Untie the Knots: An Efficient Data Augmentation Strategy for Long-Context Pre-Training in Language Models

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Instead of searching for scarce long data, we can augment existing data to explicitly train the model's ability for long-range information retrieval.

Motivation

Problem: Data Scarcity

Naturally long, high-quality documents are extremely rare.

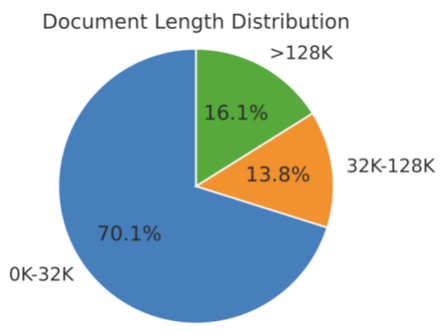


Figure: Document Length Distribution. Over 70% of tokens originate from documents shorter than 32K.

Goal: Train for Long-Range Attn

The key is to teach the model to attend to relevant information across long, distractor-filled contexts.

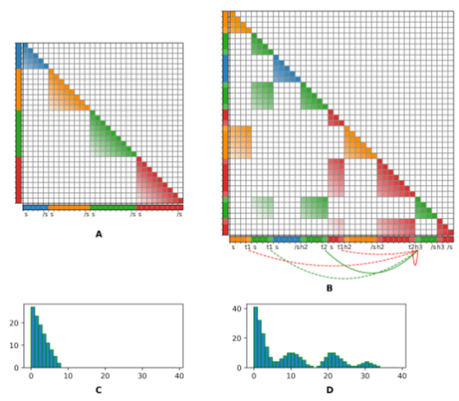
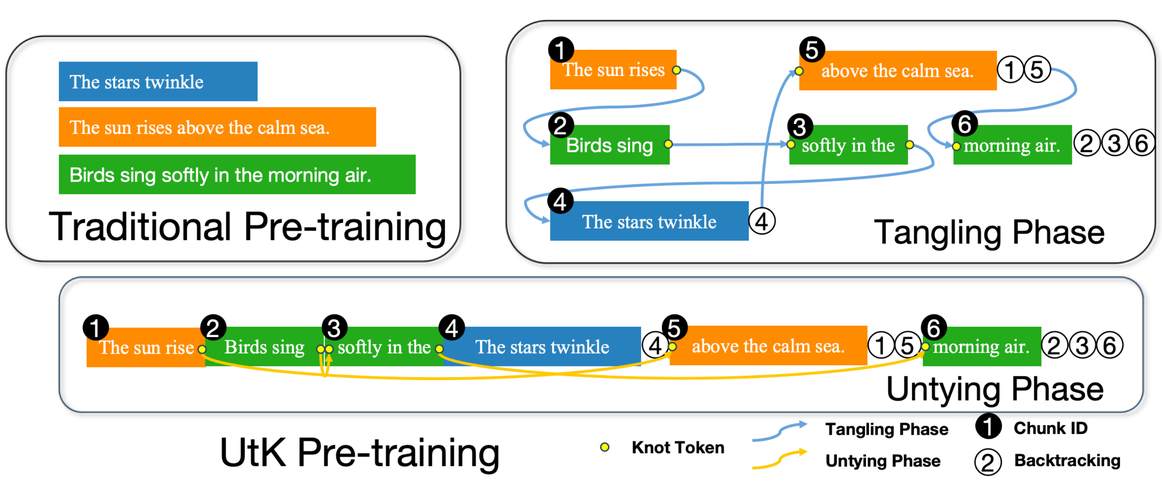


Figure: The Target Attention Pattern. We want to train the model to learn this complex, non-local attention, effectively 'untying' shuffled information.

Method

UtK transforms standard pre-training into a challenging long-context reasoning task, forcing the model to develop robust long-range attention capabilities.



Tangling Phase (Data Augmentation):
A. **Chunking**: Documents are split into several segments.
B. **Tying**: Chunks from different documents are shuffled and "knotted" together into a single long sequence.
C. **Backtracing**: the model must explicitly output the correct order of the chunks for a document.

Untying Phase (Training Task)
The model is trained on this "knotted" sequence.
Its objective is three-fold:
A. **Next Token Prediction**: Standard language modeling.
B. **Untie the Knots**: The model must learn to attend to the correct preceding chunk (e.g., Chunk5->Chunk1) across thousands of distractor tokens.
C. **Backtracing**: Predict the original sequence of [Chunk IDs] at the end, forcing it to learn the full document structure.

Conclusion

The path to better long-context models may not be through finding more long data, but by making better use of the data we already have.

✓ SOTA Performance on RULER, LV-Eval, and InfiniteBench.
✓ No new data required
✓ Maintain performance on Short-Context Tasks
Models & Code Available at: https://github.com/rgtjf/Untie-the-Knots

Results

UtK Outperforms Existing Strategies

On the RULER benchmark, we compared UtK against various long-context training strategies on the Qwen2-7B model.

Models	32K	64K	128K
LONG-CONTEXT			
Qwen2-base (7B)‡	81.1	73.2	65.2
Qwen2-CT (7B)	78.2	73.6	54.8
Qwen2-ABF (7B)	78.9	75.2	65.9
Qwen2-Upsampling (7B)	80.7	76.4	67.4
Qwen2-AttnMask (7B)	80.4	75.6	72.0
Qwen2-Synthetic (7B)	83.2	80.5	72.7
Qwen2-CIP (7B)	80.5	76.3	71.0
Qwen2-UtK-base (7B)	80.5	79.2	**75.0**

At 128K context, our UtK model achieves 75.0%, significantly outperforming other methods like Upsampling (67.4%) and Synthetic data (72.7%).

