Exploring Iterative Controllable Summarization with Large Language Models

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Abstract

Large language models (LLMs) have demonstrated remarkable performance in abstractive summarization tasks. However, their ability to precisely control summary attributes (e.g., 005 *length* or *topic*) remains underexplored, limiting their adaptability to specific user preferences. In this paper, we systematically explore the controllability of LLMs. To this end, we revisit summary attribute measurements and introduce iterative evaluation metrics, failure rate and average iteration count to precisely evalu-011 012 ate controllability of LLMs, rather than merely assessing errors. Our findings show that LLMs struggle more with numerical attributes than with linguistic attributes. To address this chal-016 lenge, we propose a guide-to-explain framework (GTE) for controllable summarization. 017 Our GTE framework enables the model to identify misaligned attributes in the initial draft and 020 guides it in self-explaining errors in the previous output. By allowing the model to reflect on 021 its misalignment, GTE generates well-adjusted 022 summaries that satisfy the desired attributes with robust effectiveness, requiring surprisingly fewer iterations than other iterative approaches.

1 Introduction

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Large language models (LLMs) have demonstrated superior performance in text summarization, outperforming encoder-decoder models by generating more contextually appropriate and natural summaries (Goyal et al., 2023; Zhang et al., 2024; Pu et al., 2023; Ryu et al., 2024b). However, given individuals' diverse preferences for summary styles, it is essential to generate summaries tailored to individual needs (Zhang et al., 2023b). For instance, some users may prefer specific topic-focused summaries or retain exact phrases. While LLMs excel in generating fluent summaries, their ability to precisely control attributes remains underexplored (Liu et al., 2024), limiting their adaptability to diverse user preferences.

Controllable summarization has recently garnered attention (Zhong et al., 2021; Ahuja et al., 2022; Maddela et al., 2022; Mehra et al., 2023; Xu et al., 2023; Zhang et al., 2023b), with prior studies primarily utilizing encoder-decoder architectures (Mao et al., 2022; Zhang et al., 2022; Vig et al., 2022; He et al., 2022; Pagnoni et al., 2023; Wang et al., 2023; Urlana et al., 2024) that incorporate attribute-specific training signals to constrain summary generation. However, these systems lack scalability due to their dependence on attribute-specific training. In contrast, LLMs offer flexibility yet rely on in-context learning and prompting without explicit training-based constraints, hindering finegrained attribute control (Yuan et al., 2024; Tang et al., 2023), necessitating further investigation.

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To systematically explore the controllability of LLMs, we first revisit the measurements for four key attributes: extractiveness, length, topic, and speaker, and refine them for more precise measurement. Specifically, instead of previous attribute measurement strategies that rely solely on word presence for topic- or speaker-focused summaries, we adopt embedding similarity to incorporate semantic information into the measurements. Building on this refined attribute measurement, we move beyond the previous controllability evaluation, which primarily assesses the disparity between the reference and the generated summary (He et al., 2022; Zhang et al., 2023b). To fully explore the LLMs' controllability, we shift focus from merely measuring attribute errors to evaluating whether LLMs can accurately control specified attributes via iterative refinement. Thus, we introduce two evaluation metrics: the *failure rate*—the proportion of control failures within the maximum iterations—and the average iteration count required for successful control. Our findings reveal that while LLMs excel at controlling linguistic attributes such as topic and speaker, they severely struggle with numerical attributes such as extrac-

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tiveness and *length*. We assume that unlike linguistic attributes, which rely on semantic coherence, numerical ones demand strict quantitative constraints, making fine-grained control challenging.

To address this challenge, we propose a guideto-explain (GTE) framework, which enables precise attribute control solely through LLMs without relying on additional attribute-specific training. We first design a step-by-step attribute identification phase to instruct the model on calculating misaligned attributes of its previously generated summary, then guide it to explain the rationales behind its errors. Through self-reflection, the model corrects its previous mistakes and generates a wellaligned summary in the regeneration phase. By integrating a self-refinement strategy-proven effective in complex reasoning tasks (Weng et al., 2023; Madaan et al., 2023; Dhuliawala et al., 2024; Gou et al., 2024)-into controllable summarization, we enhance LLMs' attribute controllability while ensuring summary quality.

We evaluate GTE on mixed-attribute summarization datasets, MACSum_{Doc} and MACSum_{Dial} (Zhang et al., 2023b). GTE successfully controls each attribute with minimal iterations, significantly outperforming other iteration methods, while demonstrating robustness by consistently adjusting attributes across data samples. Further, we also demonstrate the high quality of the controlled summaries across multiple generic summarization evaluation metrics, including UniEval (Zhong et al., 2022) and QuestEval (Scialom et al., 2021). Finally, we analyze whether LLMs can control multiple attributes simultaneously, revealing their struggles in jointly managing correlated numerical attributes. Our contributions are as follows:

- We systematically explore LLM's controllability in text summarization.
- We refine the measurement of summarization attributes and introduce *iterative evaluation* metrics for evaluating LLMs' controllability.
- We propose a guide-to-explain (GTE), which guides the model to explain its misalignments and effectively adjusts misaligned attributes within just a few iterations.

2 Related work

Controllable summarization Controllable summarization has recently gained attention due to its

practical applications (Zhong et al., 2021; Ahuja et al., 2022; Maddela et al., 2022; Mehra et al., 2023; Xu et al., 2023; Zhang et al., 2023b; Ribeiro et al., 2023). Previous research employed encoderdecoder models to control attributes (Fan et al., 2018; Liu and Chen, 2021; Dou et al., 2021; He et al., 2022; Mao et al., 2022; Zhang et al., 2022; Goyal et al., 2022; Vig et al., 2022; Bahrainian et al., 2022; Liu et al., 2022; Pagnoni et al., 2023; Wang et al., 2023; Urlana et al., 2024). For example, CTRLSum (He et al., 2022) trains models by prepending a keyword sequence to the source document. Similarly, MACSum (Zhang et al., 2023b) adopts prompt learning by prepending each attribute's value to the input source using a combination of hard prompts and soft prefixes. HY-DRASUM (Goyal et al., 2022) leverages a single encoder and multiple decoder framework, using a mixture-of-experts where the decoders share probabilities to effectively control the attributes.

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Most controllable summarization research relied on encoder-decoder frameworks. In addition, they required attribute-specific training or custom datasets to control each attribute, limiting the flexibility of attribute manipulation. Therefore, we propose a generalizable approach to enable flexible attribute control without the need for tailored training for each attribute, leveraging underexplored LLMs for controllable summarization (Tang et al., 2023; Yuan et al., 2024; Liu et al., 2024).

