

# Confidence Leaps in LLMs: Enabling Early Stopping and Cross-Model Reasoning Transfer

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## Abstract

We challenge the assumption that large language models (LLMs) build confidence gradually while reasoning. Instead, we find that confidence often appears in a discrete “moment of insight”, a sharp increase in the probability of the correct answer, which we call a confidence leap. Leveraging this finding, we introduce a training-free, model-agnostic early-stopping heuristic. When a confidence leap is present, we can halt the generation, reducing reasoning tokens by up to 31% without accuracy loss. We further show that the reasoning preceding a leap is semantically transferable: providing this partial reasoning to a different model family substantially improves its accuracy. These results suggest that confidence leaps mark shared, interpretable reasoning milestones rather than model-specific artifacts.

## 1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in multi-step reasoning, largely driven by techniques like Chain-of-Thought (CoT) prompting (Wei et al., 2022). By generating intermediate reasoning steps, LLMs can decompose complex problems and arrive at more accurate solutions. However, the internal dynamics of how confidence evolves during this reasoning process remain poorly understood.

A common assumption is that model confidence builds gradually as the reasoning chain progresses. In this work, we challenge this view and argue that conviction is often not reached through gradual accumulation, but through a discrete “confidence leap”: a sudden and sharp increase in the probability of an answer. This “moment of insight” signals a critical juncture where the model has effectively processed the core of the problem. Understanding this phenomenon has direct implications for optimizing inference costs and interpreting reasoning mechanisms.

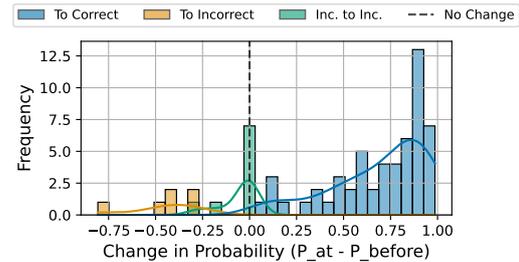


Figure 1: **Confidence Leaps**: when an LLM switches to the correct answer during reasoning, the probability of that answer jumps sharply (mean +0.69). This bimodal distribution shows that large positive leaps occur almost exclusively for correct switches, enabling a training-free early-stopping heuristic. Data: Qwen3-32B on GPQA.

Based on this discovery, we propose a simple yet powerful early-stopping heuristic. Recent efforts in this direction have explored training auxiliary classifiers on internal model activations (Fu et al., 2023; Snell et al., 2023; Chen et al., 2024; Zhang et al., 2025; Afzal et al., 2025), requiring architectural access and model-specific training, as well as answer consistency heuristics that monitor output stability across consecutive steps (Liu and Wang, 2025; Mao et al., 2025). Our training-free, model-agnostic method monitors the output probability distribution and terminates generation upon detecting a confidence leap, significantly reducing generation length while maintaining or even improving accuracy.

To further probe the nature of these leaps, we connect our work to the interpretability and transfer of reasoning traces (Lanham et al., 2023; Lampinen et al., 2024) and investigate whether they represent genuine semantic insights or are merely model-specific artifacts. We demonstrate that the reasoning text leading up to a confidence leap is transferable: feeding this partial reasoning to a model from a different family dramatically increases its likelihood of arriving at the correct answer. This

suggests that the “moment of insight” is not a statistical quirk but a portable, interpretable reasoning milestone.

Our contributions are three-fold:

- We identify and characterize “confidence leaps”, sudden leaps in answer probability that mark key moments in CoT reasoning.
- We propose an effective early-stopping heuristic based on this phenomenon that reduces computation and can improve accuracy.
- We provide evidence that the reasoning chunks causing these leaps contain transferable semantic insights, not just model-specific artifacts.

Our code and collected datasets are publicly available at <https://github.com/tikhonovpavel/confidence-leaps-in-llm>.

## 2 Data and Models

We use *GPQA* (Rein et al., 2024), a graduate-level multiple-choice benchmark, and *LogiQA* (Liu et al., 2020), a logical reasoning dataset. We collect reasoning traces from Qwen3-32B (Yang et al., 2025), QwQ-32B (QwenTeam, 2025) and DeepSeek-R1 Distill Llama-70B (Guo et al., 2025).

Similar to (Galichin et al., 2026), we segment reasoning traces into chunks by splitting on trigger words (e.g., “Wait”, “However”, “Hmm”) that signal reasoning shifts. A new chunk begins when a paragraph starts with a trigger word, yielding a sequence  $C_1, C_2, \dots, C_N$  for each trace.

For each chunk  $C_i$ , we truncate the reasoning chain, append `</think>` followed by `\boxed{}`, and extract the predicted answer and probability distribution over choices (A, B, C, D). This yields the sequence  $P_1, P_2, \dots, P_N$ .

## 3 Analysis of Reasoning Dynamics

We analyze how often models revise their predictions. A “change” is a modification of the predicted answer from one chunk to the next. Figure 2 shows accuracy as a function of length, broken down by number of changes.

Notably, across both datasets, a substantial fraction of examples involve at least one answer change. The most frequent type of revision is a single change.

### 3.1 The Critical Leap in Confidence

Given the prevalence of single-change traces, we now ask: *what happens within the reasoning pro-*

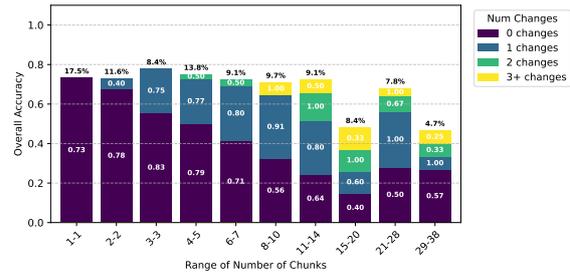


Figure 2: Accuracy vs. reasoning chain length for Qwen3-32B on GPQA, stratified by number of answer changes. Each stacked segment represents a different change category, with segment height reflecting its contribution to overall accuracy. The percentage on top of each bar shows the proportion of examples in that bin. A substantial portion of reasoning chains involve one or more changes. Similar patterns are observed for other models and datasets (see Appendix D).

*cess at the moment of this change?* To investigate this, we focus on the subset of traces with exactly one change. We define the “critical chunk” ( $k$ ) as the point of change and analyze the model’s probability distribution over the correct answer immediately before (at chunk  $k - 1$ ) and at the critical chunk ( $k$ ).

Figure 1 shows the distribution of this probability change ( $P_k(\text{correct}) - P_{k-1}(\text{correct})$ ) for Qwen3-32B on GPQA. The distribution is clearly bimodal. When the model switches *to* the correct answer, the probability change is sharply positive, with a mean of +0.69 for Qwen3-32B. Conversely, when the model switches *from* the correct answer, the change is negative. This sharp increase, which we term a “critical leap”, demonstrates that the model’s confidence in the correct answer rises dramatically and decisively upon processing the critical chunk. This bimodal distribution (Figure 1) addresses the concern that model confidence is generally a poor proxy for accuracy: massive positive leaps (mean +0.69) occur almost exclusively when the model switches to the correct answer, while switches to incorrect answers typically show negative or negligible probability changes. Similar patterns are observed for other models and on LogiQA (see Appendix A; a detailed example is provided in Appendix F).