UtK is a Scalable Solution

The benefits of UtK scale effectively across different model sizes (7B to 72B) and architectures (Qwen2, Llama).

7B MODEL Models	32K	64K	128K
Llama3.1-base (8B)†	**90.2**	80.4	66.1
Qwen2-base (7B)‡	81.1	73.2	65.2
Llama3.1-UtK-base (8B)†	88.8	**83.6**	73.8
Qwen2-UtK-base (7B)	80.5	79.2	**75.0**
70B MODEL			
Llama3.1 (70B)§	**94.8**	88.4	66.6
Qwen2 (72B)§	94.1	79.8	53.7
Llama3.1-base (70B)†	91.7	84.6	66.0
Qwen2-base (72B)‡	93.3	85.9	78.0
Qwen2-UtK-base (72B)	93.3	**90.6**	**84.5**

UtK boosts the 72B model to an impressive 84.5%. It also improves the already strong Llama3.1, showing its general applicability.

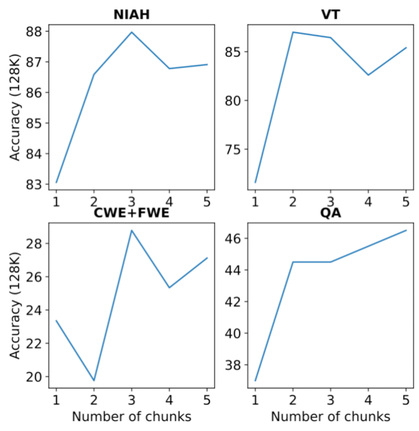
Discussion

A critical question: Does training for long context hurt performance on standard, short-context tasks?

Models	Understanding BBH 3shot	NQ 5shot	TriviaQA 5shot	Code HumanEval 0shot	Math MBPP 3shot	GSM8K 4shot	Avg.	Δ
Llama3.1-base (8B)	**63.9**	33.5	**80.2**	35.4	54.5	58.0	54.2	-
Llama3.1-UtK-base (8B)	61.9	**34.0**	79.6	38.4	54.6	59.3	54.6	+0.7%
Qwen2-base (7B)	61.4	30.3	70.2	**46.3**	64.6	**80.9**	59.0	-
Qwen2-CT-base (7B)	61.1	29.6	70.3	44.5	**66.2**	77.6	58.1	-1.5%
Qwen2-UtK-base (7B)	61.6	29.5	70.2	45.1	64.2	78.1	58.2	-1.4%
Llama3.1-base (70B)	**81.0**	**49.3**	**91.2**	59.2	72.8	82.3	72.6	-
Qwen2-base (72B)	79.8	45.6	88.0	**61.6**	**76.9**	**88.8**	**73.3**	-
Qwen2-UtK-base (72B)	80.6	45.0	87.6	61.0	75.9	87.8	73.0	-0.4%

No. UtK preserves short-context capabilities.

How many chunks are optimal?



Performance generally peaks at 2 or 3 chunks. Too few chunks (1) is just standard training. Too many chunks can make the task overly difficult, hindering learning.

Which components of UtK matter most?

Models	Average	NIAH	VT	CWE+ FWE	QA
Qwen2-UtK-80%	**75.0**	90.3	**97.6**	**29.9**	**48.0**
- Disrupt order	73.0	90.4	97.8	17.4	46.0
- W/o backtracing	74.3	**91.3**	94.8	23.5	46.5
Qwen2-UtK-30%	73.1	88.8	94.8	28.5	44.0
- Disrupt order	72.3	89.0	89.8	21.7	47.0
- W/o backtracing	70.8	88.5	86.2	21.2	42.0

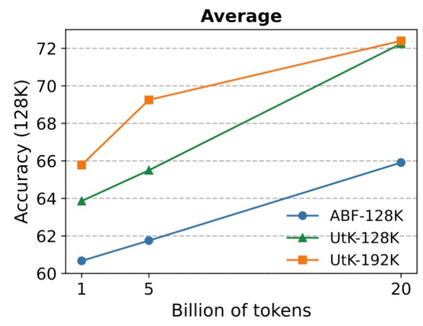
1. Backtracing is critical: Removing it causes a significant performance drop.

2. Preserving Order is important: Completely disrupting the order hurts performance, especially on aggregation tasks (CWE+FWE).

3. More is Better: A higher UtK probability (80% vs. 30%) yields better results.

Training Efficiency: Faster and Better

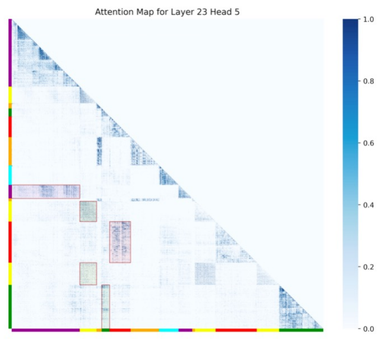
We tracked model performance on RULER 128K as a function of the number of training tokens.



With only 1 billion tokens, our UtK-192K strategy already matches the performance of the baseline trained on 20 billion tokens—a 20x improvement in data efficiency.

Attention Visualization: Learning to Untie

To understand how the model handles knotted context, we visualized its attention patterns.



The attention map clearly shows that the model learns to attend to non-adjacent but related chunks of the same document (highlighted in red boxes). It effectively 'untying the knots' as intended.

We also trained and open sourced dots.llm1.base and dots.llm1.inst based on UtK.

- A MoE model with 14B activated and 142B total parameters trained on high-quality corpus.
- Intermediate model checkpoints are released spanning the entire training process.

dots.llm1

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