Self-correction Recently, the self-correction approach has been used to refine their initial attempts to solve complex problems (Weng et al., 2023; Shinn et al., 2023; Madaan et al., 2023; Dhuliawala et al., 2024; Gou et al., 2024), mirroring humans. In summarization tasks, self-correction has been employed to enhance the overall quality of summaries (Zhang et al., 2023a; Sun et al., 2024). Zhang et al. (2023a) utilizes iterative feedback from an evaluator to instruct ChatGPT to produce higher-quality summaries. Unlike prior works, we focus on generating summaries tailored to user preferences, which involve a multitude of factors to consider.

3 Problem formulation for controllable summarization

We conduct a systematic exploration of LLMs' controllability evaluation. While generic evaluation metrics (e.g. *consistency*, *fluency*) favor higher scores, controllability requires aligning summaries with user-specified attribute values. Previous re-

Attribute	Metrics	Paper
Extractiveness	ROUGE, word overlap	Goyal et al. (2022); Zhang et al. (2023b)
Length	Absolute length, length ratio	Goyal et al. (2022); He et al. (2022); Maddela et al. (2022); Zhang et al. (2023b)
Topic, Query	ROUGE, LDA, topic word count, classifier	Zhong et al. (2021); He et al. (2022); Zhang et al. (2023b); Xu et al. (2023)
Speaker, Entity	ROUGE, speaker utterance word overlap	Maddela et al. (2022); Zhang et al. (2023b)

Table 1: Previous methods for measuring attributes.

search mainly assessed deviations from target values rather than ensuring precise control (Zhang et al., 2023b). To address this, we introduce iterative evaluation metrics, assessing whether LLMs can precisely adjust attributes, even through multiple iterations. Before evaluating a controllability, we first refine attribute measurement.

3.1 Controllable attribute measurement

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We revisit attribute measurement to quantify key attributes for controllable summarization: *extractiveness*, *length*, *topic*, and *speaker*. Table 1 summarizes how previous controllable summarization studies have measured each attribute. However, the measurements for certain attributes have not yet been clearly defined. Thus, we outline our newly defined approach for attribute measurements below.

Extractiveness quantifies the degree of lexical 197 overlap between a summary and its source docu-198 ment. Highly extractive summary is required when users need to retain the original context, such as in legal documents, whereas paraphrasing is preferred 201 in general cases. To measure the *extractiveness*, MACSum (Zhang et al., 2023b) employs the average precision scores of ROUGE-2 and ROUGE-3. HYDRASUM (Goyal et al., 2022) calculates the proportion of words in the summary that appear in 206 the source document as well as the average length of copied contiguous spans in the summary. Following the definition of *extractiveness*, we measure 209 this attribute as the proportion of words in the sum-210 mary directly reused from the source text.

Length refers to the number of words or sen-212 tences in the summary or the ratio of the summary's 213 length to the original text. By controlling the length, 214 the amount of information in the summary can be 215 adjusted according to user preferences. Prompts 216 suggested by earlier works specify a fixed number 217 218 of sentences, e.g., "3 sentences," but this approach fails to account for variations in sentence length 219 and does not accurately reflect the summary's actual length (Goyal et al., 2023; Liu et al., 2024; Yuan et al., 2024). As the summary length may 222

vary depending on the source document, we use the length ratio instead of absolute length. 223

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Topic refers to generating a summary centered around one or multiple themes. Query-focused summarization (QFS), which generates summaries based on a specific query, and entity-based summarization, which focuses on a particular individual, are variations of topic-focused summarization. Zhang et al. (2023b) measured topic word frequency in summaries. Similarly, most QFS methods have relied solely on ROUGE scores, evaluating generated summaries by comparing them to human-annotated references (Zhong et al., 2021). However, even if topic words do not explicitly appear, the summary can still reflect the core context of the topic, especially for LLM-generated summaries, which tend to paraphrase the content. Therefore, rather than simply counting the frequency of word occurrences, we evaluate the semantic similarity between the summary and each topic-related word. We compute the embedding similarity \mathcal{B} between the topic word and each word in the summary s: $\frac{1}{n} \sum_{i \in s} \mathcal{B}(topic, word_i)$, where n is the number of words in the summary. If multiple topics k are present, we use the average embedding similarity across all topics: $\frac{1}{k} \sum_{i \in k} \frac{1}{n} \sum_{i \in s} \mathcal{B}(topic_k, word_i).$

Speaker refers to generating a summary that focuses on the utterances of a specific speaker from a long document or dialogue. Zhang et al. (2023b) calculate the frequency of the speaker's spoken words appearing in the summary. Similar to *topics*, measuring the proportion of words from a specific speaker's dialogue included in the summary does not fully capture semantic elements. Therefore, we extract speaker utterances and construct speaker set \mathcal{U} and leverage BERTScore F1 (Zhang et al., 2020) to compute the embedding similarity between the summary *s* and \mathcal{U} : BERTScore(*s*, \mathcal{U}).

3.2 Iterative controllablility evaluation

Previous evaluations of the model's controllability were conducted using metrics such as mean absolute deviation (MAD) between predicted and

Attribute	Label	MAG	$CSum_{Doc}$		MACSum _{Dial}			
	Laber	Distributions	Relabel	# of summaries	Distributions	Relabel	# of summaries	
	normal	35.7 - 100.0% (85.2%)	85.0%	3731	53.2 - 100.0% (86.4%)	85.0%	1661	
Extractiveness	high	55.0 - 100.0% (90.0%)	90.0%	287	63.0 - 100.0% (88.9%)	90.0%	340	
	fully	84.6 - 100.0% (99.7%)	100.0%	260	75.9 - 100.0% (98.4%)	100.0%	337	
	short	0.7 - 15.0% (4.8%)	7.5%	1059	0.2 - 20.8% (2.0%)	7.5%	300	
Length	normal	0.5 - 48.6% (6.9%)	20.0%	2194	0.3 - 41.9% (3.7%)	20.0%	1693	
0	long	1.5 - 39.8% (13.9%)	32.5%	1025	0.7 - 32.4% (6.0%)	32.5%	345	
Topic	-	74.8 - 88.8	74.0	2013	73.6 - 87.0	74.0	2317	
Speaker	-	-	-	-	75.6 - 92.0	75.0	1796	

Table 2: Data distributions of MACSum_{Doc} and MACSum_{Dial}.

reference summary attributes (He et al., 2022), or label-based control error rate (CER) and control 267 correlation (Zhang et al., 2023b). While these met-268 rics capture the differences between the reference 269 and the model-generated summaries, they do not 270 explicitly determine whether LLMs can ultimately 271 exert effective control over the summaries. Since precisely controlling attributes in a single genera-273 tion is challenging, we evaluate LLMs' ability to iteratively refine and adjust attributes over multiple 275 revisions. Specifically, we introduce two metrics: 276 (1) the failure rate, which quantifies the propor-277 tion of cases where the model reaches predefined maximum iterations without achieving the desired 279 modifications, and (2) the average iteration count required for successful attribute control. A failure or reaching the maximum number of iterations is denoted as 🖒. We set the maximum number of iterations to 20 due to cost constraints.

