Nearest Neighbor Speculative Decoding for LLM Generation and Attribution

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Large language models (LLMs) often hallucinate and lack the ability to provide attribution for their generations. Semi-parametric LMs, such as kNN-LM, approach these limitations by refining the output of an LM for a given prompt using its nearest neighbor matches in a non-parametric data store. However, these models often exhibit slow inference speeds and produce non-fluent texts. In this paper, we introduce Nearest Neighbor Speculative Decoding (NEST), a novel semi-parametric language modeling approach that is capable of incorporating real-world text spans of arbitrary length into the LM generations and providing attribution to their sources. NEST performs token-level retrieval at each inference step to compute a semi-parametric mixture distribution and identify promising span continuations in a corpus. It then uses an approximate speculative decoding procedure that accepts a prefix of the retrieved span or generates a new token. NEST significantly enhances the generation quality and attribution rate of the base LM across a variety of knowledge-intensive tasks, surpassing the conventional kNN-LM method and performing competitively with in-context retrieval augmentation. In addition, NEST substantially improves the generation speed, achieving a $1.8 \times$ speedup in inference time when applied to Llama-2-Chat 70B.

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1 Introduction

Large language models (LLMs) have demonstrated strong potential as multi-task solvers, excelling in a wide range of applications (Brown et al., 2020; Chowdhery et al., 2022; Touvron et al., 2023a,b; Anil et al., 2024). Despite their advanced capabilities, LLMs frequently encounter the problem of hallucination, particularly when dealing with long-tail knowledge that is less represented in their training data (Kandpal et al., 2023; Asai et al., 2023a). To address this limitation, retrieval augmentation incorporates information retrieval and nearest neighbour search from a non-parametric data store to enhance evidence-based and situated reasoning with LLMs. The resulting semi-parametric LMs exhibit reduced tendency to generate unsupported content (Khandelwal et al., 2020; Borgeaud et al., 2022; Shi et al., 2024a,b; Asai et al., 2023a).

However, the effectiveness of retrieval-augmented language models (RALMs) in ensuring accurate and reliable content generation varies. The widely used in-context retrieval-augmentation (RA) regime (Ram et al., 2023; Shi et al., 2024a,b) softly biases the LM output distribution by prepending retrieved content to the input, which does not reliably guarantee faithful attribution of information. Approaches such as kNN-LM (Khandelwal et al., 2020) modify the LM output with a non-parametric token distribution derived from nearest-neighbor matches in a corpus, which provide more direct attribution but have also been shown to degrade the quality of text generation (Wang et al., 2023a). Additionally, retrieval augmentation can significantly increase the generation latency due to the time required for the retrieval processes to complete and the subsequent expansion of the LM's context.

In this work, we propose Nearest Neighbor Speculative Decoding (NEST). This new semi-parametric language modeling approach is capable of incorporating real-world text spans of arbitrary length into the generations of an off-the-shelf LM, leading to improved quality and latency. NEST extends the standard kNN-LM approach, which interpolates the output distribution of an LM using the distribution of possible next tokens retrieved from a corpus (Khandelwal et al., 2020). It conducts an additional passage retrieval step at the beginning to

limit the need to store and search over all tokens in the corpus, offering a balanced trade-off between search accuracy and efficiency. At each inference step, NEST performs content generation with three sub-steps:

- 1) Confidence-based interpolation. We use a novel Relative Retrieval Confidence (RRC) score to measure the uncertainty of the token retriever and use it as the interpolation coefficient of the output probability mixture. This enables flexible adaptation of the LM's output to different downstream tasks through dynamic interpolation with the token retrieval results.
- **2) Dynamic span selection.** Inspired by the Copy Generator (CoG) (Lan et al., 2023), NEST selects not only the best token predicted by the mixture probability, but also extends to the span contining from that token in the corpus when the token retrieval confidence exceeds a predefined threshold.
- **3)** Relaxed speculative decoding. If a span of more than one tokens is selected, it undergoes evaluation based on the mixture probability. Through a rejection procedure similar to that in speculative decoding (Leviathan et al., 2023), only a prefix deemed highly likely by the mixture probability is accepted.

Evaluated on various free-form generation tasks—including question answering, text completion, and factuality-aware generation—using Llama-2-Chat models (Touvron et al., 2023b) of different sizes, NEST demonstrates superior performance compared to both the base LM and the standard kNN-LM under a zero-shot setting. For example, combined with NEST, the Llama-2-Chat 70B model demonstrates 42.3% improvement of ROUGE-1 on WikiText-103 and 21.6% improvement of FACTSCORE on Biography. Furthermore, NEST performs competitively with respect to in-context retrieval-augmentation on MMLU, Pile-of-Law, and TruthfulQA. We further demonstrate that the two approaches can be combined to enhance generation quality and attribution. Additionally, by generating multiple tokens at each time step, NEST significantly improves the efficiency of long-form generation. For Llama-2-Chat 70B, it achieves a $1.8\times$ speedup in inference time without compromising attribution or fluency.

2 Background

2.1 Problem Definition

Given an input x, a mixture model \mathcal{M} predicts the output y consisting of segments $\{y_1, y_2, ..., y_T\}$. In our setting, \mathcal{M} may produce multiple tokens at a time step t, and therefore y_t indicates the t-th segment consisting of at most n tokens where $1 \leq |y_t| \leq n$. Let $\{w_t^{(1)}, w_t^{(2)}, ..., w_t^{(n)}\}$ be the tokens in segment y_t , we use $p_{\mathcal{M}}(w|x,y_{< t})$ to denote the distribution of the next token, and use $p_{\mathcal{M}}(w=w_t^{(1)}|x,y_{< t})$ to denote the probability of $w_t^{(1)}$ of the next segment y_t .

2.2 Nearest Neighbor Language Models (kNN-LM)

The mixture model \mathcal{M} involves a pre-trained LM and key-value datastore $(\mathcal{K}, \mathcal{V})$ that enables approximate nearest neighbors search without further training or fine-tuning.

Key-value datastore. To create the datastore $(\mathcal{K}, \mathcal{V})$ using the LM for a corpus \mathcal{D} , let $f(\cdot)$ be the mapping from input sequence c to the hidden states h of the LM at some fixed layer. Let w be the next word of c in the corpus \mathcal{D} . For a sample (c_i, w_i) in \mathcal{D} after segmentation, we define the i-th key-value pair (k_i, v_i) in $(\mathcal{K}, \mathcal{V})$ as (h_i, w_i) , where $h_i = f(c_i)$. The whole datastore is thus defined as the set of all possible key-value pairs in \mathcal{D} :

$$(\mathcal{K}, \mathcal{V}) = \{(h_i, w_i) | (c_i, w_i) \in \mathcal{D}\}. \tag{1}$$

The size of the datastore (K, V) is proportional to the total number of tokens in corpus D. This brings difficulty in scaling the size of the corpus and the model, which may require massive storage space and computational resources.

