recommender systems, which utilizes the LLM abilities including world knowledge integration [30], representation learning [25], and semantic understanding [1]. Among these LLM-driven solutions, Generative Recommendation (GR) [24, 39] has rapidly emerged as a dominant paradigm due to its outstanding performance, as well as its notable strengths in addressing the cold-start problem and enhancing recommendation diversity [24]. Consequently, GR has seen widespread adoption in various industrial applications and production systems [11, 29, 42, 43].

As illustrated in Figure 1, the typical GR deployment involves three stages: (a) item tokenization [14, 28, 40], (b) LLM training [6, 35], and (c) LLM serving [20, 31, 32]. While the first two stages are performed offline, the serving latency of the final stage presents a formidable obstacle to large-scale industrial adoption, particularly in latency-sensitive scenarios. For instance, in Taobao’s search advertising, a business unit that accounts for over a quarter of the company’s revenue, the core service requires a response time of less than 30 milliseconds. However, the latency of the current GR solution we deployed in this scenario exceeds 1 second, thus hindering the full commercial potential of real-time serving.

Method	Model Size	Beam Size	Prefill	Decode	System	Total
Vanilla	3B		1.58	6.87	0.96	9.41
Vanilla	0.6B	512	1.0	2.95	0.91	4.86
NEZHA	0.6B		1.0	0.78	0.08	1.86

Table 1: Serving latency decomposition.

LLM inference proceeds in two stages: a prefill stage, where the LLM processes the input prompt in parallel, followed by a decoding stage that autoregressively generates output tokens. For GR, this decoding is typically performed using beam search [9] to produce a diverse set of high-quality candidate items, leading to the excessive inference latency as identified in prior literature [18, 31]. For instance, Lin et al. [20] reports that the decoding can consume nearly 90% of the total inference time for Llama-7B. To empirically validate this claim, we profiled the serving latency and decomposed it into three components: prefilling, decoding, and system overhead. The results are presented in Table 1, where all timings are normalized by the prefilling time of the 0.6B model for confidentiality. We benchmarked two LLMs of different sizes (0.6B and 3B) using a beam size of 512, a common setting for recall tasks in industrial practice. The first two rows reveal that decoding consistently accounts for over 60% of the total inference time (prefilling + decoding), corroborating the findings in [20]. Furthermore, we observe that while model compression significantly reduces the decoding time, the prefilling and system overheads remain relatively stable. *These empirical observations underscore the urgent need for a dedicated solution to accelerate the decoding stage.*

Algorithm-level solutions for this problem, i.e., efficient LLM inference, broadly fall into two categories [27]: KV-cache optimization [32] and speculative decoding (SD) [20, 36]. However, optimizing the KV cache alone is often insufficient: these techniques, e.g., FlashAttention [5], yield negligible efficiency gains when generating the extremely short sequences (e.g., 3-4 tokens) common in GR [4]. The results presented in Table 1, which already incorporate KV-cache enhancements, still significantly exceed the requirements of industrial applications. Consequently, this paper focuses on developing SD solutions to bridge the efficiency gap. Despite considerable efforts in designing SD frameworks for efficient LLM inference [33, 37, 38], a deployable solution for industrial-scale GR systems remains elusive. Existing SD frameworks tailored for applications exhibit critical shortcomings in both core stages: drafting and verification [37, 38]:

- **Drafting:** Current approaches predominantly rely on external draft models, such as smaller language models [20, 36] or retrieval models [7, 31]. This strategy not only necessitates the costly training and maintenance of an extra model but also introduces additional inference overhead, partially offsetting the intended speed gains.
- **Verification:** Prevailing methods still depend on invoking the original large model to validate the drafted tokens [7, 20, 31, 36]. This reliance means they fail to completely avoid the time-consuming decoding steps of LLM, thereby placing a fundamental ceiling on the achievable acceleration.

For these reasons, we design the Nimble drafting and Efficient verification, thus propose a **Zero-sacrifice and Hyperspeed decoding Architecture** for industrial-scale GR systems (NEZHA). Specifically, NEZHA possesses a self-drafting capability [2, 19, 33]. This allows the model to efficiently predict the next item by itself, thus avoiding the training and serving of extra models. Additionally, we design a model-free verification method specific to GR problems: we attribute the poor performance of drafted results to hallucination (invalid semantic IDs) and verify the draft item using a hash set. We further boost performance by incorporating the autoregressive drafting head [3, 19] and setting prompts with special tokens to enforce the sequential integrity required for GR. The proposed NEZHA achieves satisfactory performance and hyperspeed decoding, as outlined in Table 1, and has been successfully deployed in Taobao, impacting billions-level advertising revenues. We summarize the major contributions of this paper as follows:

- We identify high-latency decoding as the critical barrier to the large-scale deployment of GR systems. To address this, we propose NEZHA, an accelerated architecture designed to meet strict industrial latency requirements.
- We design a novel framework combining a nimble self-drafting mechanism with an efficient, model-free verifier. This approach preserves the high-fidelity output of autoregressive models while effectively mitigating hallucinations, thus ensuring the zero-sacrifice recommendation quality.
- We conduct extensive experiments on three public datasets across two LLM backbones. The results demonstrate the superior effectiveness, efficiency, and adaptability of NEZHA.
- We validate NEZHA’s performance on a large-scale industrial dataset and detail its successful deployment in Taobao, a leading e-commerce platform in China. The system now serves hundreds of millions of daily active users and has yielded substantial advancements in key business.