Iteration threshold We set attribute-specific thresholds and iteratively regenerate summaries until they are met. Each attribute is measured using the criteria outlined in Section 3.1 to determine its threshold. For extractiveness and length, we consider control successful if the attribute values fall within ± 5 of the target value. For *topic* and *speaker*, we use the minimum embedding similarity values of the reference summaries in the training dataset (Table 2) as thresholds to determine whether a summary is topic-focused or speaker-focused. The 295 threshold can be adjusted based on the strictness of 296 the evaluation criteria.

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Label reinterpretation We use the two publicly available MACSum datasets (Zhang et al., 2023b) for controllable summarization. However, existing 301 labels are ambiguous since the criteria are not numerically defined (e.g., how short must a summary be to qualify as short?). We believe that these ambiguous criteria may confuse LLMs, so we assign clear numerical values to each label. To provide de-305

tailed criteria, we reinterpret the labels based on the attribute distributions in each training set. For ex*tractiveness*, we set labels as {normal: 85%, high: 90%, fully: 100%}, following the mean value. Unlike Zhang et al. (2023b), we define the summary length as a ratio of the original text rather than a fixed value. The existing labels do not distinctly differentiate these ratios, as the average length ratios between labels show minimal differences. Specifically, short is 2.0, while normal is 3.7, indicating a relatively small gap. To allow for greater variability, we expand the range. Importantly, our method generates summaries based on the specified numerical values, regardless of predefined labels. The broader range allows for a more adaptive and effective evaluation of LLM controllability. we set the lengths to {short: 7.5%, normal: 15%, long: 32.5%}, providing clearer distinctions with evaluating a broader range of controllability.

4 Controllability of LLMs in text summarization

	Extractiveness	Length	Topic
Phi-3-medium	100.00% / ひ	100.00%/心	38.08% / 0.22
Llama3-8B	100.00% / 🖒	100.00% / 🖒	57.14% / 0.12
Llama3-70B	49.91% / 8.05	49.36% / 8.24	0.00% / 0.24
GPT-3.5	49.73% / 9.80	76.42% / 0.00	0.00% / 0.00
GPT-40	39.31% / 6.63	69.84% / 0.00	0.38% / 0.02

Table 3: The left number represents the averaged control failure rate, and the right side denotes the average iteration count for successful control.

As research on leveraging LLMs for controllable summarization remain limited, we evaluate the controllability of various LLMs using the iterative evaluation method from Section 3.2. We first provide an initial control prompt and generate a summary. If the generated summary fails to meet the specified attribute threshold, the result is fed back into the LLM's input, prompting it to regenerate until the attribute is correctly controlled. As shown in Table 3,

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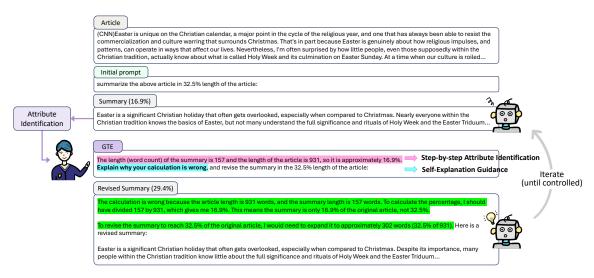


Figure 1: Overview of guide-to-explain system (GTE). The pink parts () represent the step-by-step attribute-identification, and the blue parts () correspond to the self-explanation guidance.

smaller-scale LLMs, such as Phi-3-medium (Abdin et al., 2024) and Llama3-8B (Dubey et al., 2024), partially control topic, but fail to control extractiveness and length. Similarly, large-scale LLMs such as Llama3-70B, GPT-3.5 (Brown, 2020), and GPT-40 (Achiam et al., 2023) effectively control topic, demonstrating low failure rates. However, they also struggle to control extractiveness and length, showing failure rates of around 50%. Notably, when initial attempts fail, GPT-3.5 and GPT-40 could not adjust despite multiple iterations, ultimately reaching the maximum iteration limit, resulting in an iteration count of zero. As a result, we find that generating summaries while controlling attributes remains challenging for LLMs, even with iterative attempts, especially for numerical attributes such as extractiveness and length.

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5 Method: Guide-to-Explain (GTE)

Therefore, we introduce a guide-to-explain (GTE) framework to adjust various attributes via LLMs. As shown in Figure 1, our GTE framework consists of two key phase: the step-by-step attribute identification and the self-explanation guidance. We provide an step-by-step attribute identification to teach precise adjustment for incorrectly generated responses then guide LLMs to reflect by explaining the rationales behind their mistakes. Our approach allows the model to make appropriate adjustments in subsequent iterations.

5.1 Step-by-step attribute identification

We first instruct the LLM to generate an initial summary s' that reflects the specified attribute. If the

LLM fails to control the attributes accurately, we provide step-by-step attribute identification (SAI) to guide the model on how to adjust the attributes. LLM may struggle to measure numerical attributes such as *extractiveness* or the *length* ratio. Therefore, we instruct the model on how to measure the attribute step-by-step so that it can revise its previously generated summary precisely.

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5.2 Self-explanation guidance

After the identification phase, we provide selfexplanation guidance (SEG) to the model, guiding the model to explain why it initially failed to control the attributes. This mirrors how humans solve complex problems by reviewing their mistakes to improve future responses. Building on this, in the next iteration, the document (d), initial instruction (i), and previously generated summary (s')are provided as inputs, along with SAI and SEG. Despite LLMs being known to struggle with numberrelated tasks (Akhtar et al., 2023; Imani et al., 2023), our guidance helps the model effectively control numerical attributes by self-explaining its miscalculations before generating summaries, especially when combined with the step-by-step attribute identification phase. We introduce GTE as a framework that integrates step-by-step attribute identification and self-explanation guidance.