### 3.2 Location of the Critical Leap

Having established the existence of a critical leap, a natural next question is: *where in the reasoning chain does this leap tend to occur?* We analyzed the relative position of the critical chunk ( $k/N$ )

Metric	Qwen3-32B		DeepSeek-R1		QwQ-32B	
	GPQA	LogiQA	GPQA	LogiQA	GPQA	LogiQA
Optimal Threshold ( $\tau$ )	0.81	0.56	0.21	0.26	0.56	0.46
Baseline Accuracy (%)	69.7	78.4	68.9	67.3	74.8	79.0
Heuristic Accuracy (%)	69.7	79.0	77.6	68.3	74.8	79.5
<b>Accuracy Change (%)</b>	<b>0.0</b>	<b>+0.6</b>	<b>+8.7</b>	<b>+1.0</b>	<b>0.0</b>	<b>+0.5</b>
Coverage (%)	10.6	3.5	54.0	12.9	27.6	4.7
Avg Savings (% / tokens)	31.5 / 1,323	19.2 / 625	24.2 / 876	26.4 / 468	32.7 / 1,201	28.5 / 747

Table 1: Performance of the leap heuristic at the optimal threshold across two datasets. The heuristic achieves substantial token savings (19-33%) while maintaining or even improving accuracy.

across all single-change instances. Figure 3 shows the distribution of this relative position for Qwen3-32B on GPQA. We observe that the critical chunk does not appear at a fixed location; instead, it is distributed broadly across the entire length of the reasoning chain. This pattern holds across both datasets and all models (Appendix B). It implies that any potential optimization, such as early stopping, cannot rely on a fixed-length prefix of the reasoning. The crucial insight can emerge at any point.

## 4 A Heuristic for Early Stopping

### 4.1 The Probability Leap Heuristic

The existence of a decisive probability leap motivates a simple, training-free heuristic for early stopping: terminate the reasoning process as soon as the probability for any answer choice increases by more than a predefined threshold  $\tau$  from one chunk to the next. The predicted answer is the one that experienced the leap. If no such leap occurs, the model’s final answer after the full chain is used.

### 4.2 Performance

We evaluated this heuristic across a range of thresholds. For each model, we selected the threshold that maximized overall accuracy. The results are summarized in Table 1.

The heuristic demonstrates substantial token savings across all models and datasets. For Qwen3-32B on GPQA, it achieves 31.5% reduction in reasoning tokens on a subset of samples where confidence leap is present, with no loss in accuracy. For DeepSeek-R1 on GPQA, the heuristic saves 24.2% of tokens while simultaneously *improving* accuracy by a substantial 8.7 percentage points. This suggests that for some models, later reasoning steps can be detrimental, and our heuristic effectively identifies the point at which the core insight has been reached. QwQ-32B demonstrates consistent

savings of around 30% across both datasets. Similar patterns are observed on LogiQA, with token savings ranging from 19% to 28% alongside modest accuracy improvements. A visualization of this trade-off for DeepSeek-R1 on GPQA is shown in Figure 4. Additional visualizations for all models and datasets are provided in Appendix C. A concrete example of a reasoning trace and its segmentation is provided in Appendix F.

## 5 Transferability of Reasoning

Having identified critical chunks that precipitate answer changes, we now ask: *do these chunks contain model-specific computational artifacts, or do they encode semantic insights that can transfer across model families?* To answer this question, we conduct a cross-model transfer experiment, providing reasoning chains from a source model (Qwen3-32B) to a target model from a different architecture (gpt-oss-20b).

### 5.1 Experimental Setup

We select the subset of traces with exactly one answer change from Qwen3-32B. For each trace, we extract the reasoning chunks  $C_1, \dots, C_N$  and identify the critical chunk index  $k$ . We then con-

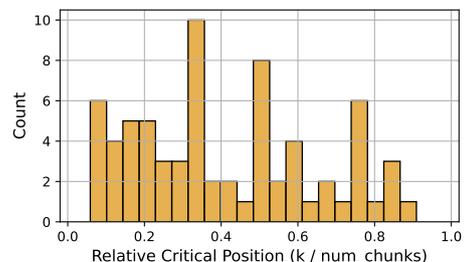


Figure 3: Distribution of the relative position of the critical chunk for Qwen3-32B on GPQA. The leap in confidence can happen at nearly any point in the reasoning process.

Table 2: Accuracy and agreement of gpt-oss-20b when provided with reasoning chains from Qwen3-32B.

Scenario	Direct Transfer		With Continuation	
	Accuracy (%)	Agreement (%)	Accuracy (%)	Agreement (%)
At pre-pre-critical chunk ( $k - 2$ )	33.33	35.71	42.86	40.48
At pre-critical chunk ( $k - 1$ )	41.79	44.78	56.72	58.21
<b>At critical chunk (<math>k</math>)</b>	<b>70.59</b>	<b>88.24</b>	72.46	84.06

struct prompts for the target model by including the original question followed by varying amounts of the source model’s reasoning. The target model is then forced to produce an answer by appending a special stopping sequence that terminates the reasoning process.

We evaluate six scenarios that test both direct information transfer and the target model’s ability to build upon partial reasoning:

- **Direct transfer scenarios:** Provide reasoning up to chunk  $k - 2$ ,  $k - 1$ , or  $k$ , then immediately force an answer.
- **Continuation scenarios:** Provide reasoning up to chunk  $k - 2$ ,  $k - 1$ , or  $k$ , let the target model generate 128 tokens of its own reasoning, then force an answer.

## 5.2 Progressive Information Transfer

Table 2 shows the target model’s accuracy across all scenarios. We first examine the direct transfer cases. When provided with reasoning only up to chunk  $k - 2$  (two steps before the critical change), the target model achieves 33.33% accuracy. Advancing to chunk  $k - 1$  improves this to 41.79%. However, including the critical chunk  $k$  yields a dramatic increase to 70.59% accuracy.

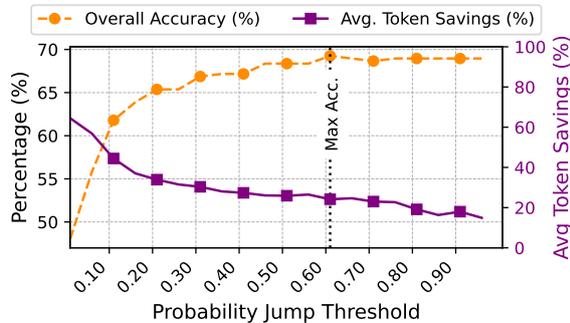


Figure 4: Performance of the leap heuristic for DeepSeek-R1 on GPQA. The plot shows overall accuracy and token savings percentage as a function of the probability leap threshold. The vertical line indicates the threshold that maximizes accuracy.

This progressive improvement demonstrates that the reasoning chain is not simply a binary “insightful or not” signal. Rather, earlier chunks lay groundwork that becomes fully actionable only when the critical chunk is present with a significant leap at chunk  $k$ .

## 5.3 The Role of Continuation

The continuation scenarios reveal two critical insights. First, when the target model is given partial reasoning and allowed to continue with its own generation, accuracy consistently improves: from  $k - 2$ , accuracy increases by +9.53 (33.33% to 42.86%); from  $k - 1$ , by +14.93 (41.79% to 56.72%); and from  $k$ , by +1.87 (70.59% to 72.46%). This consistent improvement demonstrates that the target model is *capable of continuing the reasoning trajectory initiated by a different model family*, providing strong evidence that the transferred reasoning encodes genuine semantic content rather than model-specific artifacts.

Second, and most revealing, is the asymmetry in these improvements: continuation from  $k - 1$  yields a substantial +14.93 gain, while continuation from  $k$  adds only +1.87. This dramatic reduction in the benefit of continuation suggests that chunk  $k$  is genuinely *critical*—it is self-contained and model-agnostic, already encoding the essential insight needed to reach the correct answer. Once this chunk is provided, there is little left for the target model to “fill in”, confirming that the confidence leap marks a portable reasoning milestone rather than an incomplete intermediate state.

## 5.4 Cross-Model Agreement as Evidence of Semantic Content

Beyond absolute accuracy, we measure the target model’s agreement with the source model’s final answer. At chunk  $k$ , the target model agrees with Qwen3-32B in 88.24% of cases, compared to only 44.78% at chunk  $k - 1$ . The target model becomes more accurate and converges on the *same answer* as the source model. This convergence provides strong evidence that the critical chunk encodes se-

semantic reasoning rather than model-specific computational patterns.