2 Preliminary

This section provides the necessary background on the standard deployment of GR and existing acceleration techniques for autoregressive decoding, with a focus on SD.

2.1 Generative Recommendation (GR)

The typical process for constructing a GR system is illustrated with the scenario of our E-Commerce Search Advertising in Figure 1, which consists of three steps: item tokenization, LLM training, and LLM serving:

1. **Item Tokenization.** The first stage involves converting each item into multi-token semantic IDs [24]. In this step, quantization methods (e.g., RQ [17], PQ [15]) are usually applied to map item contextual representations to discrete codes. These codes are then added to the LLM’s vocabulary as special tokens. For instance, this paper represents an item v_i as with a three-token ID $[t_1^i, t_2^i, t_3^i]$ based on multi-modal representations (visual and textual), a process visualized in Figure 1(a) with a phone case.
2. **LLM Training.** Next, the LLM is trained to understand item semantics and predict user preferences by learning from historical user behavior sequences. The training data consists of tuples $\mathcal{D} = \{(q, x), y\}$, where q is the search query, $x = [v_1, \dots, v_N]$ is the

Algorithm 1 Beam Search for GR Decoding.

Input: LLM \mathcal{M}_p , query q , user sequence x , beam size K , length of semantic ID L

Output: \hat{Y}_L (Top K items represented by semantic IDs)

```

1: Initialization:  $l = 1, \hat{Y}_0 = \{\emptyset\}$ 
2: for  $l \leq L$  do
3:   for  $\hat{y} \in \hat{Y}_{l-1}$  do
4:     Prefilling contexts with LLM:  $\mathbf{h}_l = \mathcal{M}_p(q, x, \hat{y})$ 
5:     Calculating the probabilities of the next token:
        $p_l = \text{lm\_head}(\mathbf{h}_l)$ 
6:     Selecting  $K$  tokens with top probabilities:  $\{t_l^k, p_l^k\}_{k \leq K}$ 
7:      $\hat{Y}_l \leftarrow \hat{Y}_l \cup [\hat{y}, t_l^k]$  for  $k \leq K$ 
8:   end for
9:   Keeping  $K$  candidates in  $\hat{Y}_l$  with the largest cumulative probability ( $\prod_{t_l^k \in \hat{Y}_l} p_l^k, \hat{y} \in \hat{Y}_l$ )
10:   $l \leftarrow l + 1$ 
11: end for
12: return  $\hat{Y}_L$ 

```

user interaction history, and $y = v_y$ is the ground-truth target item ID (e.g., the item the user clicked). All item IDs are flattened into a sequence of tokens. Specifically, the input token sequence is [$<\text{BOS}>, q, t_1^1, t_2^1, t_3^1, \dots, t_1^N, t_2^N, t_3^N, t_1^y, t_2^y, t_3^y, <\text{EOS}>$] and the loss is only calculated on $[t_1^y, t_2^y, t_3^y]$. Figure 1(b) visualizes this process with $N = 1$.

3. LLM Serving. Finally, the trained model is deployed to generate recommendations for live user requests (Figure 1(c)). For an incoming search query q from a user with history x , the model autoregressively generates the semantic ID of the predicted item, token by token, usually with Beam Search [9]. Denoting the LLM as \mathcal{M}_p , this inference process is formally described in Algorithm 1. The algorithm unifies the beam search steps by initializing the candidate set with a single empty element ($\hat{Y}_0 = \{\emptyset\}$ in line 1)). Each step then iterates through the current set of top beams (line 3). For each beam, it generates new, longer sequences by prefiling the context and predicting the next possible tokens (lines 4-7). After all candidates have been expanded, the algorithm prunes the resulting set, retaining only the top K candidates with the highest cumulative probabilities (line 9) for the next iteration or output (line 10&12).

A critical bottleneck hinders the fully deployment of GR in high-throughput businesses with strict latency requirements. The issue stems from the autoregressive decoding process in beam search, where the LLM \mathcal{M}_p is called iteratively to prefill the context for each new candidate sequence (line 4 in Algorithm 1). Specifically, the LLM is invoked $(K \times (L - 1))$ times after the initial context prefill, where K is the beam size and L is the number of tokens in the semantic ID. While L is configurable for different GR systems, K is inevitably large in specific applications; for instance, in item retrieval scenarios, K can be as large as 1,000. Although standard optimizations like KV-Caching [5, 32] can accelerate these LLM calls, they remain insufficient as evident in Table 1, which shows that even with KV-Cache, the beam search decoding phase requires nearly triple the time of the initial prefilling for 0.6B-parameterized LLM. Consequently, developing novel acceleration techniques is imperative for the industrial adoption of LLM-based GR systems.

Algorithm 2 Speculative Decoding for GR.