Probability interpolation. During inference, the language model outputs the token distribution $p_{\text{LM}}(w|x, y_{< t})$, together with the hidden state q_t . The model uses q_t as a query to search the datastore $(\mathcal{K}, \mathcal{V})$ and retrieve the r-nearest neighbors π according to the similarity s(q, k) between a query q and a key k. The final

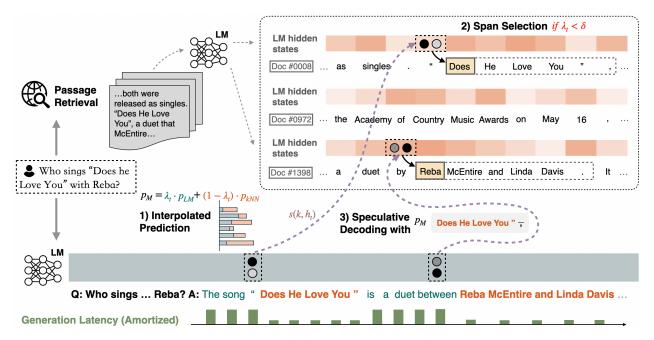


Figure 1 The NEST approach first locates the tokens in the corpus using the LM hidden states. The retrieval distribution $p_{k\text{-NN}}$ is dynamically interpolated with p_{LM} based on the retriever's uncertainty λ_t . The token and its n-gram continuation are then selected from the mixture distribution $p_{\mathcal{M}}$, while the final span length is determined by speculative decoding to remove undesired tokens. The spans incorporated in the final generation provide direct attribution and amortize the generation latency.

non-parametric distribution $p_{k\text{-NN}}(w|x,y_{< t})$ is computed using a softmax function over the similarity of all retrieved neighbors:

$$p_{k-\text{NN}}(w|x, y_{< t}) \propto \sum_{(k_i, v_i) \in \pi} \mathbb{I}_{w=v_i} \exp(\mu \cdot s(q_t, k_i)), \tag{2}$$

where μ is the inverse temperature. We use $1/\sqrt{\dim(q_t)}$ for μ in practice where $\dim(q_t)$ is the hidden state dimension. This is similar to computing attention in the Transformer model (Vaswani et al., 2017). For similarity s(q,k), we follow Khandelwal et al. (2020) and use the negative squared ℓ_2 distance. Items not in π are assigned with 0 probability based on the indicator function $\mathbb{I}_{w=v_i}$.

Finally, the next token is sampled from the mixture distribution $p_{\mathcal{M}}$ of the non-parametric distribution p_{LM} using a fixed hyper-parameter $\lambda \in [0, 1]$:

$$p_{\mathcal{M}}(w|x, y_{< t}) = \lambda \cdot p_{\text{LM}}(w|x, y_{< t}) + (1 - \lambda) \cdot p_{k-\text{NN}}(w|x, y_{< t}). \tag{3}$$

3 Nearest Neighbor Speculative Decoding

3.1 Two-Stage k-NN Search

As mentioned in Section 2.2, maintaining a token-level key-value store can be expensive in terms of both latency and storage. To provide a better trade-off between latency and accuracy, we adopt the two-stage design, which is widely applied in information retrieval and search engines.

First-stage passage retrieval Given the corpus \mathcal{D} , we segment the documents into separate passages of less than m tokens each. We then encode the corpus and use a hybrid retrieval system (Ma et al., 2022) to select the relevant passages, as dense retrievers are good at handling semantics in queries (Karpukhin et al., 2020) and sparse retrievers are good at lexical matching (Sciavolino et al., 2021).

Second-stage k-NN token search—After obtaining the top-b retrieved passages $\{d_1, d_2, ..., d_b\}$ at time step t, we use the encoder $f(\cdot)$ of LM to encode the prefixes of all tokens as keys as shown in Figure 1. The key-value datastore $(\mathcal{K}, \mathcal{V})$ therefore is created on the fly. Similarly, we use the negative squared ℓ_2 distance as the similarity function and q_t as the queries to search for the top-r nearest neighbors π in $(\mathcal{K}', \mathcal{V}')$.

The two-stage design provides a trade-off between search latency and accuracy and the passage-level index only takes a fraction of the token-level index in Section 2.2. In addition, the first-stage passage search also acts as a filter to remove deceptively similar tokens in non-relevant contexts.

3.2 Confidence-Based Output Interpolation

Similar to Equation (3), we linearly interpolate the language model's distribution p_{LM} and non-parametric distribution $p_{k-\text{NN}}$ using a coefficient λ_t for a time step t in generation. The difference is that we use the token retrieval score to compute λ_t :

$$\lambda_t = \sigma \left(\left(\frac{\min_i |s(q_t, k_i)|}{\max_i |s(q_t, k_i)|} - \alpha \right) / \tau \right), \tag{4}$$

where σ is the sigmoid function and the min-max ratio expresses the uncertainty of the k-NN component. We use the sigmoid activation to re-center and re-scale this uncertainty, where α is the offset and τ is the scale for the sigmoid function. We refer to this method as Relative Retrieval Confidence (RRC).

If the downstream task does not involve generation, such as perplexity evaluation and multi-choice tasks, our method will end at Equation (4). The mechanisms introduced in the following sections are only applied to generation, including token/span selection and post-hoc revision.

3.3 Dynamic Span Selection

Directly sampling tokens from the mixture distribution $p_{\mathcal{M}}$ might escalate the exposure bias since the seemingly coherent tokens might be retrieved from completely different sources. To maintain coherence, we extend the context of the current sampled token by using its n-gram continuation in the corpus. Given the current time step t, we first select the next token w_t from the mixture distribution $p_{\mathcal{M}}$. However, the sampled token w_t may correspond to multiple retrieved w_i (i.e., the value v_i), in the neighbors π which have different n-gram continuations. We use a simple max-pooling strategy to select the starting token $w_t^{(1)}$ of the n-gram from π :

$$w_t^{(1)} = \underset{\{w_i | w_i = w_t, w_i \in \pi\}}{\operatorname{argmax}} p_{k-NN}(w = w_i | x, y_{< t})$$
(5)

The corresponding n-gram for time step t is $\{w_t^{(1)}, w_t^{(2)}, ..., w_t^{(n)}\}$ where n is fixed hyper-parameter. The final output is determined by the interpolation coefficient λ_t in Equation (4):

$$y_t = \begin{cases} w_t, & \text{if } \lambda_t > \delta; \\ \{w_t^{(1)}, w_t^{(2)}, ..., w_t^{(n)}\}, & \text{otherwise.} \end{cases}$$
 (6)

where δ is a threshold and y_t is the segment output at time step t.

3.4 Relaxed Speculative Decoding

Despite the dynamic selection, the hyper-parameter n is hard to control over different tasks. To produce spans with adaptive length, we take inspiration from Leviathan et al. (2023), where we use \mathcal{M} to revise the proposed n-gram. Originally, speculative decoding uses a small model to generate a draft and uses a large model to evaluate the draft. However, the draft distribution $q(w|x, y_{< t})$ is unknown besides the first token $w_t^{(1)}$. Therefore, we use a relaxed version of speculative decoding that upper bounds the acceptance probability. The probability of accepting the token $w_t^{(i)}$ in a span is:

$$P(\text{accept token } w_t^{(i)}) = \min \left(1, \ \frac{p_{\mathcal{M}}(w = w_t^{(i)} \mid x, y_{< t}, w_t^{(1)}, w_t^{(2)}, ..., w_t^{(i-1)})}{\gamma \cdot \max_{w} p_{\mathcal{M}}(w \mid x, y_{< t}, w_t^{(1)}, w_t^{(2)}, ..., w_t^{(i-1)})} \right), \tag{7}$$

where $\gamma \in (0,1]$ is the relaxation factor, which is referred to as "leniency" by Leviathan et al. (2023). The smaller γ is, the less often \mathcal{M} rejects the draft. If token $w_t^{(i)}$ is rejected, we will remove all the tokens from $w_t^{(i)}$ to $w_t^{(n)}$, and then re-select a token $w_t^{(i)}$ from the distribution $p_{\mathcal{M}}$ without going through the span selection. The computation for processing multiple tokens can be parallelized and Nest can thus maintain the latency or even accelerate the generation. Moreover, suppose all tokens in the draft are not rejected. In that case, we will directly fetch the n-gram's continuation in the corpus and use it for the next draft proposal until rejection, removing the reliance on the hyper-parameter n.