## 6 Conclusion

We identified “critical leaps” in confidence during LLM reasoning and leveraged them for an effective early-stopping heuristic that reduces computational cost while maintaining or improving accuracy. We showed that these critical reasoning steps transfer across model families, highlighting their semantic value and opening avenues for more efficient inference. Future work will focus on extending this framework to open-ended generation tasks, where confidence must be approximated through metrics such as entropy shifts or semantic consistency rather than discrete token probabilities. Additionally, we aim to investigate the mechanistic underpinnings of these leaps, exploring whether the behavioral “moment of insight” correlates with identifiable shifts in internal activation patterns or attention head specialization. Finally, there is significant potential in incorporating confidence dynamics directly into training objectives, potentially steering models to arrive at correct reasoning paths more efficiently.

## Limitations

Our method relies on extracting probability distributions over discrete answer choices (A, B, C, D) at each reasoning step. Consequently, it is currently applicable only to multiple-choice question answering tasks where the answer space is finite and enumerable.

Additionally, our chunking methodology depends on linguistic trigger words that signal reasoning transitions. The effectiveness of this approach may vary across languages and domains where such markers are less prevalent or have different distributions.

In future work, we plan to extend our approach to open-ended generation tasks by developing alternative confidence metrics that do not rely on discrete answer distributions.

## Ethical considerations

This study examines the working mechanisms of large language models and, therefore, does not introduce risks beyond those typically associated with natural language processing or computational linguistics research.

We utilize the GPQA dataset (Rein et al., 2024), which is licensed under the CC BY-NC 4.0 license and LogiQA (Liu et al., 2020), which is licensed under CC-BY-SA-4.0, both license suitable for research purposes.

**Use of AI Assistants** We utilize Grammarly to enhance and proofread the text of this paper, correcting grammatical, spelling, and stylistic errors, as well as rephrasing sentences. Consequently, certain sections of our publication may be identified as AI-generated, AI-edited, or a combination of human and AI contributions.

## Acknowledgements

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## A Probability Change at the Critical Chunk

This section contains figures analyzing the change in probability for the correct answer at the identified critical chunk.

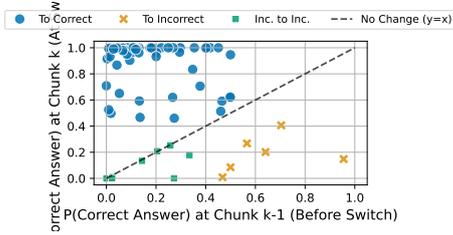


Figure 5: Scatter plot of probability change at the critical chunk for Qwen3-32B on GPQA. Points above the diagonal ( $y=x$ ) indicate probability increases.

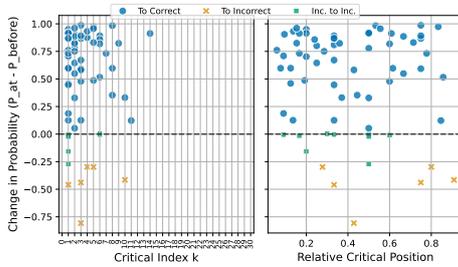


Figure 6: Probability change as a function of critical chunk position (absolute and relative) for Qwen3-32B on GPQA.

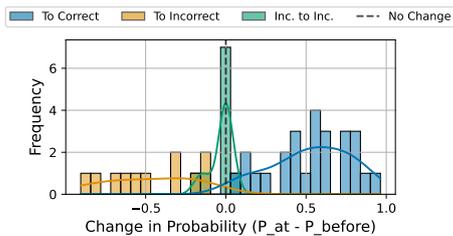


Figure 7: Distribution of probability change at the critical chunk for Qwen3-32B on LogiQA.

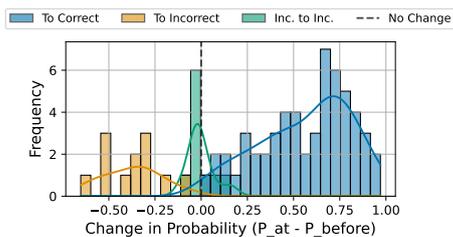


Figure 8: Distribution of probability change at the critical chunk for DeepSeek-R1 on GPQA.

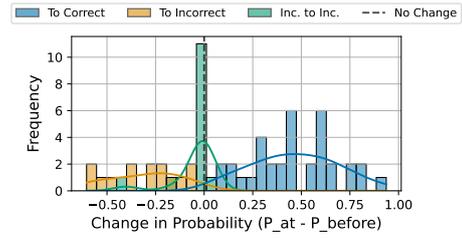


Figure 9: Distribution of probability change at the critical chunk for DeepSeek-R1 on LogiQA.

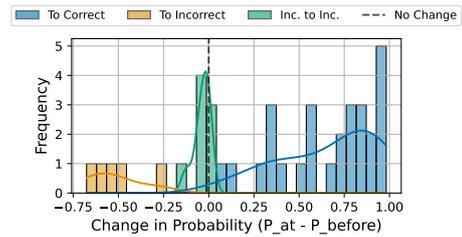


Figure 10: Distribution of probability change at the critical chunk for QwQ-32B on GPQA.

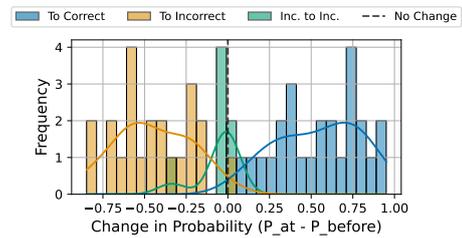


Figure 11: Distribution of probability change at the critical chunk for QwQ-32B on LogiQA.

## B Position of the Critical Chunk

This section shows the distribution of the position of the critical chunk within the reasoning trace.

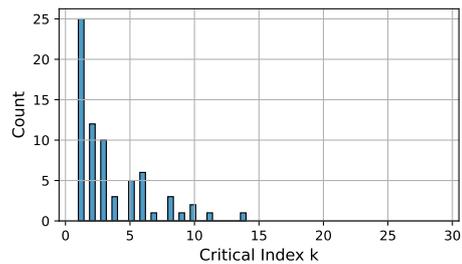


Figure 12: Distribution of the absolute position of the critical chunk for Qwen3-32B on GPQA.

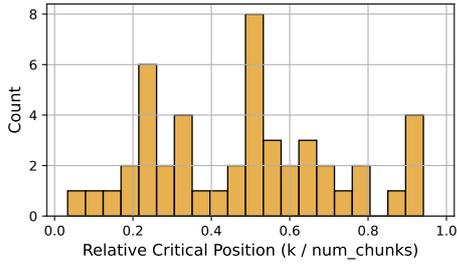


Figure 13: Distribution of the relative position of the critical chunk for Qwen3-32B on LogiQA.

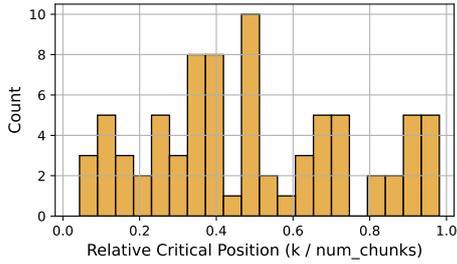


Figure 14: Distribution of the relative position of the critical chunk for DeepSeek-R1 on GPQA.

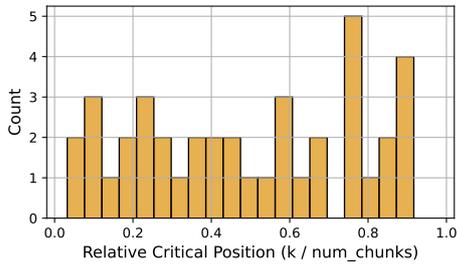


Figure 15: Distribution of the relative position of the critical chunk for QwQ-32B on GPQA.