Input: target LLM \mathcal{M}_p , draft model \mathcal{M}_q , query q , user sequence x , beam size K , length of semantic ID L

Output: \hat{Y}_L (top K items represented by semantic IDs)

```

1: Initialization:  $l = 1, \hat{Y}_0 = \{\emptyset\}$ 
2: while  $l \leq L - 1$  do
3:    $\hat{Y}_l, \dots, \hat{Y}_L \leftarrow \text{BeamSearch}(\mathcal{M}_q, q, x, \hat{Y}_{l-1}, K, L)$ 
4:   Verifying  $\hat{Y}_l, \dots, \hat{Y}_L$  with  $\mathcal{M}_p$  in parallel
5:   if  $\hat{Y}_m$  is rejected then
6:     Updating  $\hat{Y}_m$  with  $\mathcal{M}_p$ 
7:      $l \leftarrow m + 1$ 
8:   end if
9: end while
10: return  $\hat{Y}_L$ 

```

2.2 Speculative Decoding (SD)

Beyond KV-Caching, SD has emerged as the primary choice for algorithm-level acceleration technique [33, 38]. It has garnered significant attention in academia [2, 19, 20] and recently seen successful deployments in industrial applications [31, 36].

We illustrate the SD for GR in Algorithm 2, where we configure the draft model to generate the entire multi-token semantic ID in a single step. For clarity, we denote the Algorithm 1 as $\text{BeamSearch}(\cdot)$ in Algorithm 2, which alternatively predicts future tokens with the draft model \mathcal{M}_q based on the given initialization \hat{Y}_{l-1} and returns the intermediate candidate set \hat{Y}_l for any step l , not just the final result \hat{Y}_L . The core process involves two main steps: drafting and verification. In the drafting stage, SD employs a smaller, faster draft model \mathcal{M}_q to generate a sequence of candidate tokens for the larger, more powerful target LLM \mathcal{M}_p (line 3). For example, a 68M draft model might be used to generate outputs for a 7B target model, as in AtSpeed [20]. The drafted tokens are then verified using a single, parallel forward pass of the target LLM (line 4). Based on this verification, if the draft matches the target model's predictions, it is accepted (line 10). If a mismatch is found, the draft is rejected from the point of the first incorrect token (line 5), and a new token is sampled from the target model's output before the drafting process repeats (line 6-7).

While SD has seen successful industrial applications in domains with relaxed latency requirements, such as travel planning [36] and recommendation knowledge generation [31], and has been explored academically for GR [20], a production-ready solution for high-throughput businesses remains elusive. These industrial systems operate under severe latency constraints that current SD methods cannot meet. Their drafting process relies on an additional model \mathcal{M}_q , while the verification process requires at least one call to the large model \mathcal{M}_p . To address these issues, we propose NEZHA, which is based on two key innovations: eliminating the need for an independent draft model through **self-drafting** and verifying drafts using a **hash set** without calling \mathcal{M}_p .

3 Methodology

This section provides a detailed exposition of our proposed method, NEZHA. We begin with a high-level overview of the framework. Subsequently, we examine its two core components: nimble drafting

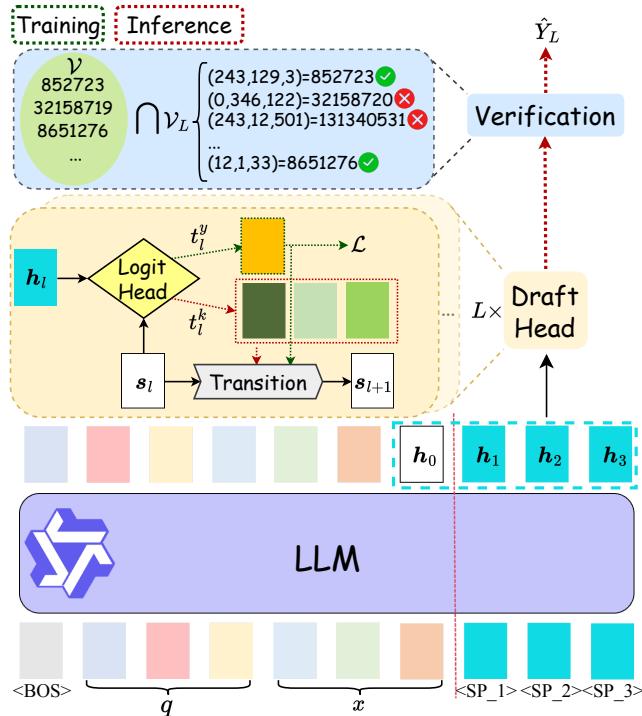


Figure 2: An illustration of the NEZHA framework for $L = 3, K = 3$. The diagram differentiates between the training path (green dotted lines), the inference path (red dotted lines), and the shared computations (black solid lines).

and efficient verification. The section concludes by detailing the training and inference pipeline.

3.1 Overview

The NEZHA framework, outlined in Figure 2, introduces several key modifications to the standard decoding process.

