VIENNI RoToR: Towards More Reliable Responses





Overview



Soyoung Yoon^{1*}, Dongha Ahn¹², Youngwon Lee¹, Minkyu Jung², HyungJoo Jang², Seung-won Hwang^{1†} ¹Seoul National University ²Channel Corporation

Channel Talk

Which one is red? Which one is red?

A. Apple

B. Orange

C. Grape

Answer:

for invariance.

-> A. Apple

A. Orange

C. Grape

Answer:

-> A. Orange

Paper

Code

†Corresponding Author *Work done during an internship at Channel Corporation

We introduce RoToR: a zero-shot order-invariant Language Model, with (1) Global Sorting + Circular Position IDs and (2) Selective Routing for Mixed Inputs, which

achieve SOTA robustness on 3 benchmarks & 25-45% lower FLOPs v.s. Baselines (PINE) **Motivation: Positional Bias for Listwise Inputs**

- Lost-in-the Middle (RAG)
- First-choice bias (75%) in LLM-as-a-judge
- MMLU rank shifts by 8 with shuffle -> need neutral handling for sets, tables, multiple-choice questions
- Zero-shot invariant LMs have been proposed as a solution, but had 2 limitations:

Limitations of previous Zero-shot order-invariant LMs

- Limitation 1: Training and inference distribution mismatch
- PCW, Set-based prompting: No cross-segment content
- PINE: per-query sort -> O(O(n²) + instability
- Frequent ID changes cause **OOD behavior** -> drops its ability
- Limitation 2: Fail to extend to real-life scenarios (orderinvariant + order-sensitive)
- Does not consider, cannot be applied to hybrid cases (e.g., MMLU)

PINE: Bidirectional processing with Q-K similarity

- Has to obtain the same attention representation, regardless of initial ordering of segments
- Places query IDs last, sorts other segments in a order-invariant way

Challenges of PINE

- Frequent alterations on position IDs (layer, head, suffix, generation tokens)
- Computationally expensive
- Numerical Instability (arising from attention assignment)

Proposed Method: RoToR

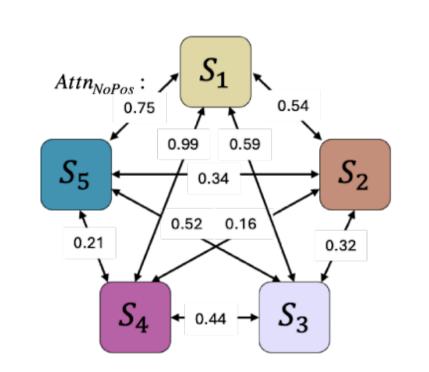
- Keep the bidirectional structure, but alter the position assignment in a simple and stable way!
- Define a single global ordering + circular assignment
- We propose three different global ordering methodology: (1) Lexical: Hierarchical sort on tokenized ID numbers, (2) Reranking (monot5), (3) Frequency-normalized

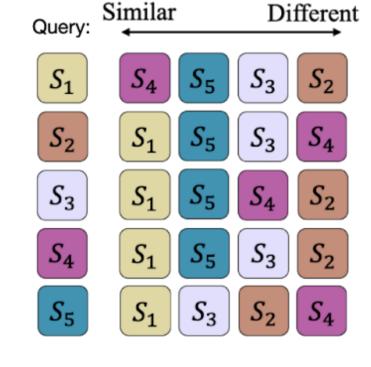
1. Training and inference distribution mismatch