Once the *n*-gram is accepted, the corresponding parts are masked in the corpus and will never be used again in this generation. This is to prevent the k-NN component from repetitively retrieving the same segments in a small key-value store ($\mathcal{K}', \mathcal{V}'$). We provide the complete procedure in Algorithm 1.

4 Experiments

We evaluate NEST and other baselines on various tasks including text completion, question-answering, fact-verification, and multi-choice tasks, providing a comprehensive picture of factuality, fluency, and attribution of NEST in different domains. In all experiments, we focus on evaluating instruction-following models. We use Llama-2-chat under a zero-shot setting, where we remove the few-shot demonstrations from the instructions to simulate the realistic usage of these models.

4.1 Benchmark Datasets

Text completion. WikiText-103 (Merity et al., 2017) is a standard benchmark for language modeling, extracted from the set of verified articles on Wikipedia. Pile of Law (Henderson et al., 2022) is a growing dataset of legal and administrative data. We use the datasets from Huggingface and further split the test data into validation and test sets. For language modeling, we report the perplexity score. For free-form generation, we report ROUGE-1, 2, L (Lin, 2004) and MAUVE (Pillutla et al., 2021).

Question answering. We select four knowledge-intensive question-answering datasets, including NaturalQuestions (NQ) (Kwiatkowski et al., 2019), TriviaQA (TQA) (Joshi et al., 2017), HotpotQA (HQA) (Yang et al., 2018), and MedMCQA (MQA) (Pal et al., 2022). Since the in-context demonstrations are removed for free-form generation, we use answer-level recall (i.e., Hit@1) (Karpukhin et al., 2020) which checks if the output contains any correct answers instead of exact match.

Fact verification. We evaluate a biography-generation task (Min et al., 2023) and TruthfulQA (Lin et al., 2022) which is a benchmark for testing false beliefs or misconceptions. We use FACTSCORE (Min et al., 2023) for biography. For TruthfulQA, we follow Lin et al. (2022) which uses the difference between the max similarity to a true reference answer and the max similarity to a false reference answer for BLEU and ROUGE-1.

Closed-set tasks. MMLU (Massive Multitask Language Understanding) (Hendrycks et al., 2021) benchmark covers 57 subjects across STEM, the humanities, the social sciences, and more. We report the macro accuracy for each domain.

4.2 Implementation

Knowledge Sources. Wikipedia (CC BY-SA 3.0): For tasks except text completion on Pile of Law, we use the Wikipedia 2021 dump released by Izacard et al. (2024) as the knowledge source and follow the same pre-processing procedures in RA-DIT (Lin et al., 2024), yielding \sim 33M passages with each less than 200 tokens. Pile of Law (CC BY-NC-SA 4.0): We use the training split from Huggingface and select only the English data. We then follow the same procedure applied in Wikipedia, yielding a corpus containing \sim 15M passages after filtering. More details are provided in Appendix A.

¹https://huggingface.co/datasets/pile-of-law/pile-of-law/tree/main

Inference setting. kNN-LM and NEST share the same first-stage retriever. We use DRAGON+ (Lin et al., 2023) and BM25 (Robertson and Zaragoza, 2009) to encode the segments into dense and sparse vectors, respectively. Given the input, we query both the dense and sparse indexes at the same time and retrieve their corresponding top- $(b \cdot l)$ passages. We linearly interpolate the similarity scores between the two search results (also known as fusion) and sort them before selecting the top-b passages. The number of passage candidates b is set to be 40 and the scaling factor l is set to be 100. For RA, we use the top-3 passages in the prompt due to the context window limit. We further combine NEST and RA since they are independent methods. Greedy decoding is used during generation. More details about retrieval, decoding, and hyper-parameters are described in Appendix B.

Evaluation setting. For text completion tasks and perplexity evaluation, we use 128 tokens as the prefix and the consecutive 256 tokens as the target. For the other tasks, we use 128 tokens as the max generation length for question answering and 512 for fact verification. For retrieval-based models, only the prefix will be used for retrieval. Hyper-parameters of all baselines and NEST are tuned on the dev set of WikiText-103, NaturalQuestions, and Biography. Each baseline uses the same hyper-parameters for all tasks evaluated. We first tune the related hyper-parameters for perplexity and then tune the rest for generation metrics to reduce the search space. More details are provided in Appendix B.

4.3 Baselines

Base LMs. We evaluate publicly available, instruction-tuned language models, Llama-2-chat series², with model sizes ranging from 7B, 13B to 70B.

Two-Stage kNN-LM. We apply the two-stage strategy described in Section 3.1 to kNN-LM as well, where we retrieve the top-b passages and encode a key-value datastore $(\mathcal{K}', \mathcal{V}')$ on the fly.

In-Context Retrieval Augmentation (RA). A common retrieval-augmentation method is adding the retrieved evidence into the prompt. We perform retrieval given the only input instead of retrieving new passages every k step due to the expense of refreshing the kv-cache.

4.4 Main Results

Table 1 shows the main results of Nest and other baselines. For language modeling, RA-Nest is able to achieve the lowest complexity on both WikiText-103 and Pile of Law. For text completion, RA has the best MAUVE scores and ROUGE scores in Wikitext-103 while RA-Nest works better for 7B and 13B models on Pile of Law. We observe that for legal documents, quoting the exact clauses from the source might be more favourable compared to Wikipedia.

For question-answering, RA-NEST tends to work better for smaller models (7B and 13B) in general. The gap between base LMs and other methods diminishes for 70B LMs, which is consistent with previous work where retrieval is found most useful for smaller models (Borgeaud et al., 2022).

For fact-verification, Nest is able to outperform the base LMs but underperform RA in terms of the FACTSCORE. RA-NEST is able to outperform RA for the 70B model. The degradation for RA-70B is caused by generating shorter claims which is punished by the FACTSCORE. On TruthfulQA, the semi-parametric LMs consistently outperform base LMs and RAs where in-context retrieval seems to have a negative effect on the scores. This is because TruthfulQA is an adversarial dataset containing difficult questions where in-context RA is more susceptible to the "evidence" in the prompt (e.g., astrology and myths). In contrast, Nest only interpolates the results at the output level and therefore performs better in this case. The combination RA-Nest is also affected by the in-context retrieval.

For **closed-set tasks**, NEST is comparable to RA and RA-NEST manages to achieve the best macro scores on average. Overall, NEST is able to outperform base LMs and kNN-LM's on most tasks while being on par with RA. The combination of RA and NEST further improves over the two methods on some tasks. Despite