First, NEZHA uses a specialized input prompt. Instead of the default format, we append L special placeholder tokens (e.g., “<SP_1>” for the first ID token), visualized as cyan rectangles, to represent the positions of the ground-truth semantic ID. This unique prompt structure enables a critical optimization: with a single prefill pass, the model generates $L + 1$ hidden states: one for the context and one for each placeholder. These hidden states are then fed into the draft head. The draft head consists of two components: a logit head (the yellow diamond), which predicts token probabilities, and a transition module (the gray step), which updates the context representation after each new token is generated. The behavior of this head differs between training and inference: During training, it learns to predict the known ground-truth tokens from the offline data (\mathcal{L}). During inference, it performs a beam search, generating the top- K candidate tokens at each step. After L iterative calls to the draft head, a pool of candidate items \hat{Y}_L is generated. Finally, NEZHA performs a fast, model-free verification. Instead of invoking the target LLM, it simply checks the generated sequences against a pre-computed hash set of all valid item IDs \mathcal{V} . The top- K valid sequences with the highest cumulative probabilities are returned as

the final recommendations. The figure provides an example where two of four candidates are valid (marked with checks).

3.2 Nimble Drafting

This section constructs the drafting framework for NEZHA, including the prompting and the autoregressive draft head.

Existing SD applications typically rely on an external draft model [20, 31, 36], which introduces significant maintenance overhead and deployment complexity. To circumvent these issues, we adopt a self-drafting architecture [2, 33], which empowers the target LLM itself to generate candidate tokens.

However, applying general self-drafting architectures like multi-token-prediction (MTP) head [2, 10] to GR systems introduces a unique challenge: the highly structured nature of semantic IDs. Unlike free-form text, a semantic ID is a strictly ordered sequence. For an item v_i with three-digit ID $[t_1^i, t_2^i, t_3^i]$, any permutation like $[t_3^i, t_2^i, t_1^i]$ would represent an invalid or entirely different item. The token combinations are not arbitrary but are highly constrained, creating strong sequential dependencies. This means that only a sparse subset of all possible sequences is valid. For instance, knowing the prefix $[t_1^i, t_2^i]$ significantly narrows the set of possible values for the final token t_3^i .

Our design for NEZHA directly addresses this structural constraint. By prompting the input with positional placeholder tokens and utilizing an autoregressive draft head, we explicitly provide the model with the positional awareness and sequential modeling capabilities necessary to generate valid, structured IDs.

Specifically, NEZHA first modifies the input prompt for each training instance $\{(q, x), y\}$. Instead of appending the ground-truth semantic ID $y = [t_1^y, t_2^y, t_3^y]$, we append a sequence of L special tokens as the placeholder for item ID: [<SP_1>, ..., <SP_L>]. This is visually revealed by the modification from Figure 1(b) to Figure 2.

The purpose of these placeholders is twofold. First, drawing inspiration from [26], they explicitly encode positional information, prompting the model to leverage its full contextual understanding for each step of the subsequent autoregressive generation. Second, they allow the LLM to pre-compute the hidden states for all future token positions in a single forward pass, as visualized in the cyan block of Figure 2.

We now formally define the autoregressive draft head. Let $\mathbf{h}_0, \mathbf{h}_1, \dots, \mathbf{h}_L$ be the hidden states from the LLM’s final layer, corresponding to the prefix (\mathbf{h}_0) and the L placeholder tokens, respectively. The draft head is defined as follows:

$$\mathbf{s}_1 = \mathbf{h}_0 \quad (1)$$

$$\mathbf{p}_l = \text{logit_head}_l(\mathbf{h}_l, \mathbf{s}_l) \quad (2)$$

$$\mathbf{s}_{l+1} = \text{Transition}_l(\mathbf{s}_l, \mathbf{e}_l) \quad (3)$$

Here, \mathbf{s}_l represents the evolving context state, which is initialized by the prefix representation \mathbf{h}_0 . In each step, the logit_head_l produces the next-token probability distribution \mathbf{p}_l . Concurrently, the transition module, Transition_l , updates the context state from \mathbf{s}_l to \mathbf{s}_{l+1} by incorporating the embedding \mathbf{e}_l of the newly selected token t_l^1 , achieving the autoregressive prediction.

¹Note that for clarity in this general formulation, we omit the superscripts identifying specific candidates in the beam. This process is detailed further in Section 3.4.

Algorithm 3 NEZHA.**Training Process**

Input: LLM \mathcal{M}_p with the draft head, training data $\mathcal{D} = \{(q, x), y\}$, length of semantic ID L

Output: Optimized LLM \mathcal{M}_p with the trained draft head

- 1: **for** $(q, x), y \in \mathcal{D}$ **do**
- 2: Prefilling context and placeholders with LLM:
 $\mathbf{h}_0, \mathbf{h}_1, \dots, \mathbf{h}_L = \mathcal{M}_p(q, x, <SP_1>, \dots, <SP_L>)$
- 3: Initialization: $l = 1, \mathbf{s}_1 = \mathbf{h}_0$
- 4: **for** $l \leq L$ **do**
- 5: Calculating the probabilities \mathbf{p}_l of the next token according to Equation (2)
- 6: Selecting the probability p_l^y and obtaining the embedding \mathbf{e}_l^y for the ground-truth token t_l^y
- 7: Updating the context state: $\mathbf{s}_{l+1} \leftarrow \text{Transition}_l(\mathbf{s}_l, \mathbf{e}_l^y)$
- 8: **end for**
- 9: Calculating the loss \mathcal{L} according to Equation (6)
- 10: Updating the parameter of \mathcal{M}_p and the draft head (Transition_l and logit_head_l)
- 11: **end for**
- 12: **return** \mathcal{M}_p with the trained draft head