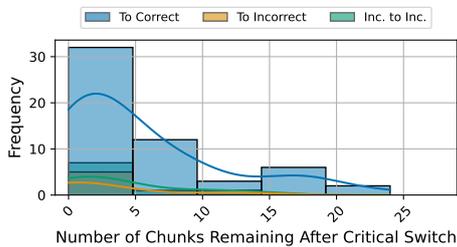


Figure 16: Distribution of chunks remaining after the critical switch for Qwen3-32B on GPQA.

### C Leap Heuristic Performance

This section evaluates the performance of the leap heuristic across all models and datasets.

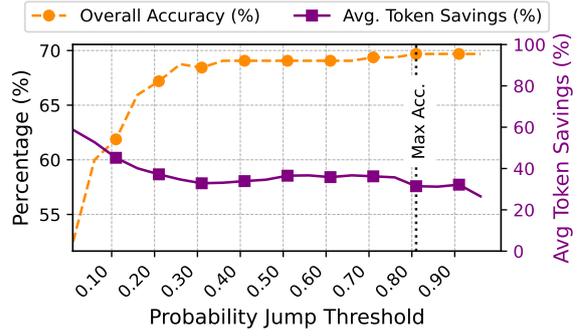


Figure 17: Performance of the leap heuristic for Qwen3-32B on GPQA.

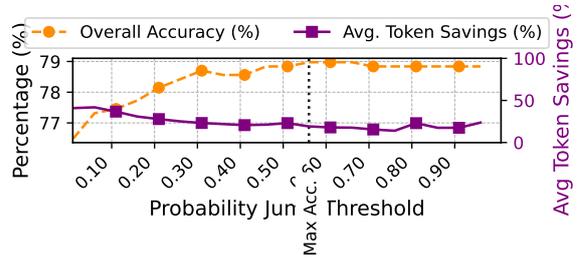


Figure 18: Performance of the leap heuristic for Qwen3-32B on LogiQA.

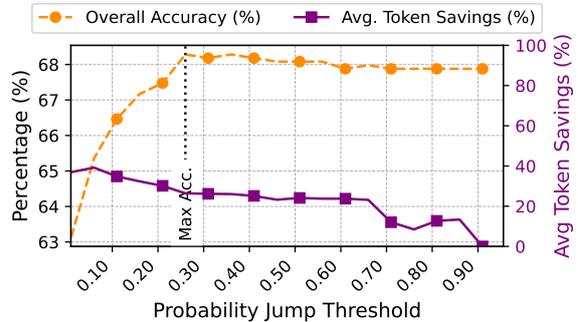


Figure 19: Performance of the leap heuristic for DeepSeek-R1 on LogiQA.

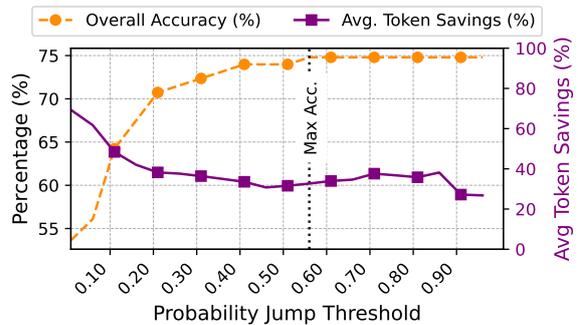


Figure 20: Performance of the leap heuristic for QwQ-32B on GPQA.

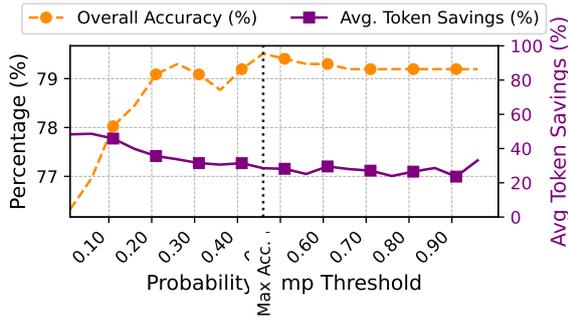


Figure 21: Performance of the leap heuristic for QwQ-32B on LogiQA.

### D Accuracy vs. Reasoning Length

This section shows the relationship between accuracy and reasoning chain length across all models and datasets, stratified by the number of answer changes.

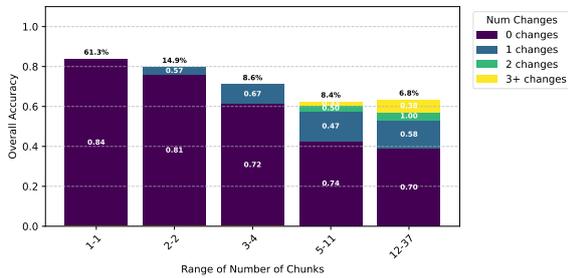


Figure 22: Accuracy vs. reasoning chain length for Qwen3-32B on LogiQA.

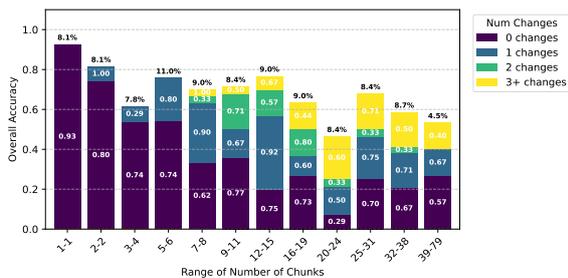


Figure 23: Accuracy vs. reasoning chain length for DeepSeek-R1 on GPQA.

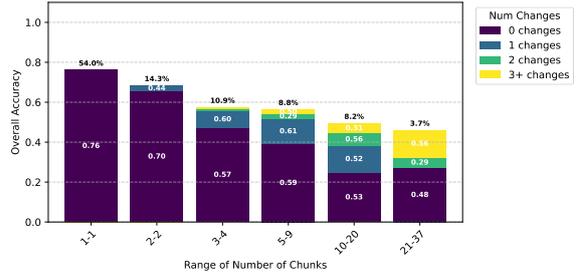


Figure 24: Accuracy vs. reasoning chain length for DeepSeek-R1 on LogiQA.

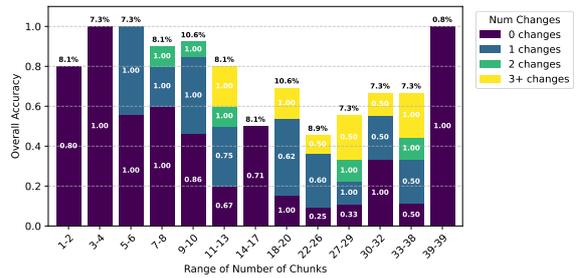


Figure 25: Accuracy vs. reasoning chain length for QwQ-32B on GPQA.

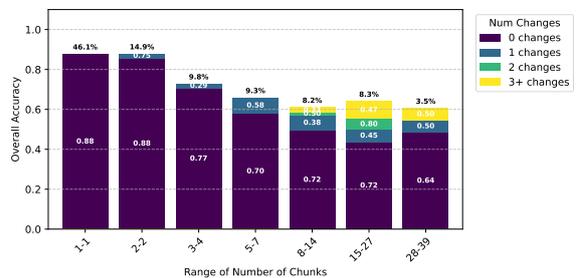


Figure 26: Accuracy vs. reasoning chain length for QwQ-32B on LogiQA.

### E Chunking Statistics

This section provides basic statistics on the chunking process, such as the number and length of chunks.

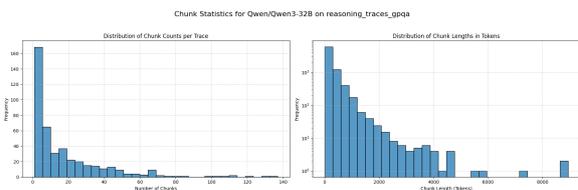


Figure 27: Distribution of chunk counts and lengths for Qwen3-32B on GPQA.