²https://huggingface.co/meta-llama/Llama-2-70b-chat-hf

Models			Wikite	xt-103					Pile of	f Law		
	$PPL(\downarrow)$	MAUVE	RG-1	RG-2	RG-L	Avg. Len	$PPL(\downarrow)$	MAUVE	RG-1	RG-2	$\operatorname{RG-L}$	Avg. Len
Llama-2-Chat _{7B}	14.6	58.8	15.8	3.7	14.4	175.4	10.1	80.7	19.1	5.5	17.1	211.4
+RA	7.2	74.6	35.7	23.1	34.4	204.5	7.1	84.7	23.1	8.9	21.1	222.0
$+k{ m NN-LM}$	9.8	82.5	23.7	7.7	21.7	238.2	8.8	81.1	19.4	5.7	17.4	214.3
+Nest	8.4	73.2	28.4	14.2	27.1	218.4	8.1	88.0	23.7	8.7	21.5	226.5
+RA-Nest	6.4	72.6	35.2	22.7	34.0	202.0	6.7	90.0	24.4	9.0	22.2	232.1
Llama-2-Chat _{13B}	12.0	75.9	19.9	4.9	18.0	218.4	8.2	72.8	17.5	5.3	15.7	181.7
+RA	6.5	91.5	38.9	24.2	37.2	249.3	5.9	86.6	23.6	9.1	21.5	228.7
+kNN-LM	8.6	76.3	23.7	8.2	21.9	238.5	7.4	71.5	17.7	5.3	15.9	183.7
+Nest	7.2	67.1	29.3	15.6	28.1	207.1	6.8	86.0	22.9	8.7	20.9	212.3
+RA-Nest	5.8	86.8	38.6	24.0	37.0	245.5	5.7	90.1	24.7	9.2	22.4	229.4
Llama-2-Chat _{70B}	9.9	88.6	22.9	6.2	20.8	239.6	6.9	93.4	23.0	7.1	20.7	250.1
+RA	5.3	91.6	40.5	26.1	38.8	235.9	4.9	95.5	26.3	10.1	24.0	253.2
$+k{ m NN-LM}$	7.1	83.6	26.1	9.6	24.1	253.9	6.3	94.4	23.1	7.2	20.8	251.3
+Nest	6.3	82.6	32.6	17.2	31.1	236.3	5.9	95.4	25.6	9.4	23.2	251.3
+ RA-Nest	4.8	90.0	40.2	25.9	38.6	233.1	4.7	97.6	26.2	9.5	23.7	253.6
Models	TQA	NQ HQA	MQA	Avg.	Truth	fulQA	Biograp	hy		ММ	LU	
	A	Answer-Leve	l Recal	l	ΔBLEU	$\Delta \text{RG-1}$	FS # I	Facts Hum	an. ST	EM S	ocial O	ther Avg.
Llama-2-Chat _{7B}	61.1	38.9 30.6	9.3	35.0	-0.02	0.42	27.2 7	1.2 37.	8 3	2.6	38.9	37.2
+RA	69.5	48.4 44.1	12.8	43.7	-0.34	0.18	56.5 67	7.1 41.	8 3	5.3	42.2 4	13.3 40.7
LANN TM	69.4	49.4 99.5	0.5	27.0	0.47	0.00	20.6 50	10 20	0 9	91 6	20.9	10.1 97.6

Models	TQA	NQ	HQA	MQA	Avg.	Truth	fulQA	Bio	graphy		N	1MLU		
		Answe	r-Leve	l Recal	1	$\Delta \mathrm{BLEU}$	$\Delta \text{RG-1}$	FS	# Facts	Human.	STEM	Social	Other	Avg.
Llama-2-Chat _{7B}	61.1	38.9	30.6	9.3	35.0	-0.02	0.42	27.2	71.2	37.8	32.6	38.9	39.6	37.2
+RA	69.5	48.4	44.1	12.8	43.7	-0.34	0.18	56.5	67.1	41.8	35.3	42.2	43.3	40.7
$+k{ m NN-LM}$	63.4	42.4	33.5	9.5	37.2	0.13	0.66	30.6	59.8	38.0	33.1	39.2	40.1	37.6
+Nest	61.5	43.2	33.5	10.2	37.1	0.03	0.45	38.9	58.2	42.0	35.4	42.0	43.4	40.7
+RA-Nest	69.0	48.8	45.3	13.3	44.1	-0.32	0.21	55.1	57.7	37.9	32.7	39.3	39.8	37.4
Llama-2-Chat _{13B}	63.5	42.3	32.6	10.2	37.2	0.13	0.81	28.8	49.9	41.5	35.0	40.2	43.8	40.1
+RA	70.9	51.6	44.6	14.0	45.3	-0.16	0.25	59.1	51.2	43.4	37.4	43.5	46.4	42.7
$+k{ m NN-LM}$	64.7	43.5	34.2	11.2	38.4	0.20	0.95	31.1	46.1	41.4	34.7	40.6	44.2	40.2
+Nest	64.2	44.2	34.3	10.9	38.4	0.29	0.98	35.7	47.2	41.3	34.9	40.2	43.7	40.0
+RA-Nest	70.9	51.7	45.3	14.7	45.7	-0.14	0.25	58.4	52.4	43.5	37.7	43.5	46.7	42.8
Llama-2-Chat _{70B}	74.0	50.1	39.5	12.8	44.1	0.14	0.70	34.2	58.8	43.5	37.9	44.4	47.0	43.2
+RA	75.5	55.4	52.5	16.0	49.9	-0.13	0.40	52.9	42.1	45.9	39.7	46.2	48.6	45.1
$+k{ m NN-LM}$	74.6	51.2	40.2	13.5	44.9	0.08	0.58	36.1	54.4	44.0	37.4	44.1	47.1	43.2
+Nest	74.2	51.6	41.4	13.8	45.2	0.17	0.70	41.6	56.2	43.8	38.0	44.4	47.8	43.5
+RA-NEST	75.4	55.2	52.4	16.3	49.8	-0.19	0.31	59.2	53.8	45.8	39.7	46.2	48.9	45.1

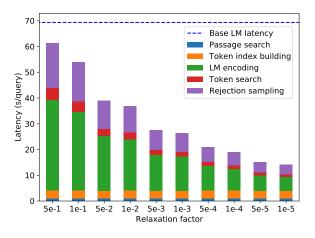
Table 1 Results on text completion (upper table) and other tasks (lower table). Bold numbers indicate the best performance. PPL: Perplexity. RG: ROUGE score. Avg. Len: Average generation length. $\Delta BLEU/\Delta RG$: The difference between the max score to correct references and the max score to incorrect references. FS: FACTSCORE with length penalty.

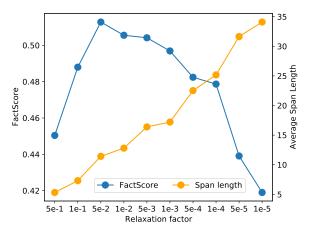
the limited improvement, we will show that NEST is able to provide better attribution and latency in the following sections.

4.5 Latency Analysis

Latency breakdown. The combination of dynamic span selection and relaxed speculative decoding can improve the latency of the LLM generation by quick draft proposal and processing multiple tokens at a time step. Figure 2a shows the latency breakdown of a Nest-70B model ($\alpha=0.3, \tau=0.1, \delta=0.5$) for different relaxation factors on the Biography validation data. The latency experiment is done on $8\times A100$ GPUs (for model parallelization) and 32 CPU threads (for search). The batch size is set to 1. We use internal, research-purpose implementation of the base Llama-2-chat model which did not optimize for latency. As we can see, the LM encoding time takes about half of the latency, while the sum of the others takes the rest. Noticeably, the cost of passage search and token index building stay relatively constant per query, while the others are related to the number of tokens processed per time step. Still, even with extra retrieval overheads, the slowest Nest model is faster than the base LM, showing the efficacy of span selection and speculative decoding.

Latency-accuracy trade-off. To understand why NEST can accelerate generation, we first show the latency-accuracy trade-off by tuning the relaxation factor in Figure 2b. The smaller γ is, the less often NEST rejects





(a) Latency Breakdown.

(b) Span length and FACTSCORE on Biography.

Figure 2 Latency-accuracy trade-off and breakdown on Biography using Llama-2-Chat 70B+Nest. As the relaxation factor γ decreases, Nest tends to accept longer spans from the corpus. We choose $\gamma = 5e-2$ in our main experiments, which accelerates the generation and improves the FACTSCORE.