5.3 Overall process

By receiving [d; i, s'; SAI; SEG] as input, the model first reflects on the reasons for the initial error before generating a revised summary. If the revised summary still fails to satisfy the attributes, we re-

Model	Extractiveness $(\downarrow / \downarrow)$				Length $(\downarrow / \downarrow)$				Topic(↓)	Speaker(↓)
	normal	high	full	avg	short	normal	long	avg		
Phi-3-medium-Iter Phi-3-medium-GTE	100.00% / 心 100.00% / 心	100.00% / ご 100.00% / ご	100.00% / ඊ 100.00% / ඊ	100.00% / 心 100.00% / 心	100.00% / ඊ 100.00% / ඊ	100.00% / 心 100.00% / 心	100.00% / ひ 100.00% / ひ	100.00% / 心 100.00% / 心	38.08% / 0.22 37.97% / 0.04	
Llama3-8B-Iter	100.00% / 🖱	100.00% / 心	100.00%/心	100.00% / 心	100.00% / 心	100.00% / 🖱	100.00% / 🖱	100.00% / 心	57.14% / 0.12	-
Llama3-8B-GTE	12.63% / 3.52	11.63% / 2.53	0.00% / 1.46	11.70% / 3.26	26.40% / 3.08	10.92% / 2.26	13.18% / 3.85	14.99% / 2.80	25.56% / 0.91	-
Llama3-70B-Iter	54.82% / 8.44	37.21% / 7.47	2.70% / 3.78	49.91% / 8.05	18.40% / 6.58	54.61% / 10.42	67.44% / 12.00	49.36% / 8.24	0.00% / 0.24	-
Llama3-70B-SAI	26.55% / 6.57	18.60% / 7.81	0.00% / 1.86	24.14% / 6.52	4.80% / 5.42	2.73% / 3.81	10.85% / 4.84	5.12% / 4.39	0.00% / 0.10	-
Llama3-70B-GTE	0.21% / 3.28	0.00% / 2.83	0.00% / 1.50	0.18% / 3.22	0.00% / 1.10	0.00% / 1.61	2.32% / 3.14	0.55% / 1.90	0.00% / 0.01	-
GPT-3.5-Iter	45.18% / 9.80	60.47% / 0.00	94.59% / 0.00	49.73% / 9.80	53.60% / 0.00	80.89% / 0.00	88.37% / 0.00	76.42% / 0.00	0.00% / 0.00	-
GPT-3.5-GTE	17.56% / 3.86	51.16% / 5.00	67.57% / 4.00	23.58% / 3.90	5.60% / 4.63	44.03% / 6.62	78.29% / 7.00	43.33% / 5.95	0.00% / 0.00	-
GPT-4o-Iter	34.69% / 6.77	55.81% / 0.00	78.38% / 3.00	39.31% / 6.63	72.00% / 0.00	64.85% / 0.00	79.07% / 0.00	69.84% / 0.00	0.38% / 0.02	-
GPT-4o-SAI	35.12% / 5.50	48.84% / 15.50	62.16% / 6.00	38.03% / 6.13	60.00% / 8.79	61.09% / 9.40	78.29% / 2.00	64.90% / 8.60	0.00% / 0.04	-
GPT-4o-GTE	0.00% / 2.76	0.00% / 4.70	0.00% / 2.03	0.00% / 2.87	0.00% / 1.20	0.00% / 1.21	0.00% / 1.96	0.00% / 1.42	0.00% / 0.02	-

Table 4: The results of controllability measured on the MACSum_{Doc} dataset. The bold denotes the best performance.

Model		Extractive	ness $(\downarrow / \downarrow)$		Length $(\downarrow / \downarrow)$				Topic (↓)	Speaker (↓)
hibdei	normal	high	fully	avg	short	normal	long	avg		
Llama3-70B-Iter	31.78% / 8.13	43.59% / 8.40	8.16% / 5.39	29.63% / 7.59	12.00% / 🖱	93.75% / 6.00	98.00% / ⁽)	81.79% / 6.00	0.00% / 0.01	0.00% / 0.00
Llama3-70B-SAI	14.41% / 5.91	23.08% / 5.31	0.00% / 3.72	13.27% / 5.50	0.00% / 1.25	62.05% / 5.70	92.00% / 9.33	57.10% / 5.62	0.00% / 0.02	0.00% / 0.00
Llama3-70B-GTE	0.00% / 2.31	0.00% / 2.56	4.08% / 3.64	0.61% / 2.49	0.00% / 1.00	36.61% / 4.73	80.00% / 5.70	37.65% / 4.53	0.00% / 0.01	0.00% / 0.00
GPT-4o-Iter	79.24% / 4.36	82.05% 3.67	59.18% / 1.00	76.54% / 4.00	6.00% / 🖱	98.21% / Č	100.00% / 心	84.26% / 🖱	0.31% / 0.01	0.00% / 0.00
GPT-4o-SAI	84.75% / 4.00	87.18% 1.50	53.06% 5.10	80.25% / 4.32	2.00% / 4.50	96.43% / 🖱	100.00% / 🖱	82.41% / 4.50	0.00% / 0.01	0.00% / 0.00
GPT-40-GTE	17.80% / 7.94	25.64% / 7.92	8.16% / 4.58	17.28% / 7.53	0.00% / 1.40	9.82% / 2.75	44.00% / 4.21	13.58% / 2.90	0.00% / 0.02	0.00% / 0.00

Table 5: The results of controllability measured on the MACSum_{Dial} dataset.

peat the GTE process until the model generates an attribute-aligned summary. In Figure 1, we illustrate in detail how the GTE framework actually operates. If the initial draft fails to properly adjust an attribute, we first provide a step-by-step guide on how to measure the attribute. Then, we guide the model to explain the miscalculation and regenerate the summary. As intended, the model mimics step-by-step attribute identification, reflects on the summary based on the identification feedback, and generates an improved summary.

6 Experimental setup

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We evaluate the controllability of various LLMs, including Phi-3-medium (Abdin et al., 2024), Llama3 series (Dubey et al., 2024), and GPT series (Brown, 2020; Achiam et al., 2023). To analyze model performance by size, we utilize both the 8B¹ and quantized 70B versions ² of Llama3, as well as GPT-3.5 and GPT-40. We use BERTScore (Zhang et al., 2020) ³ to measure embedding similarity.