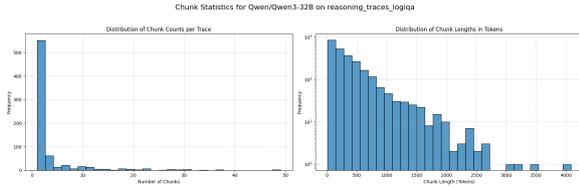


Figure 28: Distribution of chunk counts and lengths for Qwen3-32B on LogiQA.

## F Example of Reasoning Segmentation and Early Stopping

To illustrate our segmentation strategy and the potential for early stopping, we provide the full reasoning trace from Qwen3-32B solving a radioactive decay problem. The trace consists of 32 chunks. The model initially follows an incorrect reasoning path. At Chunk 14 (the “critical leap”), it identifies the correct calculation method and switches to the correct answer. It then continues to reason for another 18 chunks without changing the final answer. Our heuristic would have stopped the generation at Chunk 14, saving over 50% of the reasoning tokens.

**Question:** Imagine a radioactive nucleus  $X(Z, A)$  can decay into  $Y(Z - 2, A - 4)$  by emitting an  $\alpha$  particle with a partial half-life of 3.0 minutes.  $X(Z, A)$  can also decay into  $Q(Z + 1, A)$  by emitting a  $\beta^-$  particle with a partial half-life of 0.098 minutes. If the initial number of  $X$  nuclei was  $5 \times 10^{34}$ , then what is the activity of  $\alpha$  decay after 10 minutes? Note: here  $Z$  is the proton number and  $A$  is the mass number.

A)  $1.911 \times 10^{31}$  Bq    B) 117.555 Bq    C) 113.837 Bq    D) 3.719 Bq

*Correct Answer: D*

### Reasoning trace divided into chunks:

*Chunk 1 [Prediction: C,  $P(A)=0.344$ ,  $P(B)=0.028$ ,  $P(C)=0.567$ ,  $P(D)=0.060$ ]:*

Okay, let's see. I need to find the activity of the alpha decay after 10 minutes for the radioactive nuclei  $X$ . The initial number of  $X$  nuclei is  $5 \times 10^{34}$ . There are two decay pathways: alpha decay to  $Y$  with a partial half-life of 3.0 minutes, and beta-minus decay to  $Q$  with a partial half-life of 0.098 minutes.

First, I remember that when a nucleus can decay through multiple processes, the total decay constant is the sum of the partial decay constants. But here, the question is specifically about the activity of the alpha decay after 10 minutes. So maybe I need to consider the total half-life first?

*Chunk 2 [Prediction: C,  $P(A)=0.406$ ,  $P(B)=0.029$ ,  $P(C)=0.521$ ,  $P(D)=0.043$ ]:*

Wait, no. Partial half-life refers to the half-life for each decay mode. If there are two decay modes, the total decay constant  $\lambda_{\text{total}}$  is  $\lambda_{\alpha} + \lambda_{\beta}$ . Then, the total half-life  $T_{\text{total}}$  is  $\ln(2)/\lambda_{\text{total}}$ . But the problem is asking for the activity of alpha decay, which would be  $\lambda_{\alpha}$  multiplied by the number of remaining  $X$  nuclei after 10 minutes.

*Chunk 3 [Prediction: A,  $P(A)=0.540$ ,  $P(B)=0.013$ ,  $P(C)=0.420$ ,  $P(D)=0.027$ ]:*

But how do the partial half-lives relate to the partial decay constants? Let me think. The partial half-life for each mode is the time it would take for the number of nuclei to decrease by half if that mode were the only one acting. Therefore, each partial half-life corresponds to its own decay constant. So  $\lambda_{\alpha} = \ln(2)/T_{\alpha}$  and  $\lambda_{\beta} = \ln(2)/T_{\beta}$ .

So the total decay constant is  $\lambda_{\text{total}} = \lambda_{\alpha} + \lambda_{\beta}$ . Then, the number of  $X$  nuclei remaining after time  $t$  is  $N(t) = N_0 * e^{-(\lambda_{\text{total}} * t)}$ . But the activity of alpha decay specifically is  $A_{\alpha} = \lambda_{\alpha} * N(t)$ . Is that right?

Let me verify. If a nucleus has multiple decay modes, the probability per unit time of decaying through a specific mode is the partial decay constant for that mode. So even though the total decay is happening with  $\lambda_{\text{total}}$ , the rate of alpha decays at any time is  $\lambda_{\alpha}$  multiplied by the number of parent nuclei remaining. So yes, the approach seems correct.

So first, calculate  $\lambda_{\alpha}$  and  $\lambda_{\beta}$ . Then find the total decay constant. Then compute the remaining number of  $X$  nuclei after 10 minutes. Multiply that by  $\lambda_{\alpha}$  to get the alpha activity at that time.

Let me start by converting the half-lives into decay constants.

For alpha decay:  $T_{\alpha} = 3$  minutes. The decay constant  $\lambda_{\alpha} = \ln(2)/T_{\alpha}$ . Similarly for beta:  $T_{\beta} = 0.098$  minutes, so  $\lambda_{\beta} = \ln(2)/0.098$ .

*Chunk 4 [Prediction: A,  $P(A)=0.506$ ,  $P(B)=0.020$ ,  $P(C)=0.446$ ,  $P(D)=0.029$ ]:*

But I need to make sure the units are consistent. Since the time given (10 minutes) is in the same unit as the half-lives, maybe I can work in minutes. However, activity is usually in becquerels (Bq), which are decays per second. So I need to convert the time to seconds or adjust the units accordingly.

*Chunk 5 [Prediction: A, P(A)=0.472, P(B)=0.021, P(C)=0.472, P(D)=0.034]:*

Wait, the partial half-lives are given in minutes. Let me compute  $\lambda_{\alpha}$  and  $\lambda_{\beta}$  in per minute, then convert them to per second when calculating activity.

*Chunk 6 [Prediction: A, P(A)=0.441, P(B)=0.032, P(C)=0.343, P(D)=0.184]:*

But first, let me recall that activity  $A = \lambda N$ . So regardless of the units, if I compute  $\lambda$  in per second and  $N(t)$  in number of nuclei, then  $A$  will be in Bq.

So let me convert the half-lives to seconds.

$T_{\alpha} = 3 \text{ minutes} = 3 * 60 = 180 \text{ seconds}$ .

$T_{\beta} = 0.098 \text{ minutes} = 0.098 * 60 = 5.88 \text{ seconds}$ .

Then,  $\lambda_{\alpha} = \ln(2)/180 = 0.00385 \text{ per second}$ .

$\lambda_{\beta} = \ln(2)/5.88 = 0.1185 \text{ per second}$ .

Total decay constant  $\lambda_{\text{total}} = 0.00385 + 0.1185 = 0.12235 \text{ per second}$ .

Now, the number of  $X$  nuclei remaining after time  $t$  is  $N(t) = N_0 * e^{(-\lambda_{\text{total}} * t)}$ . The time  $t$  is 10 minutes, which is 600 seconds.

So let's compute  $N(600)$ :

$N(600) = 5e34 * e^{(-0.12235 * 600)}$ . Let me calculate the exponent first.

$0.12235 * 600 = 73.41$

Then  $e^{-73.41}$  is a very small number. Wait, that would mean almost all nuclei have decayed. But given that the half-life for beta decay is so short (0.098 minutes, which is about 5.88 seconds), the beta decay is much faster than alpha. So in 10 minutes, which is a long time compared to the beta half-life, the number of  $X$  nuclei left should be extremely small. But the question is about the activity of alpha decay after 10 minutes. Hmm.

*Chunk 7 [Prediction: C, P(A)=0.113, P(B)=0.088, P(C)=0.449, P(D)=0.349]:*

But maybe I made a mistake in the calculation. Let me check again:

$\lambda_{\alpha} = \ln(2)/T_{\alpha}$  where  $T_{\alpha}$  is 3 minutes. Let me compute it in per minute first, then convert to per second.