Task	Models	Ratio (%)	Length	Example (Generated by Nest-70B)
	Nest 7B	93.4	18.4	Question: who sings does he love me with reba?
	Nest $_{13B}$	52.4	4.4	Answer: The song "Does He Love You" [29756059] is a duet
	Nest $_{70B}$	58.8	4.3	between Reba McEntire and Linda Davis. It was
NO	RA-Nest $_{7B}$	77.5	3.1	released in August 1993 as the first single from Reba's
NQ	RA-Nest $_{13B}$	33.2	3.0	compilation album Greatest Hits Volume 2. It is one of
	RA-Nest $_{70\mathrm{B}}$	44.9	3.9	country music's several songs about a love triangle. [14963536]
				Question: Tell me a bio of Taral Hicks.
	Nest $_{7B}$	95.5	27.9	Answer: Taral Hicks (born September 21, 1974) is an American actress
	Nest $_{13B}$	53.9	10.6	and singer. Hicks is best known for her acting in such films as 1993's
Bio	Nest $_{70B}$	58.6	7.0	American crime drama film A Bronx Tale and her singing in such work
DIO	RA-Nest $_{7B}$	50.3	5.1	as her 1997 [15447985] debut studio album This Time which peaked at
	RA-Nest $_{13B}$	48.5	5.9	No. 4 on Billboard Bubbling Under Hot 100 Singles. Raised in Teaneck,
	RA-Nest $_{70B}$	80.7	11.0	New Jersey, Hicks graduated from Teaneck High School in 1994 [15447985].
				She is the younger sister of actress and singer D'atra Hicks.

Table 2 Attribution analysis. (Attribution) Ratio: Proportion of tokens that are taken from the corpus. (Attribution) Length: Average length of consecutive spans in the generation that are taken from the same document. Green: Segments taken from the corpus. Gray: Document id.

a segment retrieved from the corpus, which enables more tokens to be processed in parallel. The average proposed span length in Figure 2a can increase from 5 tokens to 35 tokens at each time step as the relaxation factor gets smaller. Combined with Figure 2a, we can reach the conclusion that fetching longer spans from the corpus results in lower generation latency per query. For the accuracy, the FACTSCORE on Biography validation data shows that there is a sweet spot around $\gamma = 5e - 2$ where both low latency and high accuracy can be achieved at the same time.

4.6 Attribution and Qualitative Analysis

One of the most important features of NEST is providing attribution directly at a span level, where the reference for the corresponding statement is accurate since it is directly taken from the corpus. Table 2 shows the attribution ratio, average attributed span length, and two examples for analysis. For NaturalQuestions and Biography tasks, depending on the model and hyper-parameters in Equation (4) and (7), the ratio of tokens that can be traced back to the corpus ranges from 33.2% to 95.5%. In addition, it is more desirable to have consecutive segments that come from the same source so that consistent attribution can be provided,

and the average length of spans taken from the corpus ranges from 3.0 to 27.9 tokens. This feature provides span-level attribution for most claims in the LLM generation. To our knowledge, neither of the baselines can achieve the same granularity and preciseness for the attribution as NEST. More qualitative results are provided in Appendix D. We also provide more analyses on sensitivity and ablation for NEST in Appendix C.

5 Related Work

5.1 Retrieval-Augmention

Retrieval Augmentation involves external knowledge sources to improve the performance of language models on knowledge-intensive tasks. Chen et al. (2017) propose DrQA which combines extractive models and independent retrievers for open-domain question-answering. Follow-up works on retrieval-augmentation such as REALM (Guu et al., 2020), RAG (Lewis et al., 2020), and Atlas (Izacard et al., 2024) further combine the retrieval component in pre-training and fine-tuning for downstream knowledge-intensive tasks. Asai et al. (2024) further divide them into three categories:

Input augmentation. REPLUG (Shi et al., 2024a) and in-context RALM (Ram et al., 2023) propose to pre-pend the retrieved passages in the prompts for zero-shot factual support. Recently, Self-RAG (Asai et al., 2023b) leverages special tokens to perform adaptive retrieval and different critics to iterative refine the RALM's output. RA-DIT (Lin et al., 2024) retrofits LLMs with retrieval capabilities via instruction fine-tuning.

Intermediate fusion. RETRO (Borgeaud et al., 2022) employs a novel attention mechanism to incorporate multiple pre-processed text fragments in intermediate layers for more efficient integration of retrieved results. This approach has been successfully applied to larger decoder-only language models as demonstrated by RETRO++ (Wang et al., 2023b) and InstructRetro (Wang et al., 2024). FiD (Izacard and Grave, 2021) applies similar an encoder-decoder structure in a zero-shot manner and achieves better performance at a document level.

Output integration. kNN-LM (Khandelwal et al., 2020) pioneers this direction and proposes to interpolate the retrieval distribution and LM's prediction. Follow-up works further propose adaptive interpolation methods which involve training (He et al., 2021; Bhardwaj et al., 2023) and excessive tuning (Drozdov et al., 2022). Another line of work proposes to joint train the phrase encoder and LM to expand the vocabulary dynamically using the retrieved phrases, such as Copy-Generator (Lan et al., 2023) and its follow-up work (Cao et al., 2024).

5.2 Inference-Time Revision

Speculative decoding (Leviathan et al., 2023; Chen et al., 2023; Miao et al., 2023; Spector and Re, 2023) is an acceleration method that leverages a small model to generate drafts for a large model to evaluate. The latency is improved as the larger model can process multiple tokens in parallel at each time step. Recently, REST (He et al., 2024) proposes to draw multiple drafts from a datastore and leverages a prefix trie tree to compute the proposal distribution, which is the closest concurrent work.

In general, speculative decoding can be categorized as an unbiased self-revision method. Previous work focusing on fact-checking follows a similar idea to generate factually consistent texts with a set of evidence via post-hoc editing, such as FRUIT (Iv et al., 2022) and PEER (Schick et al., 2022). Recently, RARR (Gao et al., 2023) leverages more complex planning with LLMs to verify the retrieved evidence and generate attribution reports.

6 Limitations

While being able to directly retrieve segments from the corpus and apply them in the generation, the output of NEST might still contain factual errors depending on the accuracy of the first-stage passage retrieval and the second-stage token retrieval. Moreover, as a plug-and-play method, our main goal is to provide a flexible solution that can combine different LLMs and data stores in zero- and few-shot manners. Without further fine-tuning, the integrated system might be sub-optimal and the results can be better if it is fine-tuned on

appropriate tasks. Lastly, such semi-parametric LMs may not improve the ability of in-context learning, since the demonstrations in the prompts are unlikely to appear in any contexts that can be found in the database. An observation from preliminary experiments is that the current neural retrievers do not have the capability to process the in-context few-shot information, where techniques such as query reformulation might be needed for parsing the demonstrations.

7 Conclusion

This paper presents NEST, an inference-time revision method for LMs that improve their factuality and attribution through nearest neighbor speculative decoding. Leveraging two-stage k-NN search, relative retrieval confidence, dynamic span selection, and relaxed speculative decoding, NEST improves both validation perplexity and free-form generation quality on nine different tasks. Its performance can be further improved when combined with in-context retrieval augmentation. With these results, we demonstrate that NEST is capable of generating text grounded to real-world sources in low latency while maintaining fluency.

8 Broader Impacts

The ability to copy real-world texts from existing data stores is useful for finding the source of the claim (credibility), preventing hallucination (factuality), as well as protecting copyright (risk management). It helps to resolve the dispute that often happens in AI tools by acknowledging the contents that are borrowed from existing human works (e.g., arts, books, and other creative content). Meanwhile, the information on the Internet is mixed and it is important to filter out false and sensitive information before directly injecting them into the generation.