We used two datasets for our experiments: MACSum_{Doc} and the MACSum_{Dial} datasets (Zhang et al., 2023b), which comprise committee meeting transcripts and news contents, respectively. Both datasets are designed for mixed-attribute summarization that controls multiple attributes simultaneously. Notably, only MACSum_{Dial} has *speaker* attribute. Since we evaluate LLM performance on individual attributes, we use attributes separately.

7 Results and Discussions

Main results We denote the naive iteration approach, which repeatedly adjusts attributes, as Iter. The strategy that only provides step-bystep attribute identification is defined as SAI, while our full guiding framework is referred to as GTE. As shown in Table 4, our GTE demonstrate remarkably lower failure rates and require fewer iterations when adjusting summaries across all attributes, including challenging numerical attributes in MACSum_{Doc}. Surprisingly, our method reduced the failure rate to nearly 0% when applied to Llama3-70B and GPT-40, successfully controlling both extractiveness and length within just 1-3 iterations. For smaller models such as Phi-3-medium and Llama3-8B, which initially exhibited high failure rates, our approach significantly reduced their failure rates, demonstrating its effectiveness across different model scales. In particular, for long length, the most challenging attribute, our method achieved a remarkably low failure rate of just 2.32% within an average of 3.14 iterations.

LLMs encounter more difficulties with the MACSum_{Dial} dataset (Table 5). The dataset, which is derived from QMSum (Zhong et al., 2021), consists of lengthy and diverse content parliamentary and committee meetings, making it more challenging compared to the CNN-news-based MACSum_{Doc}. Notably, length control proved to be

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¹meta-llama/Meta-Llama-3-8B-Instruct

²casperhansen/llama-3-70b-instruct-awq

³https://github.com/Tiiiger/bert_score

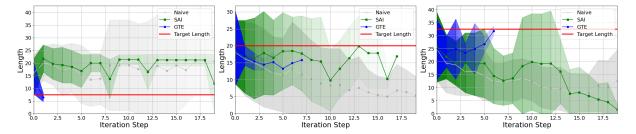


Figure 2: The graphs show how the length changes for each iteration. The intensity of the distribution color is proportional to the number of data points, and the markers represent the average values. The red line indicates the target length, with values of 7.5, 20, and 32.5 from left to right.

the most challenging attribute in the MACSum_{Dial} 458 dataset. This difficulty is likely due to the original 459 dataset being a lengthy parliamentary corpus, mak-460 461 ing it inherently challenging to generate summaries of a specific length. While the model handled short-462 length summaries well, the difficulty increased sig-463 nificantly as the requested summary length grew. 464 In fact, for long length, both GPT-4o-Iter and 465 GPT-4o-SAI showed a 100% failure rate. However, 466 our framework meaningfully improved length con-467 trollability. With GPT-40, the average failure rate 468 dropped below 50%. Especially, for normal-length 469 summaries, the failure rate further reduced from 470 over 90% to 9.82%. Regarding extractiveness, the 471 Iter and SAI of GPT-40 exhibit relatively low it-472 eration count since the models mostly exceed the 473 maximum iteration. While they fail nearly 80%, 474 our GTE demonstrates a markedly lower failure 475 rate at 17.28% with low iterations, demonstrating 476 the effectiveness of our framework. 477

Gradual change across iteration steps To an-478 alyze how attribute changes each step, we track 479 *length* adjustments per iteration (Figure 2). While 480 all methods start with a similar distribution at the 481 482 initial points, GTE consistently converges within approximately three iterations, maintaining a sta-483 ble length adjustment pattern across samples. In 484 contrast, Iter and SAI show inconsistent changes 485 across samples, leading higher variance in length 486 changes. This demonstrates that our method en-487 ables robust attribute control with fewer iterations, 488 regardless of the data sample. For the experiment, 489 we utilize Llama3-70B and randomly selected 110 490 samples from the MACSum_{Doc} test set. 491

492 Attribute types We observe that LLMs control
493 linguistic attributes (*topic* and *speaker*) better than
494 numerical attributes (*extractiveness* and *length*).
495 This aligns with previous research in mathemat496 ical reasoning, where LLM struggle with numer-

ical features (Akhtar et al., 2023), highlighting a broader challenge in precisely handling numerical constraints. From the perspective of the summarization task, *extractiveness* and *length* control the structure of the summary, whereas *topic* and *speaker* control its contents. Our findings suggest that LLMs are proficient at adjusting content to align with user preferences, but they struggle to generate summaries in a desired structural format.

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Quality of controlled summary We evaluate the quality of summaries generated by GTE. We mainly use UniEval (Zhong et al., 2022) and QuestEval (Scialom et al., 2021), as they highly correlate with human judgement and assess the overall quality of the summary itself. UniEval is a multi-dimensional evaluator that assesses coherence, consistency, fluency, and relevance of summaries. QuestEval measures precision and recall by leveraging question answering framework to compare the content between the source document and the generated summary without relying on the reference summary. Table 6 shows that our method's summaries outperform across all UniEval dimensions and QuestEval, demonstrating effective attribute control while maintaining overall summary quality. *Relevance* assesses how well a summary retains key information compared to the reference. While Iter and SAI generate misaligned summaries with lower relevance scores, GTE effectively aligns them, leading to a substantial gain.

Although previous studies have shown that ROUGE scores (Lin, 2004) are insufficient for assessing summary quality (Scialom et al., 2021; Zhong et al., 2022; Ryu et al., 2024a), and given that our goal is to control the summary rather than make it similar to the reference, we still include ROUGE and BERTScore (Zhang et al., 2020) in our evaluation to provide clearer assessment. Our framework exhibits higher scores than other ap-

Model		ι	JniEval	OuestEval	BERTScore	ROUGE-1			
moder	Coherence	Consistency	Fluency	Relevance	Overall				
Iter (Ext)	0.820	0.800	0.859	0.696	0.794	0.523	0.826	0.194	
SAI (Ext)	0.884	0.843	0.905	0.785	0.864	0.554	0.848	0.229	
Iter (Len)	0.836	0.803	0.836	0.759	0.808	0.484	0.829	0.235	
SAI (Len)	0.934	0.834	0.942	0.887	0.899	0.548	0.867	0.270	
GTE (Ext)	0.941	0.873	0.937	0.880	0.908	0.590	0.861	0.236	
GTE (Len)	0.937	0.840	0.944	0.901	0.905	0.553	0.868	0.272	

Table 6: Quality of the controlled summaries.

proaches, demonstrating through various evaluation metrics that GTE not only enhances controllability, but also improves overall summary quality.