If I compute  $\lambda_{\alpha}$  in per minute:  $\ln(2)/3 = 0.231 \text{ per minute}$ .

Similarly,  $\lambda_{\beta}$  in per minute:  $\ln(2)/0.098 = 7.11 \text{ per minute}$ .

Total decay constant  $\lambda_{\text{total}} = 0.231 + 7.11 = 7.341 \text{ per minute}$ .

Then, the time  $t$  is 10 minutes. So  $N(t) = N_0 * e^{(-\lambda_{\text{total}} * t)} = 5e34 * e^{(-7.341 * 10)} = 5e34 * e^{-73.41}$ .

Yes, same as before. So  $e^{-73.41}$  is practically zero. So  $N(t)$  is negligible, which would imply that the activity is also negligible. But looking at the options, none of them are zero. The options given are A) a large number, B) 117, C) 113, D) 3.7. So perhaps I made a wrong assumption here.

*Chunk 8 [Prediction: C, P(A)=0.130, P(B)=0.079, P(C)=0.515, P(D)=0.276]:*

Wait, maybe the partial half-life is not the same as the total half-life. Let me recall the concept of partial half-life. In a branching decay process, the partial half-life is the reciprocal of the probability of that decay occurring. The partial decay constants add up, but the half-life is not the reciprocal of the sum. Wait, the total decay constant is the sum of the partial decay constants. So the total half-life would be  $\ln(2)/\lambda_{\text{total}}$ . However, the question is about the activity of the alpha decay after 10 minutes. But the activity of alpha decay is the rate at which alpha decays happen, which is  $\lambda_{\alpha} * N(t)$ .

*Chunk 9 [Prediction: C, P(A)=0.135, P(B)=0.072, P(C)=0.470, P(D)=0.323]:*

But if the total decay constant is  $\lambda_{\text{total}} = \lambda_{\alpha} + \lambda_{\beta}$ , then  $N(t)$  is indeed  $N_0 * e^{(-\lambda_{\text{total}} * t)}$ . However, given that the beta decay is so fast,  $N(t)$  after 10 minutes would be extremely small. But the options don't reflect that. Let me check the math again.

*Chunk 10 [Prediction: C, P(A)=0.104, P(B)=0.063, P(C)=0.468, P(D)=0.364]:*

Alternatively, maybe the problem is not considering the total decay but treating the two decay processes separately. But that doesn't make sense because the presence of both decays affects the number of remaining  $X$  nuclei.

*Chunk 11 [Prediction: C, P(A)=0.179, P(B)=0.075, P(C)=0.486, P(D)=0.260]:*

Wait, perhaps the question is using the concept of partial half-lives in a different way. Let me think. If  $X$  has two decay modes with partial half-lives  $T_1$  and  $T_2$ , then the total decay constant is  $\lambda_{\text{total}} = \lambda_1 + \lambda_2 = \ln(2)/T_1 + \ln(2)/T_2$ . Therefore, the total half-life is  $1 / ( (1/T_1 + 1/T_2) / \ln(2) )$ . But the activity of each decay mode is  $\lambda_i * N(t)$ .

So the initial activity would be  
 $A_{\alpha, \text{initial}} = \lambda_{\alpha} * N_0$ . But  
 after time  $t$ , the activity is  $A_{\alpha}(t) =$   
 $\lambda_{\alpha} * N_0 * e^{(-\lambda_{\text{total}} * t)}$ .

**Chunk 12 [Prediction: C, P(A)=0.174, P(B)=0.064, P(C)=0.537, P(D)=0.224]:**

But let's compute this properly. Let me check the values again.

First, compute  $\lambda_{\alpha}$  and  $\lambda_{\beta}$ . Let me do it step by step.

$\lambda_{\alpha} = \ln(2) / T_{\alpha}$ .  $T_{\alpha}$  is 3 minutes. So if I want  $\lambda_{\alpha}$  in per second, divide by 60.

Similarly for  $\lambda_{\beta}$ .

**Chunk 13 [Prediction: C, P(A)=0.275, P(B)=0.042, P(C)=0.515, P(D)=0.167]:**

But let me compute the total decay constant first in per minute:

$\lambda_{\alpha}$  (per minute) =  $\ln(2)/3 = 0.231$  per minute

$\lambda_{\beta}$  (per minute) =  $\ln(2)/0.098 = 7.101$  per minute

$\lambda_{\text{total}}$  (per minute) =  $0.231 + 7.101 = 7.332$  per minute

So the total half-life  $T_{\text{total}} = \ln(2)/\lambda_{\text{total}} = 0.693 / 7.332 = 0.0945$  minutes = 5.67 seconds. Which is much shorter than the alpha half-life. So after 10 minutes, which is about 170 total half-lives, the number of remaining nuclei is  $N(t) = N_0 * e^{(-\lambda_{\text{total}} * t)}$ .

$t$  is 10 minutes. So  $\lambda_{\text{total}} * t = 7.332 * 10 = 73.32$ . So  $N(t) = 5e34 * e^{(-73.32)}$ .

Calculating  $e^{-73.32}$ : Let's see.  $e^{-70}$  is roughly  $1e-30$  (since  $e^{70} = 1e30$ ). Then  $e^{-73.32} = e^{-70} * e^{-3.32} = 1e-30 * 0.036 = 3.6e-32$ .

So  $N(t) = 5e34 * 3.6e-32 = 5 * 3.6 * 1e2 = 18 * 100 = 1.8e3$  nuclei remaining.

Then the alpha activity is  $\lambda_{\alpha} * N(t)$ .

**Chunk 14 [CRITICAL LEAP] [Prediction: D, P(A)=0.007, P(B)=0.008, P(C)=0.105, P(D)=0.880]:**

But  $\lambda_{\alpha}$  is 0.231 per minute. To get activity in Bq (per second), need to convert that to per second. 0.231 per minute is  $0.231 / 60 = 0.00385$  per second.

So  $A_{\alpha} = 0.00385 * 1.8e3 = 0.00385 * 1800 = 6.93$  Bq.

Looking at the options, D is 3.719 Bq, which is close but not exactly. Hmm. Maybe my approximations are off. Let me do precise calculations.

First, let's compute  $\lambda_{\alpha}$  and  $\lambda_{\beta}$  accurately.

$\lambda_{\alpha} = \ln(2) / 3$  minutes. Let's keep it in minutes for now.

$\ln(2) = 0.693147$ .

$\lambda_{\alpha} = 0.693147 / 3 = 0.231049$  per minute.

$\lambda_{\beta} = 0.693147 / 0.098 = 7.073$  per minute.

**Chunk 15 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

Wait, 0.098 minutes is 5.88 seconds. So 7.073 per minute is  $7.073 / 60 = 0.1179$  per second.

Total decay constant in per minute:  $0.231049 + 7.073 = 7.304$  per minute.

Total decay constant in per second:  $7.304 / 60 = 0.1217$  per second.

Then  $\lambda_{\text{total}} * t = 0.1217 * 600$  seconds (since  $t$  is 10 minutes = 600 sec) = 73.02.

So  $N(t) = 5e34 * e^{(-73.02)}$ . Let's compute  $e^{-73.02}$ .

First,  $\ln(10) = 2.3026$ . So  $73.02 / \ln(10) = 73.02 / 2.3026 = 31.72$ . So  $e^{-73.02} = 10^{-31.72} = 1.9e-32$ .

So  $N(t) = 5e34 * 1.9e-32 = 5 * 1.9 * 1e2 = 9.5 * 100 = 950$  nuclei.

Then  $A_{\alpha}$  is  $\lambda_{\alpha} * N(t)$ . But  $\lambda_{\alpha}$  is in per minute. Wait, if I compute  $A_{\alpha}$  in per minute, then convert to Bq (per second), that might be better.

$\lambda_{\alpha}$  is 0.231049 per minute. So  $A_{\alpha}$  (per minute) =  $0.231049 * 950 = 219.5$  decays per minute. To convert to Bq (decays per second), divide by 60:

$219.5 / 60 = 3.658$  Bq. Which is close to option D) 3.719 Bq.