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A Additional Implementation Details

Two-stage k-NN search For the first-stage passage search, we use a Faiss (Douze et al., 2024) dense index and Pyserini (Lin et al., 2021) BM25 index for efficient search. For the dense index, we first use DRAGON+ to encode each passage in the corpus into a single vector, and then use Faiss (index string "IVF65536,PQ256") to cluster the vectors into 65536 centroids and quantize them into 256 codes of 8 bits each. For the sparse index, we use the default hyper-parameters and the "optimize" option in Pyserini to reduce the index size. For the approximate nearest neighbor retrieval, we use nprobe= 4096. During passage search, we retrieve 4000 passages from each index and keep the similarity score for fusion. The fusion coefficient η is determined by the relative confidence of dense and sparse retrievers similar to Equation (4). We set the dense coefficient $\eta_{\text{dense}} = 1 - \text{top-}100(s_{\text{dense}}(q,d))/\max s_{\text{dense}}(q,d)$ and same for the sparse coefficient η_{sparse} . The final interpolation coef is $\eta = 0.7 * (1 - \eta_{\text{sparse}}) + 0.3 * \eta_{\text{dense}}$. The fusion score for each document $s(q,d) = \eta * s_{\text{dense}} + (1-\eta) * s_{\text{sparse}}$. If a document is missing in either dense or sparse retrieval results, we set its score to the minimum similarity of the dense/sparse retrieval results. The first-stage search is done on RAM and CPUs with 32 threads. The final Wikipedia dense index size is about 8.96GB, and the sparse index size is about 3.48GB on disk.

For the second-stage token search, we use the LLM to encode the sequence and use the input to the final layer's feed-forward network after layer normalization as the key and query vectors following Khandelwal et al. (2020). We retrieve the top-1024 tokens using the squared ℓ_2 distance and compute the non-parametric probability according to Equation (2).

Rest of NEST For relative retrieval confidence, we set $\alpha=0.3, \tau=0.1$ for all Wikipedia-based tasks and $\alpha=0.2, \tau=0.1$ for Pile of Law for all model sizes in Equation (4). For dynamic span selection, we set the n-gram length to be 64 and $\delta=0.5$ for all model sizes and all tasks in Equation (6). For relaxed speculative decoding, we set $\gamma=5e-4$ for Pile of Law tasks for all model sizes in Equation (7). For Wikipedia-based tasks, we set $\gamma=5e-4$ for the 7B model, $\gamma=5e-3$ for the 13B model, and $\gamma=5e-2$ for the 70B model. For RA-NEST, all models use the same $\gamma=5e-1$ for all tasks except Pile of Law which still uses $\gamma=5e-4$ We observe that as the model gets stronger, using larger γ which leads to more rejection, is more beneficial to generation quality. The complete NEST procedure is provided in Algorithm 1.

B Evaluation Details and Hyper-parameter Tuning

Datasets. We sample subsets of WikiText-103, NaturalQuestions, and Biography as dev sets for hyperparameter tuning. We use the validation sets of WikiText-103 (CC BY-SA 3.0), NaturalQuestions (Apache License 2.0), TriviaQA (Apache License 2.0), MedMCQA (MIT License), HotpotQA (Apache License 2.0), MMLU (MIT License), and Biography (MIT License) for validation. TruthfulQA (Apache License 2.0) only has the test set. We finally test all datasets shown in Table 1. For HotpotQA and MedMCQA, we do not have access to the test set and therefore the validation results are reported. For Biography, we use the labeled data that have human annotation as the validation and dev set, and the unlabeled data as the test set. In the original FACTSCORE paper, the authors use InstructGPT (Ouyang et al., 2022) to perform fact decomposition

Algorithm 1 Nest w/ Greedy Decoding

```
Inputs: Language model LM, hidden state encoder f, first-stage retriever R, corpus C, input x.
\triangleright First-stage retrieval: Retrieve documents d_1, d_2, \ldots, d_b from corpus \mathcal{C}
d_1, d_2 \dots, d_b \leftarrow R(x, \mathcal{C})
▷ Second-stage retrieval: Construct token-level key-value memory
(\mathcal{K}', \mathcal{V}') \leftarrow \varnothing
for i = 1 \text{ to } b \text{ do}
    \begin{array}{c} w_1^{d_i}, w_3^{d_i}, ..., w_m^{d_i} \leftarrow d_i \\ w_1^{d_i}, w_3^{d_i}, ..., w_m^{d_i} \leftarrow f(d_i) \\ h_1^{d_i}, h_3^{d_i}, ..., h_m^{d_i} \leftarrow f(d_i) \\ \text{for } i = 1 \text{ to } m - 1 \text{ do} \\ (\mathcal{K}', \mathcal{V}').\text{add}(h_j^{d_i}, w_{j+1}^{d_i}) \end{array}
     end for
end for
▶ Generation
y_{< t} \leftarrow x
for t=1\ {\bf to}\ T\ {\bf do}
     q_t \leftarrow f(y_{< t})[-1]
     \triangleright Token embeddings search, return top-r scores and values
     \pi \leftarrow (\mathcal{K}', \mathcal{V}').\operatorname{search}(q_t, r)
     (s_1, v_1), (s_2, v_2), ..., (s_r, v_r) \leftarrow \pi
     ▷ Compute non-parametric distribution
     p_{k\text{-NN}}(w|y_{< t}) \leftarrow 0, \forall w \in \text{vocabulary}
     for i = 1 to r do
          p_{k-NN}(w = v_i | y_{< t}) \leftarrow p_{k-NN}(w = v_i | y_{< t}) + \exp(\mu \cdot s_i) / \sum_{i=j}^r \exp(\mu \cdot s_j)
     end for
     ▷ Confidence-based Interpolation
     \begin{aligned} & \lambda_t \leftarrow \text{sigmoid}((\frac{\min_i s_i}{\max_i s_i} - \alpha)/\tau) \\ & p_{\mathcal{M}}(w|y_{< t}) \leftarrow \lambda_t \cdot p_{\text{LM}}(w|y_{< t}) + (1 - \lambda_t) \cdot p_{k\text{-NN}}(w|y_{< t}) \end{aligned}
     ▷ Dynamic span selection
    w_{t} \leftarrow \underset{w}{\operatorname{argmax}} p_{\mathcal{M}}(w|y_{< t})
v_{t} \leftarrow \underset{v_{i}=w_{t}}{\operatorname{argmax}} p_{k-\operatorname{NN}}(w=v_{i}|y_{< t})
v_{t:t+n} \leftarrow \mathcal{C}.\operatorname{get-ngram}(v_{t}, n)
y_{t} \leftarrow \begin{cases} w_{t}, & \text{if } \lambda_{t} > \delta; \\ v_{t:t+n}, & \text{otherwise.} \end{cases}
     ▶ Relaxed Speculative Decoding
     for i = 1 to n do
          p_{\text{accept}}(w_t^{(i)}) \leftarrow \frac{p_{\mathcal{M}}(w = w_t^{(i)} | x, y_{< t}, w_t^{(1)}, w_t^{(2)}, ..., w_t^{(i-1)})}{\gamma \cdot \max_{w} p_{\mathcal{M}}(w | x, y_{< t}, w_t^{(1)}, w_t^{(2)}, ..., w_t^{(i-1)})}
          Break if p_{\text{accept}}(w_t^{(i)}) \leq 0.5
     end for
     \label{eq:continuous_potential} \begin{aligned} & \text{if } i < n \text{ and } n > 1 \text{ then} \\ & w_t^{(i)} \leftarrow \operatorname{argmax} \ p_{\mathcal{M}}(w|y_{< t}, w_t^{(1)}, w_t^{(2)}, ..., w_t^{(i-1)}) \end{aligned}
     y_{< t} \leftarrow \text{concatenate}(y_{< t}, w_t^{(1)}, w_t^{(2)}, ..., w_t^{(i)})
end for
Return y_{< t}
```

Category	Base LM, k NN-LM and NEST	RA-based Methods		
QA, MMLU, Fact Check	[INST] Question: {question} Answer: [/INST]	[INST] Answer the question with the background context as reference. Background: {retrieved passages}\nQuestion: {question} Answer: [/INST]		
Text Completion	[INST] Write an article.\nArticle: [/INST] {prefix}	[INST] Write an article with the background context as reference. Background: {retrieved passages}\nArticle: [/INST] {prefix}		

Table 3 Instruction template used for different datasets. [INST] and [/INST] are special markers denoting the start and the end of an instruction.

before verification. We hereby train our own decomposition model by further fine-tuning Llama-2 7B using publicly available datasets (Chen et al., 2022; Liu et al., 2023; Malaviya et al., 2024). For fact verification, we use the option retrieval+llama+npm to evaluate the decomposed atomic facts.