8 Mixed attributes

We extend our evaluation to assess whether LLMs 540 could precisely handle mixed-attribute control. 541 While models manage to control linguistic at-542 tributes but struggle with numerical attributes. Si-543 multaneous control over all attributes remains challenging for all iterative methods, including GTE. Our GTE framework guides LLMs to identify the 546 causes of their errors and regenerate summaries by incorporating this feedback. However, in a mixed attribute setting, the model needs to handle multiple SAI and GS for each attribute simultaneously, increasing the cognitive load and making precise 551 control of all attributes more challenging. There-552 553 fore, unlike single-attribute evaluation, which assesses whether attributes are precisely controlled, 554 we evaluate mixed-attribute control by measuring 555 errors using root mean squared error (rMSE). We compare the error between the attributes of the gen-557 erated summary and the requested values, provid-558 ing a more flexible evaluation of attribute control. 559

Sequential-planning Discovering the challenges 560 561 in precisely controlling all attributes simultaneously, we introduce a sequential planning strategy, 562 min-planning, which gradually adjusts attributes 563 from the ill-controlled with the initial draft using 564 GTE. Figure 3 shows the results comparing single 565 attribute control with iterations to mixed-attribute control using min-planning on the MACSum_{Doc} dataset. We refer to the initial summary in the mixed-attribute control as the mixed-draft. The min-planning method shows a modest improve-571 ment in controlling both attributes compared to the mixed-draft. Attributes are still not fully controlled compared to single-attribute models, highlighting 573 the challenge of balancing multiple attributes. We anticipate that modifying one attribute often dis-575

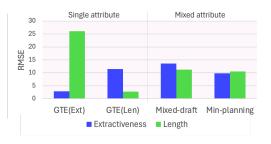


Figure 3: Performance in mixed-attribute.

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rupts previously adjusted attributes due to correlations. For example, even if *length* is adjusted first, it may still change when *extractiveness* is controlled. Additionally, *min-planning* only adjusts each attribute once without iterations, which may account for its failure to fully control the attributes. A single refinement is often insufficient to control all attributes, whereas GTE iteratively regenerates the summary until the attribute is successfully adjusted in single-attribute control. Exploring ways for LLMs to control multiple attributes simultaneously would be promising future work.

9 Conclusion

In this work, we systematically explore the controllability of LLMs. To this end, we revisit the measurement of various attributes. We evaluate the controllability of LLMs via iterative assessment, finding that LLMs struggle more with numeric attribute control than linguistic attributes. To address this, we propose a guide-to-explain (GTE) approach, where the model is guided to explain its misalignments through attribute identification and then grounds this explanation to generate better-controlled summaries in subsequent iterations. GTE enables LLMs to control challenging numerical attributes with lower failure and fewer iterations. Furthermore, we demonstrate the high quality of controlled summaries using various generic summarization evaluation metrics.

605 Limitation

We explore the controllability of various attributes in LLMs and introduced a novel guide-to-explain 607 (GTE) framework to address challenges in numerical attributes. While GTE enhanced successfully control over challenging numerical attributes, it still struggled with highly correlated mixed numer-611 ical attributes. Additionally, min-planning, which 612 adjusts attributes in order of least alignment, also faced difficulties achieving precise control. Even after properly adjusting one attribute, modifying 615 the correlated numerical attribute caused the pre-616 viously adjusted attribute to change. We believe 617 further research could explore more effective meth-618 ods for addressing these challenges. 619

Ethics

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We used publicly available MACSum datasets for our research, conducting experiments with Phi-3, Llama3⁴, GPT-3.5, and GPT-40 from April to October 2024.

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B Guide-to-explain (GTE) prompts 915

Α

(CNN)Easter is unique on the Christian calendar, a major point in the cycle of the religious year, and one that has always been able to resist the commercialization and culture warring that surrounds Christmas. That's in part because Easter is genuinely about how religious impulses, and patterns, can operate in ways that affect our lives. Nevertheless, I'm often surprised by how little people, even those supposedly within the Christian tradition, actually know about what is called Holy Week and its culmination on Easter Sunday. At a time when our culture is roiled by questions of identity and ethics (and tolerance) that have profound religious implications, it's worth pausing to explore this crucial holiday -- and the awareness of the human condition, in all its sadness and glory, that it engenders. After all, Holy Week calls mostly to those who incline their minds and hearts in its direction with seriousness of intent.

Initial prompt

summarize the above article in 32.5% length of the article:

Summary (16.9%)

Easter is a significant Christian holiday that often gets overlooked, especially when compared to Christmas. Nearly everyone within the Christian tradition knows the basics of Easter, but not many understand the full significance and rituals of Holy Week and the Easter Triduum, which are three days of prayer that begin on Good Friday and end on Easter Sunday. Holy Communion originated from the Last Supper, a Passover meal that Jesus shared with his disciples before being crucified. On Maundy Thursday, Jesus washed the disciples' feet to demonstrate humility...

GTE

The length (word count) of the summary is 157 and the length of the article is 931, so it is approximately 16.9%. Explain why your calculation is wrong, and revise the summary in the 32.5% length of the article:

Revised Summary (29.4%)

The calculation is wrong because the article length is 931 words, and the summary length is 157 words. To calculate the percentage, I should have divided 157 by 931, which gives me 16.9%. This means the summary is only 16.9% of the original article, not 32.5%.

evise the summary to reach 32.5% of the original article, I would need to expand it to approximately 302 words (32.5% of 931). Here is a revised summary:

Easter is a significant Christian holiday that often gets overlooked, especially when compared to Christmas. Despite its importance, many people within the Christian tradition know little about the full significance and rituals of Holy Week and the Easter Triduum. This three-day period of prayer begins on Good Friday, commemorating Jesus' crucifixion, and concludes on Easter Sunday, celebrating his resurrection...

Figure 4: Length guide-to-explain (GTE).