Inference Process

Input: LLM \mathcal{M}_p with the trained draft head, query q , user sequence x , beam size K , length of semantic ID L , index set for valid semantic IDs \mathcal{V}

Output: \hat{Y} (top K items represented by semantic IDs)

- 13: Prefilling context and placeholders with LLM:
 $\mathbf{h}_0, \mathbf{h}_1, \dots, \mathbf{h}_L = \mathcal{M}_p(q, x, <SP_1>, \dots, <SP_L>)$
- 14: Initialization: $l = 1, \mathbf{s}_1 = \mathbf{h}_0, \hat{Y}_0 = \{\emptyset\}, \mathcal{S}_0 = \{\mathbf{s}_1\}$
- 15: **for** $l \leq L$ **do**
- 16: $\hat{Y}_l, \mathcal{S}_l \leftarrow \{\}, \{\}$
- 17: **for** $\hat{y} \in \hat{Y}_{l-1}, \mathbf{s}_l \in \mathcal{S}_{l-1}$ **do**
- 18: Calculating the probabilities \mathbf{p}_l of the next token according to Equation (2)
- 19: Selecting K tokens with top probabilities: $\{t_l^k, p_l^k\}_{k \leq K}$
- 20: Obtaining the embedding \mathbf{e}_l^k for each beam t_l^k ,
 $\mathbf{s}_{l+1} \leftarrow \text{Transition}_l(\mathbf{s}_l, \mathbf{e}_l^k)$,
- 21: $\hat{Y}_l \leftarrow \hat{Y}_l \cup [\hat{y}, t_l^k], \mathcal{S}_l \leftarrow \mathcal{S}_l \cup \mathbf{s}_{l+1}, \forall k$
- 22: **end for**
- 23: **if** $l=L$ **then**
- 24: Calculating the index \mathcal{V}_L for $K \times K$ candidates in \hat{Y}_L according to Equation (4)
- 25: Retaining valid predictions according to Equation (5)
- 26: **end if**
- 27: Keeping K candidates in \hat{Y}_l and corresponding states \mathcal{S}_l with the largest cumulative probability ($\prod_{t_l^k \in \hat{Y}_l} p_l^k, \hat{y} \in \hat{Y}_l$)
- 28: $l \leftarrow l + 1$
- 29: **end for**
- 30: **return** \hat{Y}_L

3.3 Efficient Verification

We elaborate the model-free verification for NEZHA in this section.

Conventional SD verification requires a computationally expensive forward pass of the target model \mathcal{M}_p to evaluate complex

grammar and semantics [2, 18, 19]. This step can be a primary latency bottleneck in online systems.

The highly structured nature of semantic IDs, which are defined by strict combinatorial rules rather than linguistic grammar, enables a far more efficient verification process. This key property allows us to verify a candidate sequence's validity by performing a near-instantaneous lookup against a pre-computed set of all valid item IDs, instead of executing a costly forward pass. The power of this approach stems from the extreme sparsity of the valid ID space. As supported by both public datasets [28] and our own industrial practice, the ratio of valid IDs is exceptionally low (around 0.1% in our system).

To implement this model-free verification with minimal computational overhead, we first encode each multi-token semantic ID into a single, unique integer [41]:

$$V_i = \mathcal{P}(v_i) = \sum_{l=1}^L (t_l^i \times \prod_{j=1}^{l-1} T_j) \quad (4)$$

where this equation maps the semantic ID $[t_1^i, \dots, t_L^i]$ to a unique integer index V_i using a mixed-radix conversion. T_j is the vocabulary size for the j -th token position. The product term $\prod_{j=1}^{l-1} T_j$ acts as a positional multiplier. For the first token ($l = 1$), this product is empty and evaluates to 1 by convention to correctly initialize the formula.

Equation (4) provides a bijective mapping from this multi-dimensional token space to a one-dimensional integer space, assigning a unique index to every possible ID within the range $[0, \prod_{l=1}^L T_l - 1]$. For example, consider the three-token ID (243, 129, 3) from Figure 2, and assume the vocabulary size for each token position is 512. The unique integer index is calculated as: $243 \times 1 + 129 \times 512 + 3 \times (512 \times 512) = 852723$.

Let \mathcal{V} be the set of all valid semantic IDs, implemented as a hash set for efficient, constant-time lookups. A batch of predicted sequences from the LLM can then be verified by computing the intersection with this set of valid IDs:

$$\hat{Y}_L = \hat{Y}_L[\mathcal{V} \cap \mathcal{V}_L] \quad (5)$$

where \mathcal{V}_L is the set of integer indices corresponding to the candidate items in the final step \hat{Y}_L . This set is then filtered in-place according to the verification process detailed in Equation (5), retaining only the indices of valid items, i.e., with indecies included in $\mathcal{V} \cap \mathcal{V}_L$. The visualized example in Figure 2 illustrates this process, where (0, 346, 122), (12, 1, 33) is included by the updated \hat{Y}_L while excluding other candidates.

The impact of this model-free verification is substantial. On our production data, it boosts the ratio of valid drafted candidates from just 43% to over 93%. This directly translates to a 12 percentage point uplift in key offline evaluation metrics. A detailed component-wise analysis with public datasets confirming this contribution is provided in Section 4.3.