**Chunk 16 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

But my approximated calculation gives around 3.66 Bq. The exact calculation might give a slightly different value. Let me check the exact steps.

First, let's compute the exact  $\lambda_{\alpha}$  and  $\lambda_{\beta}$ .

$\lambda_{\alpha} = 0.693147 / 3 = 0.231049$  per minute.

$\lambda_{\beta} = 0.693147 / 0.098$  Let me compute  $0.693147 / 0.098$ :

Dividing 0.693147 by 0.098:

$$0.098 \times 7 = 0.686, \text{ which is } 0.686. \text{ So } 0.693147 - 0.686 = 0.007147.$$

$$\text{So } 0.693147 / 0.098 = 7 + 0.007147 / 0.098 = 7 + 0.073 = 7.073 \text{ per minute.}$$

$$\text{So } \lambda_{\text{total}} = 0.231049 + 7.073 = 7.304 \text{ per minute.}$$

$$\text{Convert } \lambda_{\text{total}} \text{ to per second: } 7.304 / 60 = 0.12173 \text{ per second.}$$

$$t = 10 \text{ minutes} = 600 \text{ seconds.}$$

$$\text{Compute exponent: } \lambda_{\text{total}} * t = 0.12173 * 600 = 73.038.$$

Compute  $N(t) = 5e34 * e^{(-73.038)}$ . Let's calculate  $e^{-73.038}$  more accurately.

Since  $e^{-x} = 1 / e^x$ . Let's compute  $e^{73.038}$ .

**Chunk 17 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

But this is a huge number. Let me use a calculator approach. Let's note that  $\ln(10) = 2.302585093$ .

$$\text{So } 73.038 / \ln(10) = 73.038 / 2.302585 = 31.72. \text{ So } e^{-73.038} = 10^{-31.72}.$$

$$\text{Breaking down } 10^{-31.72} = 10^{(-31 - 0.72)} = 10^{-31} \times 10^{-0.72}.$$

$$10^{-0.72} = 10^{(-0.7)} = 0.1995... \text{ but more accurately, let's compute } \log_{10}(e^x) = x / \ln(10). \text{ So if I have } x = 73.038, \text{ then } \log_{10}(e^x) = 73.038 / 2.302585 = 31.72. \text{ So } e^{-73.038} = 10^{-31.72}.$$

$$\text{Now, } 10^{-31.72} = 10^{(-31.72)} = 1.91 \times 10^{-32}. \text{ Because } 10^{-0.72} = 0.191.$$

$$\text{So } N(t) = 5 \times 10^{34} \times 1.91 \times 10^{-32} = 5 \times 1.91 \times 10^2 = 9.55 \times 10^2 = 955 \text{ nuclei.}$$

Now, the alpha activity is  $\lambda_{\text{alpha}} * N(t)$ . But  $\lambda_{\text{alpha}}$  is per minute. Let's compute it in per second for Bq.

$$\lambda_{\text{alpha}} \text{ in per second is } 0.231049 \text{ per minute} / 60 \text{ sec/min} = 0.0038508 \text{ per second.}$$

$$\text{So } A_{\text{alpha}} = 0.0038508 * 955 = ?$$

$$0.0038508 * 955 = \text{Let's compute } 955 * 0.0038508.$$

$$\text{First, } 955 * 0.003 = 2.865$$

$$955 * 0.0008508 = 955 * 0.0008 = 0.764 \text{ and } 955 * 0.0000508 = 0.0485. \text{ So total } 0.764 + 0.0485 = 0.8125.$$

$$\text{Adding to } 2.865 \text{ gives } 2.865 + 0.8125 = 3.6775 \text{ Bq.}$$

Which is approximately 3.68 Bq. The option D is 3.719 Bq. Close enough, considering rounding errors. So maybe the exact value would be D.

**Chunk 18 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

Alternatively, perhaps the problem wants to use the total half-life and then compute the remaining  $N(t)$  using the total decay constant, and then multiply by the branching ratio for alpha decay. Wait, but the question says "partial half-life", which is the reciprocal of the partial decay constant.

**Chunk 19 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

Alternatively, maybe the activity of alpha decay is  $(\lambda_{\text{alpha}} / \lambda_{\text{total}}) * A_{\text{total}}$ , where  $A_{\text{total}}$  is the total activity. But since the total activity is  $\lambda_{\text{total}} * N(t)$ , then  $(\lambda_{\text{alpha}} / \lambda_{\text{total}}) * \lambda_{\text{total}} * N(t) = \lambda_{\text{alpha}} * N(t) = A_{\text{alpha}}$ , which is the same as before. So that approach is the same.

**Chunk 20 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

But let's think: the total activity at time  $t$  is  $A_{\text{total}} = \lambda_{\text{total}} * N(t)$ . The fraction of this that is due to alpha decay is  $(\lambda_{\text{alpha}} / \lambda_{\text{total}})$ . So  $A_{\text{alpha}} = A_{\text{total}} * (\lambda_{\text{alpha}} / \lambda_{\text{total}}) = N(t) * \lambda_{\text{alpha}}$ . Which is the same result.

$$\text{So the problem is to compute } A_{\text{alpha}}(t) = \lambda_{\text{alpha}} * N_0 * e^{(-\lambda_{\text{total}} * t)}.$$

**Chunk 21 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:**

But let's do exact calculation with precise numbers.

First, let me compute  $\lambda_{\text{alpha}}$  and  $\lambda_{\text{beta}}$  with more precision.

$$\lambda_{\text{alpha}} \text{ (per minute)} = \ln(2) / 3 = 0.693147 / 3 = 0.231049 \text{ per minute.}$$

$$\lambda_{\text{beta}} \text{ (per minute)} = \ln(2) / 0.098 = 0.693147 / 0.098 = 7.073 \text{ per minute. Let me calculate } 0.693147 / 0.098:$$

$$0.098 \times 7.073 = 0.693154, \text{ which is almost exactly } 0.693147. \text{ So actually, } \lambda_{\text{beta}} \text{ is approximately } 7.073 \text{ per minute.}$$

$$\text{So } \lambda_{\text{total}} = 0.231049 + 7.073 = 7.304049 \text{ per minute.}$$

$$\text{Then } t = 10 \text{ minutes. So the exponent is } -\lambda_{\text{total}} * t = -7.304049 * 10 = -73.04049.$$

$$\text{Compute } N(t) = 5e34 * e^{(-73.04049)}.$$

Let me calculate  $e^{-73.04049}$ . Maybe using natural exponent:

*Chunk 22 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:*

But I need a better way to compute  $e^{-73.04049}$ . Let me use the relation that  $\ln(10) = 2.302585$ , so  $73.04049 / \ln(10) = 73.04049 / 2.302585 = 31.72$ . So  $10^{-31.72}$ .

*Chunk 23 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:*

But  $31.72 = 31 + 0.72$ .

$$10^{-31.72} = 10^{-31} \times 10^{-0.72}.$$

$$10^{-0.72} = e^{(-0.72 \times \ln(10))} = e^{(-0.72 \times 2.302585)} = e^{-1.66} = 0.189.$$

$$\text{So } N(t) = 5e34 \times 0.189 \times 10^{-31} = 5 \times 0.189 \times 10^3 = 0.945 \times 10^3 = 945 \text{ nuclei.}$$

Now,  $\lambda_{\alpha}$  is  $\lambda_{\alpha}$  (per second)  $\times N(t)$ .

$\lambda_{\alpha}$  in per second is  $0.231049$  per minute /  $60 = 0.0038508$  per second.