Article

(CNN)Easter is unique on the Christian calendar, a major point in the cycle of the religious year, and one that has always been able to resist the commercialization and culture warring that surrounds Christmas. That's in part because Easter is genuinely about how religious impulses, and patterns, can operate in ways that affect our lives. Nevertheless, I'm often surprised by how little people, even those supposedly within the Christian tradition, actually know about what is called Holy Week and its culmination on Easter Sunday. At a time when our culture is rolled by questions of identity and ethics (and tolerance) that have profound religious implications, it's worth pausing to explore this crucial holiday -- and the awareness of the human condition, in all its sadness and glory, that it engenders. After all, Holy Week calls mostly to those who incline their minds and hearts in its direction with seriousness of intent. Still, the fuss must puzzle those looking on, wondering what it all means. Why do Christians make so much of this springtime week, and make so much of Easter weekend? There is a phrase that many never come across, even among Christians: Easter Triduum. This refers to the three days of Easter that begin with Good Friday, proceed through Holy Saturday, and conclude with Easter Sunday. It's definitely a progression, although the word itself -- triduum -- can refer to any three days of prayer...

Initial prompt

summarize the above article in 32.5% length of the article:

Summary (16.9%)

Easter is a significant Christian holiday that often gets overlooked, especially when compared to Christmas. Nearly everyone within the Christian tradition knows the basics of Easter, but not many understand the full significance and rituals of Holy Week and the Easter Triduum, which are three days of prayer that begin on Good Friday and end on Easter Sunday. Holy Communion originated from the Last Supper, a Passover meal that Jesus shared with his disciples before being crucified. On Maundy Thursday, Jesus washed the disciples' feet to demonstrate humility...

SAI

The length (word count) of the summary is 157 and the length of the article is 931, so it is approximately 16.9%. Summarize the above article in the 32.5% length of the article:

Revised Summary (23.4%)

Easter, a significant Christian holiday, remains untouched by commercialization and culture wars. Many people, including Christians, are unfamiliar with Holy Week and its culmination on Easter Sunday. The Easter Triduum, a three-day period, begins with Maundy Thursday, where Jesus shared the Last Supper with his disciples, demonstrating his humility by washing their feet. Good Friday, the day of the crucifixion, is a somber reminder of death, sacrifice, and fear. The Gospels provide varying accounts of Jesus' final words, including his quote from the 22nd Psalm. Holy Saturday, often overlooked, serves as a passage between the darkness of Good Friday and the hope of Easter Sunday. It's a day of anxiety and uncertainty, when the pain of the crucifixion still lingers, but hope begins to emerge. Easter Sunday, with its promise of transformation and resurrection, is a celebration of the human experience. The resurrection is not just a physical revival but a total transformation, symbolizing the possibility of change and renewal in our own lives...

Figure 5: Length attribute-identification (SAI).

(CNN)Easter is unique on the Christian calendar, a major point in the cycle of the religious year, and one that has always been able to resist the commercialization and culture warring that surrounds Christmas. That's in part because Easter is genuinely about how religious impulses, and patterns, can operate in ways that affect our lives. Nevertheless, I'm often surprised by how little people, even those supposedly within the Christian tradition, actually know about what is called Holy Week and its culmination on Easter Sunday. At a time when our culture is rolled by questions of identity and ethics (and tolerance) that have profound religious implications, it's worth pausing to explore this crucial holiday -- and the awareness of the human condition, in all its sadness and glory, that it engenders. After all, Holy Week calls mostly to those who incline their minds and hearts in its direction with seriousness of intent. Still, the fuss must puzzle those looking on, wondering what it all means. Why do Christians makes om uch of this springtime week, and make so much of Easter Weekend? There is a phrase that many never come across, even among Christians: Easter Triduum. This refers to the three days of Easter that begin with Good Friday, proceed through Holy Saturday, and conclude with Easter Sunday. It's definitely a progression, although the word itself -- triduum -- can refer to any three days of prayer...

Initial prompt

summarize the above article in 32.5% length of the article:

Summary (16.9%)

Easter is a significant Christian holiday that often gets overlooked, especially when compared to Christmas. Nearly everyone within the Christian tradition knows the basics of Easter, but not many understand the full significance and rituals of Holy Week and the Easter Triduum, which are three days of prayer that begin on Good Friday and end on Easter Sunday. Holy Communion originated from the Last Supper, a Passover meal that Jesus shared with his disciples before being crucified. On Maundy Thursday, Jesus washed the disciples' feet to demonstrate humility...

lter)

summarize the above article in 32.5% length of the article:

Revised Summary (9.1%)

Easter is a unique Christian event that resisted commercialization. Many Christians lack understanding of Holy Week and Easter. The Easter Triduum - Good Friday, Holy Saturday, and Easter Sunday - marks death, transition, and resurrection. This pattern reflects our daily struggles, suffering, and rebirth, making Easter a celebration of moving from darkness to light.

Figure 6: Length iteration (Iter).

Article

(CNN)We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. We created a culture of such deep distrust and disrespect that violence seemed the inevitable response. We let the violence flow. We let the violence stand for everything that's wrong with the things we already didn't like. By now you may be asking, "Who's we? "You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word "we" is one of the great American words. We the People. Yes we can. We are family. I use "we" a lot when I talk about our country's achievements. I like to say we won the Second World War, we put a man on the moon, we invented the Internet, we gave the world jazz. Well, if I -- a son of immigrants whose family had nothing to do with any of those accomplishments -- if I get to claim those aspects of American history, then surely I have to claim the unsavory aspects too. "We" cuts both ways. We enslaved Africans. We cut Reconstruction short and made a mockery of equal citizenship. We supported Jim Crow, then redlined, subordinated, and ghettoized African-Americans...

Initial prompt

summarize the above article using 85% of words directly from the original document:

Summary (100.0%)

We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. By now you may be asking, "Who's we?" You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word 'we'' is one of the great American words. We the People...

GTE

This summary contains 100.0% of words directly from the original document.

Explain why your calculation is wrong, and revise the summary so that 85% of the words are used directly as in the original document:

Revised Summary (86.8%)

I apologize for the mistake. Upon re-calculating, I realized that the original summary contained /9.4% of words directly from the original documer summary to meet the 85% threshold. I'll incorporate more words directly from the original document.

"We did it again, in another American city", perpetuating a cycle of violence and chaos. "We set Baltimore on fire this time", and in doing so, "we brutalized black bodies". The author emphasizes the significance of "we", underscoring collective responsibility for both accomplishments and injustices. "We the People" implies a shared history, encompassing achievements like "we won the Second World War", "we put a man on the moon", "we invented the Internet", and "we gave the world jazz", as well as darker aspects like "we enslaved Africans", "we cut Reconstruction short and made a mockery of equal citizenship", "we supported Jim Crow, then redlined, subordinated, and ghettoized African-Americans", and "we failed"...