3.4 Training and Inference

This section details the training and inference procedures for NEZHA, which are summarized in Algorithm 3. While both processes share the same core architecture, their objectives differ, leading to distinct approaches for token selection and state transition.

Table 2: The statistics of the preprocessed datasets

Dataset	# Users	# Items	# Intersections	Avg.length
Yelp	15,719	11,383	192,214	12.22
Beauty	52,204	57,288	394,908	7.56
Games	64,071	33,614	568,314	8.87

During training, the model learns to predict the ground-truth semantic ID using a teacher-forcing approach. For a given training instance with label $y = [t_1^y, \dots, t_L^y]$: LLM first initializes the representations with a single call(line 2). At each step l , the model uses Equation (2) to compute the probability distribution \mathbf{p}_l (line 5). For the subsequent transition step (Equation (3)), the context s_l is updated using the embedding of the ground-truth token, i.e., $\mathbf{e}_l = \mathbf{e}_l^y$ (line 6-7). This ensures the model learns the correct sequential path, regardless of its own predictions at step l . Finally, the probability corresponding to the ground-truth token, p_l^y , is used to compute the cross-entropy loss, which is minimized across the entire dataset \mathcal{D} (line 9-10):

$$\mathcal{L} = \sum_{y \in \mathcal{D}} \sum_{l=1}^L \log p_l^y \quad (6)$$

The model parameters are optimized by minimizing the loss \mathcal{L} using a gradient-based optimizer (e.g., Adam [16]). This training procedure yields the final model as in line 12.

In contrast, the goal for the inference is to find the most probable semantic IDs, for which we employ beam search. The process begins by prefilling the specialized prompt (line 13). Then, we initialize the step index l and context state s_1 , set up the prediction set \hat{Y}_0 and state set \mathcal{S}_0 to track the candidate beams and their respective states (line 14). For each step, we iterate each candidate beam (line 17), computing the probability distribution \mathbf{p}_l and selecting the top K tokens t_l^k with the highest probabilities p_l^k (line 18-19). The context state for each of beam is then updated independently using the embedding of its selected token \mathbf{e}_l^k as in line 20. New beams are finally included to \hat{Y} and \mathcal{S}_l (line 21) for further pruning (line 27), where the top K overall sequences are retained at each step based on their cumulative probabilities. Notably, the final decoding step ($l = L$) incorporates a crucial verification stage to filter out hallucinated (i.e., invalid) semantic IDs, instead of simply selecting the top candidates by probability (line 23-26).

We apply the verification step only at the end because we empirically observed that hallucination rates are negligible in early steps but increase sharply at the final token. However, given the near-zero cost of our lookup-based verification, it could be applied at every step to ensure validity across the inference without a significant efficiency penalty.

4 Experiment

To demonstrate the generalizability and robustness of NEZHA, this section presents an evaluation on public benchmark datasets.

4.1 Settings

Datasets. We evaluate NEZHA on three public datasets widely used as benchmarks for GR: Yelp, Amazon Beauty, and Amazon

Games [28, 39]. These datasets are particularly suitable as they contain rich contextual information, such as textual item descriptions. Following standard practice in prior work, we employ a leave-one-out strategy for data splitting. For each user, the last interaction is reserved for the test, the penultimate interaction is used for validation, and all remaining interactions constitute the training set.

Baselines and Backbones. We construct the generative recommender with two backbones, Llama-1B [8] and QWen3-0.8B [34], which have a similar size to the LLM we used in our production environments. We primarily compare with two baselines on public datasets: vanilla LLM decoding with beam search and MTP [10]. Other baselines, such as Medusa [2, 36] and AtSpeed [20], are omitted due to their excessive latency and complexity for practical use.

Evaluation Metrics. We evaluate all methods using Hit Rate (HR) and Normalized Discounted Cumulative Gain (NDCG) at cutoffs of 5 and 10, yielding four accuracy metrics: $H@5$, $H@10$, $N@5$, and $N@10$. For efficiency, we also report the average generation latency (LT) in milliseconds (ms), which is the sum of the “Prefill” and “Decode” costs shown in Table 1.

Implementation Details. The evaluation on public datasets is conducted using the same GPU devices to ensure consistency. To achieve robust results, all experiments are averaged over three runs with distinct random seeds (42, 43, 44). For item tokenization, we set $L = 3$ with $T_l = 512$ for each layer, meaning the codebook size is 512 across all layers. Item tokenization is performed using RQ-VAE [17]. These settings are consistent with our production environment, with the exception of T_l , which varies due to the different volumes of items. We convert item attributes into textual instructions and obtain item representations through the public API, such as text-embedding-ada-002². The backbone LLM is determined by the specific setting, either Llama or Qwen, and is optimized using Transformer Trainers, with the appropriate hyperparameters chosen for each test. In Equation (2), the logit_head_l represents a linear transformation layer shaped $[d_{\text{hid}}, T_l]$, which is used to convert the hidden state into logits; specifically, this is sized at 1024×512 for each layer in our case. Additionally, we employ an RNN to update the context state, i.e., Transition_l in Equation (3). For inference, the beam size N is set as 10.