So  $945 \times 0.0038508$ . Let's compute  $945 \times 0.0038508$ .

$$\text{First, } 945 \times 0.003 = 2.835$$

$$\text{Then } 945 \times 0.0008508 = ?$$

$$\text{Well, } 945 \times 0.0008 = 0.756$$

$$945 \times 0.0000508 = 945 \times 0.00005 = 0.04725 \text{ plus } 945 \times 0.0000008 = 0.000756. \text{ So total } 0.04725 + 0.000756 = 0.0480.$$

$$\text{So total } \lambda_{\alpha} = 2.835 + 0.756 + 0.048 = 2.835 + 0.804 = 3.639 \text{ Bq.}$$

Still around 3.64 Bq. Option D is 3.719 Bq. The difference could be due to more precise exponent calculation.

*Chunk 24 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:*

Alternatively, maybe I should calculate  $e^{-73.04}$  more accurately. Let me try using a calculator-like approach. Let me note that 73.04 is a large exponent.

*Chunk 25 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:*

But perhaps I can use the fact that  $\ln(2)$  is approximately 0.693, and compute the exponent as follows:

The exact exponent is  $-\lambda_{\text{total}} \times t$ . Let me compute  $\lambda_{\text{total}}$  again:

$$\lambda_{\text{total}} = \ln(2)/T_1 + \ln(2)/T_2, \text{ where } T_1 \text{ is 3 minutes and } T_2 \text{ is } 0.098 \text{ minutes.}$$

*Chunk 26 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:*

But maybe I should compute it in seconds from the start to avoid confusion. Let's try that.

Convert  $T_{\alpha}$  and  $T_{\beta}$  to seconds:

$$T_{\alpha} = 3 \text{ minutes} = 180 \text{ seconds.}$$

$$T_{\beta} = 0.098 \text{ minutes} = 5.88 \text{ seconds.}$$

$$\text{Compute } \lambda_{\alpha} = \ln(2)/180 = 0.693147 / 180 = 0.0038508 \text{ per second.}$$

$$\lambda_{\beta} = \ln(2)/5.88 = 0.693147 / 5.88 = 0.1179 \text{ per second.}$$

$$\lambda_{\text{total}} = 0.0038508 + 0.1179 = 0.12175 \text{ per second.}$$

$$\text{Now } t = 10 \text{ minutes} = 600 \text{ seconds.}$$

$$\text{Compute } N(t) = N_0 \times e^{(-\lambda_{\text{total}} \times t)} = 5e34 \times e^{(-0.12175 \times 600)} = 5e34 \times e^{-73.05}.$$

Now, compute  $e^{-73.05}$ . Let me use more accurate calculation.

Let me use the fact that  $e^{-x} = 1 / e^x$ . Let's find  $e^{73.05}$ .

*Chunk 27 [Prediction: D, P(A)=0.000, P(B)=0.000, P(C)=0.000, P(D)=1.000]:*

But how? Well, perhaps using the fact that  $e^{70} = 1 \times 10^{30.2}$  (since  $\ln(10^x) = x \times \ln(10)$ ). So if I want to find  $e^{73.05}$ , let's do:

$$\text{Let me find } 73.05 / \ln(10) = 73.05 / 2.302585 = 31.72.$$

$$\text{So } e^{73.05} = 10^{31.72}.$$

$$\text{Which is } 10^{31} \times 10^{0.72}.$$

$$10^{0.72} = 5.248 \text{ (since } 10^{0.7} = 5.0119, 10^{0.72} = 5.248).$$

$$\text{Therefore, } e^{-73.05} = 1 / (10^{31.72}) = 1 / (5.248 \times 10^{31}) = 1.905 \times 10^{-32}.$$

$$\text{So } N(t) = 5e34 \times 1.905e-32 = 5 \times 1.905 \times 10^2 = 9.525 \times 10^2 = 952.5 \text{ nuclei.}$$

$$\text{Then, } \lambda_{\alpha} = \lambda_{\alpha} \times N(t) = 0.0038508 \times 952.5$$

$$\text{Let me compute } 0.0038508 \times 952.5:$$

$$\text{First, } 952.5 \times 0.003 = 2.8575$$

$$\text{Then } 952.5 \times 0.0008508 = 952.5 \times 0.0008 = 0.762 \text{ and } 952.5 \times 0.0000508 = 0.0483.$$

Adding those gives  $0.762 + 0.0483 = 0.8103$ .

Total  $\lambda_{\alpha} = 2.8575 + 0.8103 = 3.6678$  Bq.

Which is approximately 3.67 Bq. The closest option is D) 3.719 Bq. Maybe my estimation of  $10^{0.72}$  is off. Let me check that more accurately.

*Chunk 28 [Prediction: D,  $P(A)=0.000$ ,  $P(B)=0.000$ ,  $P(C)=0.000$ ,  $P(D)=1.000$ ]:*

Alternatively, let's use more precise value for  $e^{-73.05}$ .

*Chunk 29 [Prediction: D,  $P(A)=0.000$ ,  $P(B)=0.000$ ,  $P(C)=0.000$ ,  $P(D)=1.000$ ]:*

Alternatively, using a calculator if I can approximate it.

*Chunk 30 [Prediction: D,  $P(A)=0.000$ ,  $P(B)=0.000$ ,  $P(C)=0.000$ ,  $P(D)=1.000$ ]:*

But since I don't have a calculator, perhaps I can use more accurate steps. Let me recall that  $e^{-73.05} = e^{(-70 - 3.05)} = e^{-70} * e^{-3.05}$ .

We know that  $e^{-70} = 1e-30.2$  (since  $\ln(10^{30}) = 30 * 2.3026 = 69.078$ , so  $e^{-70} = 1e-30 * e^{(-0.922)} = 1e-30 * 0.401$ ). So  $e^{-70} = 4.01e-31$ .

Then  $e^{-3.05} = e^{-3} * e^{-0.05} = 0.0498 * 0.9512 = 0.0474$ .

So total  $e^{-73.05} = 4.01e-31 * 0.0474 = 1.90e-32$ .

So  $N(t) = 5e34 * 1.90e-32 = 9.5e2 = 950$ .

Then  $\lambda_{\alpha} = \lambda_{\alpha} * N(t) = 0.0038508 * 950 = 3.658$  Bq.

Still around 3.66 Bq. The option D is 3.719. Close, but maybe there's a miscalculation in the exponent. Let me check the calculation of  $\lambda_{\alpha} * t$  again.

$\lambda_{\alpha}$  in per second:  $0.693147 / 180 = 0.0038508$  per second.

$\lambda_{\beta}$  in per second:  $0.693147 / 5.88$  Let's compute that more accurately. 5.88 seconds is  $T_{\beta}$ .

So  $0.693147 / 5.88 = 0.1179$  per second.

So  $\lambda_{\alpha} + \lambda_{\beta} = 0.0038508 + 0.1179 = 0.12175$  per second.

$t = 600$  seconds.

$\lambda_{\alpha} + \lambda_{\beta} * t = 0.12175 * 600 = 73.05$  seconds<sup>-1</sup> \* seconds = 73.05.

So exponent is -73.05.

So maybe my calculation of  $e^{-73.05}$  is more precise. Let me try another approach. Let me use the exact value of  $\lambda_{\alpha}$  and calculate the exponent.

*Chunk 31 [Prediction: D,  $P(A)=0.000$ ,  $P(B)=0.000$ ,  $P(C)=0.000$ ,  $P(D)=1.000$ ]:*

Alternatively, maybe I should calculate the exponent as follows:

Let me compute  $\ln(2)/T_1 + \ln(2)/T_2$ , but in per second.

*Chunk 32 [Prediction: D,  $P(A)=0.000$ ,  $P(B)=0.000$ ,  $P(C)=0.000$ ,  $P(D)=1.000$ ]:*

Wait,  $T_1$  is 180 seconds,  $T_2$  is 5.88 seconds.

So  $\lambda_{\alpha} = \ln(2)/180 + \ln(2)/5.88 = 0.693147/180 + 0.693147/5.88 = 0.0038508 + 0.1179 = 0.12175$  per second.

So yes, same as before