Inference and prompts. For language modelling and text completion, we use a context length of 128 tokens and a max generation length of 256 tokens. For the other tasks, we use 128 tokens as max generation length for question answering and 512 for fact verification. We remove all the in-context demonstrations from the prompt to test the zero-shot effectiveness of our model. We use greedy decoding in our experiments as the randomness in sampling can undermine factuality. Table 3 shows the instruction templates we use for different tasks. For MMLU, we compare the perplexity of each option concatenated with the template and select the one with the minimum perplexity.

Hyper-parameters and baselines. For the base LM, we do not tune the hyper-parameters released with the original Llama-2-chat models. For the in-context retrieval augmented baseline, we select the top-3 retrieved passages. For kNN-LM, we follow Equation (3) and use an interpolation coefficient of 0.7 for Wikipedia-based tasks and 0.9 for Pile of Law. For NEST and RA-NEST, we first tune the hyper-parameters in Equation (4) on language modelling tasks using perplexity. We then fix those hyper-parameters and then tune the rest of the parameters in Equation (6) and (7) on generation tasks. All hyper-parameters in the above methods are tuned on the dev sets of WikiText-103, NaturalQuestions, and Biography.

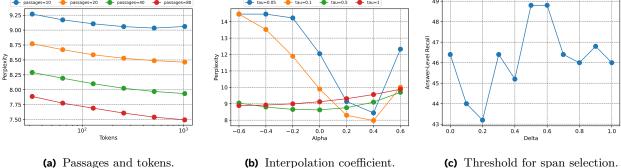
C Analysis

The following analyses are performed on the validation set of WikiText-103, NaturalQuestions, and Biography data with the Llama-7B-chat model.

C.1 Sensitivity

Number of retrieved passages and tokens—Khandelwal et al. (2020) show that increasing the size of the database and the number of tokens can improve the perplexity with proper hyper-parameter setting. We also verify whether our two-stage k-NN search and RRC approach follow the same trend. Figure 3a shows the validation perplexity on WikiText-103. For a fixed number of passages, the perplexity decreases as the number of tokens increases; for a fixed number of tokens, the perplexity decreases about $0.5 \sim 1.0$ as the number of passages doubles. However, as NEST needs to encode the retrieved passages on the fly, the latency also increases linearly w.r.t. the number of passages. Therefore, we set the passage number to be 40 and the token number to be 1024 in the main experiments.

Interpolation coefficient Figure 3b shows the sensitivity of the hyper-parameters α (offset) and τ (temperature) in Equation (4) on WikiText-103. When τ is big, λ_t is close to a uniform distribution and therefore the offset α does not have a big impact on the perplexity. When τ is small, the impact of α is enlarged and the sweet spot is achieved around $\tau = 0.1$ and $\alpha = 0.4$.



(a) Passages and tokens.

Figure 3 Sensitivity analysis on WikiText-103 and NaturalQuestions dev set for the NEST-7B model with the above hyper-parameters in the sub-figures.

Threshold for dynamic span selection Figure 3c shows how threshold δ in Equation (6) affects the generation on Natural Questions. A bigger δ means selecting the span instead of a token more often. We can see that the answer-level recall on NaturalQuestions first increases and then decreases as we increase the value of δ , where the sweet spot is around $\delta = 0.5$.

Models (7B)	Wiki./ROUGE-1	NQ/ALR	Bio./FS
kNN-LM (two-stage)	20.1	40.8	34.8
+ Relative Retrieval Confidence	24.7	44.4	41.6
+ Dynamic Span selection	24.5	44.6	41.6
+ Relaxed speculative decoding	26.8	45.4	46.8

Table 4 Ablation study on the validation set of WikiText-103, NaturalQuestions, and Biography. ROUGE-1 is reported for WikiText-103, ALR is reported for NaturalQuestions, and FACTSCORE is reported for Biography.

C.2 Ablation Study

Table 4 shows a progressive ablation of Nest on WikiText-103, Natural Questions, Biography. As mentioned in Section 3.1, it is extremely expensive to encode billion-token corpus with billion-parameter models. Therefore, we directly start with the two-stage implementation of kNN-LM and gradually add the methods applied in NEST. As we can see, adding the RRC component gives the first performance boost. The second dynamic span selection method does not seem to increase the performance, yet it is crucial to give consistent attribution for consecutive spans and tokens. The last relaxed speculative decoding method further improves the final generation quality.

D Qualitative Results.

Table 5, 6, 7, and 8 shows more qualitative analyses for attribution of Nest-70B on NaturalQuestions, HotpotQA, MedMCQA, and WikiText-103.

Question	Answer (Generated by Nest-70B)
The vascular layer of the eye is the	The vascular tunic, [21027113] also known as the "uvea", is the middle layer of the three layers that comprise the eye. It is located [12049924] between the sclera (the outer, white layer) and the retina ([31987889] the innermost is the retina, which gets its oxygenation from the blood vessels of the choroid (posteriorly) as well as the retinal vessels (anteriorly).[31482951]
When did United States enter World War I?	The United States entered World War I on April 6, 1917,[1592542] after Congress declared war against Germany. The U.S. made its major contributions in terms of supplies, raw material, and money, starting in 1917. American soldiers under General of the Armies John Pershing, Commander-in-Chief of the American Expeditionary Force (AEF), arrived at the rate of 10 [1592542]
Where are unipolar neurons found in spinal cord?	Unipolar neurons [6000295] are found in the dorsal root ganglia [19976891] (DRG) of the spinal cord. [9082117] The DRG is a cluster of neurons (a ganglion) in a dorsal root of a spinal nerve. The cell bodies of sensory neurons known as first-order neurons are located in the dorsal root ganglia. The axons of dorsal root ganglion neurons are known as af [9024943]
When was catch me if you can made?	The movie "Catch Me If You Can" was released on December 25, 2002, [27493033] in the United States. It was directed by Steven Spielberg and starred Leonardo DiCaprio as Frank Abagnale Jr., [2219100] a con man who impersonated a Pan [26808473] American World Airways pilot, a doctor, and a legal prosecutor, among other identities, and Tom Hanks as [2422879] FBI agent Carl Hanratty, who pursued him. [2422867] The movie was based on

Table 5 Qualitative analysis for attribution on NQ. Green: Correct segments taken from the corpus. Gray: Text chunk id. The span will be labelled only when 4 consecutive tokens have the same document id.

Question	Answer (Generated by Nest-70B)
Which is larger, Hunchun or Shijiazhuang?	Hunchun and Shijiazhuang [30998205] are both cities in China. Shijia zhuang [6737448] is a prefecture -level city and the capital and largest city of Hebei [7075559] Province, with a population of 120,000,000 (2020). Hunchun is a town ship-level division of Hunchun [30998199], Jilin, China, with a population of 18,000 (2004). Therefore, Shijiazhuang is larger than [27937602]
Was Pocahontas made before Born in China?	No, Pocahontas [2716717] was released in 1995 [4240514], while Born in China was released in 2016 [9704476]
How many animals does the wall running between the West Gate Lodge and Cardiff Castle depict?	The wall running between the West Gate Lodge [2843590] and Cardiff Castle depicts 15 animals on Castle Street. It is a Grade I listed structure, designed by architect William Burges in 1866, though not built until 1890. The work was completed by Burges' former assistant William Frame. The original nine animal figures were sculptured by Thomas Nicholls [16694594]
How much longer after Sambou YatabarĀ was born did Werder Bremen get founded in the northwest German federal state Free Hanseatic City of Bremen?	Sambou Yatabar \tilde{A} [29957019] was born on March 21, 1989. Werder Bremen was founded on February 4, 1899 [5536896], which was approximately 90 years before Sambou Yatabar \tilde{A} [22751848]

Table 6 Qualitative analysis for attribution on HotpotQA. Green: Correct segments taken from the corpus. Red: Wrong segments taken from the corpus. Gray: Document id. The span will be labelled only when 4 consecutive tokens have the same document id.