4.2 Overall Performance

We test NEZHA with two LLM backbones and compare it with the original beam search and efficient decoding baseline to evaluate its effectiveness. The results are listed in Table 3, which consistently NEZHA presents the satisfactory performance with outstanding efficiency. We can observe that:

- **Comparison with Beam Search.** The performance of NEZHA is comparable to that of beam search but with a significant increase in speed, achieving approximately a 10-fold improvement. This demonstrates its potential to effectively replace beam search for online GR serving. In certain instances, such as using Llama on Yelp, NEZHA even produces enhanced results.
- **Comparison with MTP.** Although MTP is more efficient than NEZHA in terms of lower latency (LT), it fails to deliver satisfactory performance due to its disregard for the characteristics of

²<https://platform.openai.com/docs/guides/embeddings>

Table 3: Overall performance of NEZHA. The boldface refers to beating all baselines. “*” indicates the statistically significant improvements (i.e., one-sided t-test with $p < 0.05$). For performance metrics, the higher is better. For “LT”, the lower is better.

Model	Finetuning	Beauty					Games					Yelp				
		H@5	H@10	N@5	N@10	LT	H@5	H@10	N@5	N@10	LT	H@5	H@10	N@5	N@10	LT
Llama	Beam Search	0.0392	0.0568	0.0254	0.0311	74.21	0.0305	0.0406	0.0224	0.0256	78.95	0.0176	0.0262	0.0110	0.0138	75.99
	MTP	0.0378	0.0555	0.0239	0.0297	6.74	0.0291	0.0400	0.0212	0.0248	7.33	0.0140	0.0240	0.0091	0.0114	7.18
	NEZHA	0.0390	0.0562	0.0253	0.0304	7.00	0.0313	0.0410	0.0231	0.0259	7.52	0.0194*	0.0332*	0.0125*	0.0168*	7.41
Qwen	Beam Search	0.0446	0.0643	0.0306	0.0370	47.70	0.0226	0.0305	0.0153	0.0179	50.06	0.0235	0.0377	0.0147	0.0192	48.31
	MTP	0.0422	0.0617	0.0287	0.0352	4.18	0.0204	0.0283	0.0136	0.0170	4.61	0.0229	0.0346	0.0114	0.0177	4.24
	NEZHA	0.0451	0.0649	0.0308	0.0377	4.41	0.0239*	0.0314	0.0165*	0.0193*	4.80	0.0235	0.0363	0.0143	0.0185	4.46

Table 4: Ablation study on Yelp with Llama.

	H@5	H@10	N@5	N@10	LT
NEZHA	0.0194	0.0332	0.0125	0.0168	7.41
NEZHA-1	0.0044	0.0083	0.0024	0.0037	7.03
NEZHA-2	0.0188	0.0309	0.0120	0.0159	7.41
NEZHA-3	0.0173	0.0322	0.0110	0.0158	7.18
NEZHA-4	0.0194	0.0328	0.0124	0.0167	7.16

GR, specifically the structured semantic IDs. The parallel decoding approach used by MTP, which relies on a shared last hidden state, cannot leverage the sequential dependency inherent in the semantic ID, resulting in a failure to predict different tokens with discriminative representations.

4.3 Ablation Study

To validate the contribution of each key component in NEZHA, we conduct an ablation study with the following four variants:

- **NEZHA-1:** This variant removes the context state s_l from the logit calculation in Equation (2), which also implies the removal of the transition head Transition_l (Equation (3)), making the prediction of each token within a semantic ID independent of the previously generated tokens.
- **NEZHA-2:** This variant removes the placeholder hidden state h_l from Equation (2). This allows us to measure the importance of providing positional information for effective self-drafting.
- **NEZHA-3:** This variant replace the RNN with simple addition for Transition_l to investigate the impact of state transition modeling.
- **NEZHA-4:** This variant disables the model-free verification step entirely. It is designed to demonstrate the crucial trade-off between efficiency and accuracy.

We evaluate these variants using the Llama backbone on Yelp, with the results summarized in Table 4. We find the following insights:

- NEZHA-1 suffers from performance collapse due to the absence of context and sequential dependency. This underlines the inadequacy of placeholder representations for context understanding, highlighting the necessity of maintaining a context state.
- NEZHA-2 performs slightly worse than the original NEZHA, which can be attributed to the loss of placeholders. When combined with the performance of NEZHA-1, it is evident that placeholders can enhance performance by providing positional information for semantic IDs, although they are not indispensable.

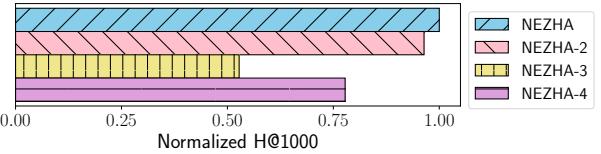


Figure 3: Ablation study on production data. We present the normalized performance for confidentiality.

- The simplification of the transition module negatively impacts the performance of NEZHA-3, indicating the importance of accurately modeling state transitions to leverage the sequential dependency patterns of GR.
- A comparison of NEZHA-4 with NEZHA shows that the slight increase in latency for verification (0.25 ms) can lead to improved performance (especially on H@10), emphasizing the effectiveness of our verification process.