Figure 7: Extractiveness guide-to-explain (GTE).

(CNN)We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. We created a culture of such deep distrust and disrespect that violence seemed the inevitable response. We let the violence flow. We let the violence stand for everything that's wrong with the things we already didn't like. By now you may be asking, "Who's we? "You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word "we" is one of the great American words. We the People. Yes we can. We are family. I use "we" a lot when I talk about our country's achievements. I like to say we won the Second World War, we put a man on the moon, we invented the Internet, we gave the world jazz. Well, if I -- a son of immigrants whose family had nothing to do with any of those accomplishments -- if I get to claim those aspects of American history, then surely I have to claim the unsavory aspects too. "We" cuts both ways. We enslaved Africans. We cut Reconstruction short and made a mockery of equal citizenship. We supported Jim Crow, then redlined, subordinated, and ghettoized African-Americans...

Initial prompt

summarize the above article using 85% of words directly from the original document:

Summary (100.0%)

We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. By now you may be asking, "Who's we?" You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word "we" is one of the great American words. We the People...

SAI

This summary contains 100.0% of words directly from the original document.

Summarize the above article using 85% of the words directly from the original document:

Revised Summary (78.0%)

Here's a rewritten summary that meets the 85% requirement:

We allowed Baltimore to burn, brutalizing black bodies and turning a funeral into a riot. We created chaos, replaying the images and fostering a culture of distrust and disrespect. When asked "Who's we?", some may object, saying "Don't lump me in with them." But the truth is, we as a nation are responsible. The word "we" is synonymous with American identity. If we claim America's achievements, we must also claim its dark past, including slavery and racial inequity. We are the authors of Baltimore's story, and it's our responsibility to address the problem. We can't just point to individual faults or structural flaws; we must acknowledge both. It's time to put aside our differences, acknowledge the truth, and work together to create opportunity and change.

Figure 8: Extractiveness attribute-identification (SAI).

Article

(CNN)We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. We created a culture of such deep distrust and disrespect that violence seemed the inevitable response. We let the violence flow. We let the violence stand for everything that's wrong with the things we already didn't like. By now you may be asking, "Who's we? "You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word "we" is one of the great American words. We the People. Yes we can. We are family. Luse "we" a lot when I talk about our country's achievements. I like to say we won the Second World War, we put a man on the moon, we invented the Internet, we gave the world jazz. Well, if I -- a son of immigrants whose family had nothing to do with any of those accomplishments -- if I get to claim those aspects of American history, then surely I have to claim the unsavory aspects too. "We" cuts both ways. We enslaved Africans. We cut Reconstruction short and made a mockery of equal citizenship. We supported Jim Crow, then redlined, subordinated, and ghettoized African-Americans...

Initial prompt

summarize the above article using 85% of words directly from the original document:

Summary (100.0%)

We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. By now you may be asking, "Who's we?" You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word "we" is one of the great American words. We the People...

Iter

Summarize the above article using 85% of the words directly from the original document:

Revised Summary (100.0%)

We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. The word "we" is one of the great American words. We the People. I use "we" a lot when I talk about our country's achievements. Well, if I get to claim those aspects of American history, then surely I have to claim the unsavory aspects too. "We" cuts both ways. We enslaved Africans. We cut Reconstruction short and made a mockery of equal citizenship. We supported Jim Crow, then redlined, subordinated, and ghettoized African-Americans. We cut blacks out of the New Deal. We created a polity in which racial inequity and economic inequality magnify each other unrelentingly. We tried to put a lid on it with heavy policing and a War on Drugs. We failed...

Figure 9: Extractiveness iteration (Iter).

(CNN)Prison life won't be pretty for Aaron Hernandez, the former NFL player and convicted murderer sentenced to life without parole. After correction officers evaluate him, he will be shipped to Massachusetts' flagship maximum-security prison, one of the most high-tech jails in the United States with no history of breakouts: the Souza-Baranowski Correctional Center in Shirley, about 40 miles outside downtown Boston. It's called Souza, for short, and it's the state's newest prison, opened in 1998, with a matrix of 366 cameras recording live 24 hours a day and a microwave detection perimeter withtaut wire."I don't know the date, but he'll be going there. That's the maximum-security facility," Department of Corrections spokesman Darren Duarte said. Legal advocates for inmates describe Souza as sterile and violent at once. Its diverse demographic includes the young and the old, many of whom are also doing life. One stubborn problem is that opiates are smuggled to inmates, the legal advocates said."It's very shiny and clean looking and very sterile," said Leslie Walker, executive director of Prisoners' Legal Services of Massachusetts, who has been visiting the Souza prison about every six weeks for the past 15 years and serves indigent prisoners there. But, she added: "It is a very dangerous prison that is right now experiencing a veritable flood of opiates."...

Initial prompt

summarize the above article focusing on hernandez:

Summary (72.6)

We did it again, in another American city. We set Baltimore on fire this time. We brutalized black bodies. We turned a funeral into a riot. We let things get out of hand. We looted. We threw stones at policemen. We threw stones at citizens. We created camera-ready chaos, and we replayed the images. By now you may be asking, "Who's we?" You may be saying with some irritation, "Don't lump me in with them. I didn't have anything to do with it." To which the only real answer can be: Stop kidding yourself. The word "we" is one of the great American words. We the People...

GTE

The similarity between this summary and the topic hernandez is 72.6, so this summary is not centered around the topic hernandez. Explain why you were unable to summarize around the topic, and revise the summary to center around the topic hernandez:

Revised Summary (76.7%)

+I was unable to summarize around the topic hernandez because the original article provided a lot of context about the prison system and the conditions that hernandez will face, but did not provide much information that is specific to hernandez himself. The article does not delve into hernandez's thoughts, feelings, o personal experiences, and instead focuses on the general details of his situation.

Here is a revised summary that centers around the topic hernandez

Aaron Hernandez, the former NFL player and convicted murderer, is facing a harsh reality as he begins his life sentence without parole. After being convicted, Hernandez was immediately transferred to the Massachusetts Correctional Institution-Cedar Junction in Walpole, where he will be processed before being sent to the Souza-Baranowski Correctional Center in Shirley. As a high-profile inmate, Hernandez's safety will be a concern for prison officials, who may need to take measures to protect him from other inmates or gang members. Despite his celebrity status, Hernandez will face harsh conditions, including being locked in his cell for 19 hours a day.

Figure 10: Topic guide-to-explain (GTE).