Question	Answer (Generated by Nest-70B)
Heavy forces on periodontal ligament causes?	Heavy forces on the periodontal ligaments [10961708] can cause a variety of issues, including: 1. Periodontal ligament [19737958] strain: The periodontal ligament can [19569905] become stretched or compressed due to heavy forces, leading to pain and a reversible increase in tooth mobility. [32678984] 2. Periodontal ligament inflammation: The periodontal ligament can become inflamed due to the constant pressure and friction from the heavy forces, leading to pain and swelling in the affected area. 3.Tooth mobility: [17809669] Heavy forces on a tooth can [2104721] cause
Gait apraxia is seen in thromboembolic episode involving?	Gait apraxia is often seen in patients with corticobasal degeneration. [4450082] Corticobasal degeneration is a neurodegenerative disorder that affects the cerebral cortex, [31300317] basal ganglia, and cerebellum, leading to a range of movement disorders, including gait apraxia. The [31300325] condition is characterized
Axonal transport is?	Axonal transport refers to the movement of mitochondria, lipids, synaptic vesicles, proteins, and other organelles to and from a neuron's cell body, through the cytoplasm of its axon called the axoplasm. Since some axons are on the order of meters long, neurons cannot [18180573]
In Erythroblastosis fetalis not involved is ?	Inerythroblastosis fetalis [26445482], the fetus is not directly involved. Erythroblastosis fetalis [14246750] is a condition that occurs in the newborn baby when the IgG molecules (one of the five main types of antibodies) produced by the mother pass through the placenta. Among these antibodies are some which attack antigens on the red blood cells in the fetal circulation, breaking down and destroying the cells. The fetus [26565066]

Table 7 Qualitative analysis for attribution on MedMCQA. Green: Correct segments taken from the corpus. Gray: Document id. The span will be labelled only when 4 consecutive tokens have the same document id.

Prefix	Prediction (Generated by Nest-70B)
casemates in the forecastle and superstructure and the remaining pair were mounted on the deck above them and protected by gun shields. They had a maximum elevation of + 20 degrees which gave them ranges of 16 @.@ 300 metres (17 @.@ 800 yd). Each gun had a rate of fire of up to 10 rounds per minute. Anti @.@ aircraft defence was provided by four 40 @.@ calibre 3rd Year Type 8 @.@ centimetre AA guns in single mounts	protected by gun shields. They had a maximum elevation of $+$ [4584350] 80 degrees, and a rate of fire of 130 rounds per minute. The [8700981] ship was also equipped with eight 53.3 cm torpedo tubes, four on each broadside, two above water and two submerged. Around 1926, the four above-water torpedo tubes were removed and the ship received three additional 76 mm AA [22329090] guns on high-angle Mark 3 mounts. These were mounted abreast the mainmast in the superstructure and had a maximum elevation of $+$ 70 degrees and a rate of fire of 13 to 20 rounds per minute. They fired a 6 kg projectile with a muzzle velocity of 680 m/s to a maximum height of [30284091]7,500 m. The ship was also fitted with eight 61 cm above-water torpedo tubes, four on each broadside, two above water and two submered. The ship had a crew of 1
, but he is thought to have given up the privilege in favour of one of his half brothers. He spent the next four years living in the Luoyang area, fulfilling his duties in domestic affairs. In the autumn of 744, he met Li Bai (Li Po) for the first time, and the two poets formed a friendship. David Young describes this as "the most significant formative element in Du Fu's artistic development" because it gave him a living example of the reclusive poet @-@ scholar life to which he was attracted after his failure in the civil	service exam. The relationship was somewhat one-sided, however. Du Fu was by some years the younger, while Li Bai was already a poetic star. We have twelve poems to or about Li Bai from the younger poet, but [24905850] none in the other direction. In 740s, Du Fu began to write poetry seriously. His early work was influenced by the works of Li Bai and other poets of the time. He also began to develop his own style and themes in his poetry. In 750s, Du Fu became increasingly involved in politics and social issues. He wrote many poems that criticized the government and its policies. He also became known for his poems [13895340] that expressed his decision to withdraw from civil service. [19467174] In 755, Du Fu was appointed an advisor to Yan Wu, [24905857] the Prince of Guangling. He served in this position for three years. During this time, let the city to escape a rebellion, but he returned in summer 760. [24905857] In 762, he was appointed an advisor to Li Yu, the Prince of Xu. He was relieved of his [24905857] duties in 764
positions to Bradley. Still farther northward in the zone of the US 38th Infantry the North Koreans were also active. After the North Korean breakthrough during the night of August 31, Keiser had ordered the 2nd Battalion, 38th Infantry, to move south and help the 23rd Infantry establish a defensive position west of Changnyong. In attempting to do this, the battalion found North Korean troops already on the ridges along the road. They had penetrated to Hill 284 overlooking the 38th Infantry command post. This	was serious, for the 38th Regiment command post [13479536] was in the process of moving back to a position south of [8986888] the river. The 2nd Battalion was then forced to occupy a lower position at 1 mi away from the Chinese. At the same time, the [29133385] 3rd Battalion, 38th Infantry, was cut off 3 mi west of [4050187] 23rd Infantry and was forced to withdraw to safer positions. In the early afternoon, another attacking force, an estimated [20154221]200 North Koreans, struck the 38th Regiment command post. The regimental commander organized a defensive perimeter [13479536] around his command post and held on until nightfall. The KPA 7th Division troops had [4050220] effected major crossings of the Naktong at two principal points against the US [13479513]23rd Infantry. The 1st Battalion, 23rd Infantry, on the ridges overlooking the river, was pushed back as its soldiers retreated without orders. Survivors from the 1st Battalion later joined the 2
northeast of Kuching 216 kilometres (134 mi) northeast of Sibu, and 200 kilometres (120 mi) southwest of Miri. Bintulu is located near the mouth of the <unk> River, in the coastal region of central Sarawak. Geology of the coastal area was formed during the Pleistocene period; silt, clay, and gravel can be found here. Geological formation from the Oligocene period is found in the inland area, which contains limestone, siltstone, and</unk>	sandstone. The soil is generally soft. [9989875] The area is located in the coastal region of central Sarawak. Geology of the coastal area was formed during the Pleistocene period; silt, clay, and gravel can be found here. Geological formation from the Oligocene period is found in the inland area, which contains limestone, [9989875] siltstone, and sandstone. The soil is generally soft. The area is located in the coastal region of central Sarawak, which is known for its rich oil and gas reserves. The [21065756] town is also surrounded by lush tropical rainforests and abundant [21065719] wildlife. Bintulu is the capital of the Bintulu District of the Bintulu Division of Sarawak, Malaysia. The name of Bintulu was derived from the local native language 'Mentu Ulau' (picking heads). Bintulu was a small fishing village when Rajah James Brooke acquired it [9989859]

Table 8 Qualitative analysis for attribution on WikiText-103. Green: Correct segments taken from the corpus. Red: Wrong segments taken from the corpus. Gray: Document id. The span will be labelled only when 4 consecutive tokens have the same document id.