Additionally, we present the ablation results on offline production data in Figure 3 to further validate our conclusions. Notably, NEZHA consistently outperforms all variants. However, the trends differ for specific variants when compared to results from public data, which may stem from variations in data distribution and volume. For instance, the volume of items significantly increases in production data, resulting in greater performance degradation for NEZHA-3 and NEZHA-4. This degradation can be led by diminishing the sequential dependency and introducing too many invalid predictions, respectively. Meanwhile, NEZHA-1 and NEZHA-2 show the consistent pattern as on public datasets: NEZHA-1 is omitted from the figure due to its limited performance, while NEZHA-2 is only slightly worse than the original version.

5 Real-world Deployment

The proposed method, NEZHA, is deployed in the candidate generation (recall) stage of the Taobao Search Advertising platform. The operational context is illustrated in Figure 4, which displays search results for the query “Dress”. Advertisements displayed on the first page (“Ad_1”) are subject to a stringent latency constraint of 30ms. Previously, our GR system’s inference time of over 1000ms precluded its use for these prime positions, limiting its deployment to subsequent pages (“Ad_2”).

With the introduction of NEZHA, we overcome this critical limitation. As detailed in Table 1, NEZHA provides a 2.6× algorithm-level speedup. This acceleration, coupled with system-level savings on queuing time, reduces the GR system’s total latency from over



Figure 4: Illustration of the method’s deployment in Taobao Search. The example shows results for the query “Dress” (top left, in the red box). Advertisements are identified by a label in the bottom-right corner of each product, in the orange box. Sensitive information has been obscured for confidentiality.

1000ms to below the 30ms threshold. Consequently, we can now deploy the GR system across all advertising slots, including the highly valuable first-page placements.

The efficacy of this deployment is confirmed through extensive experiments. Offline evaluations show an absolute increase in the hit rate on clicked items by 0.58% and 0.61% for the top 500 and 1000 results, respectively. The positive result enables the deployment of the GR system in the prime position as of October 2025, where 7-day online A/B testing registered a 1.2% revenue increase for a billion-level business.

6 Related Works

Our work is situated at the intersection of two rapidly evolving research areas: generative recommendations, which leverage the power of LLMs for recommendation tasks, and speculative decoding, a key technique for accelerating LLM inference.

Generative Recommendations. Significant research has been devoted to advancing each stage of the GR pipeline, i.e., item tokenization, LLM training, and LLM serving. For item tokenization, beyond using multi-modal content, recent work has started to incorporate collaborative information to create more effective semantic IDs [28, 44]. The design of these IDs has also been extended to more complex scenarios, such as multi-domain [40] and multi-behavior [22] recommendations, while other approaches seek to unify the training of the tokenizer and the LLM in an end-to-end framework [21]. For training, researchers have explored pre-training paradigms to align item semantics with the LLM’s linguistic space [39], as well as post-training techniques like Direct Preference Optimization (DPO) [23] to fine-tune model outputs toward specific business objectives [6, 29]. To facilitate serving, researchers have adapted speculative decoding for top-k recommendation [20], enabled out-of-vocabulary inference with SpecGR [7], and reformulated the system with long semantic IDs and graph-based parallel decoding in RPG [13].

Despite their impressive performance, the practical deployment of GR models is severely hampered by high inference latency. The

autoregressive generation of semantic IDs requires multiple sequential forward passes through the LLM, a process that is often too slow for industrial systems demanding real-time responses, motivating the proposal of NEZHA.

Speculative Decoding. To address the high latency associated with autoregressive generation, Speculative Decoding (SD) has emerged as a leading technique for accelerating inference [18, 33, 38]. The standard SD framework utilizes a small, fast “draft model” to generate a sequence of candidate tokens, which is then verified in a single parallel forward pass by the larger, original “target model”.

Subsequent research has explored various strategies to enhance both stages of this process. For instance, Medusa [2] introduces multiple lightweight decoding “heads” attached to the target model to predict future tokens in parallel [10], and it proposes tree-attention verification to validate drafts with just one call to the large model. Some researchers have replaced the parallel decoding heads with autoregressive heads, shifting from parallel multi-token drafting to token-by-token generation [3, 19]. Additionally, researchers also suggest using retrieval models as the draft model instead of relying solely on language models [12]. These innovations have led to successful deployments in various industrial applications, including travel services [36] and knowledge-based recommendations [31].

However, current practices still rely on separate draft models and require verification by the large target model. Our approach pioneers the exploration of self-drafting in large-scale production environments and introduces an instant and effective model-free verification specialized for GR.

7 Conclusion

Industrial-scale Generative Recommendation (GR) using Large Language Models (LLMs) is severely constrained by high inference latency. Existing acceleration methods, including Speculative Decoding (SD), are often impractical due to their reliance on auxiliary draft models and expensive verification steps. To overcome these limitations, we propose NEZHA, a highly efficient decoding framework for GR. NEZHA introduces two key innovations: (1) self-drafting, which allows the main LLM to generate multiple candidates in a single pass, eliminating the need for a separate draft model; and (2) model-free verification, which uses a near-instantaneous hash lookup to validate candidates, bypassing costly model-based checks. Experiments show that NEZHA achieves zero-sacrifice accuracy while reducing latency to levels suitable for large-scale industrial deployment.

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