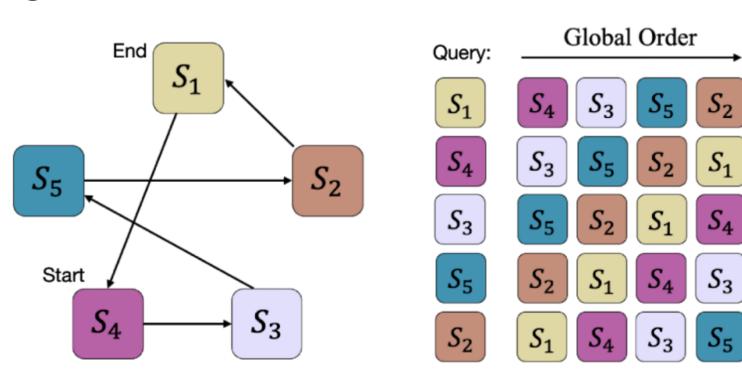
- Stable, order-invariant solution (RoToR)
- Query-agnostic global ordering with minimal positional ID modifications

2. Fail to extend to hybrid cases

- Selective Routing, which switches between original / invariant LMs based on confidence









Self-attention patterns (x = query, y = key) across order-invariant models

Example of order-sensitive and order-invariant cases

In 8085 name/names of the 16 bit registers is/are: Order sensitive Order invariant A. stack pointer A. stack pointer

> C. both A and B. D. none of these

B. program counter

C. accumulator D. microprocessor

B. program counter

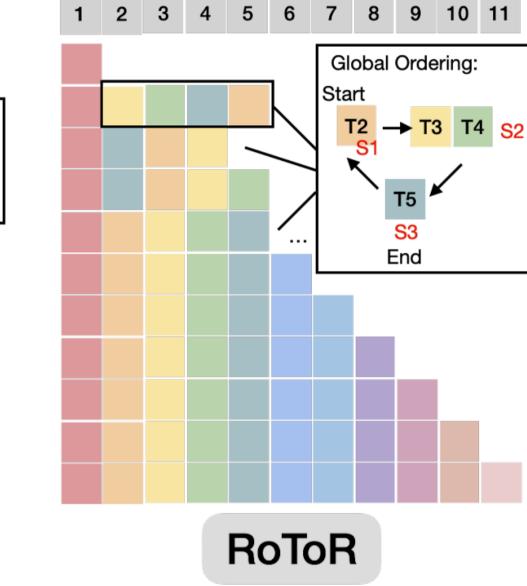
Orange (O) Kiwi (K) Grape (G) Which one relates to monkeys? Causal LM (order-sensitive) RoToR (ours) 1 2 3 4 5 6 7 8 9 10 11 Attention matrix of original model **PINE**, shown by position id Attention matrix of PINE

Position Assignment of Key Token -> Query Token: 1 2 3 4 5 6 7 8 9 10 11 Given Apple $Attn_{NoPos}$ scores on T2 Ban-T5 < (T3 T4 S3 Orange which one T6 is most related to T8 the color T9 red? Generated Token A: It is T11 PINE

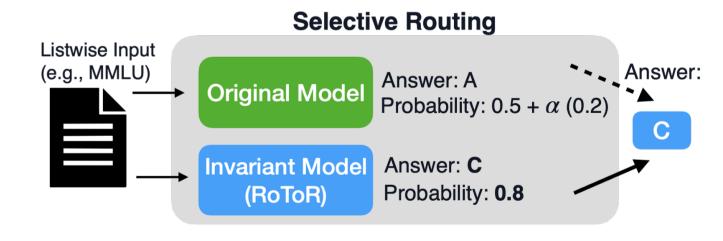
Query $Q \downarrow$

Apple (A)

Banana (B)



PINE: query-dependent grid, **RoToR:** fixed order, rotate per query -> Stable IDs, zero collisions, less computation



Reduction

Experimental Setup

- Benchmarks:
 - Lost-in-the-Middle (LitM)

0.16 / 0.18 / 0.18

0.02 / 0.07 / 0.03

 \hookrightarrow stdev. (\pm)

- Knowledge Graph QA (KGQA): Mintaka

PINE

- MMLU: selective routing cases
- LongBench: long context scenarios (Appendix)

- Model backbones:

- Llama-3.1-8B/70B
- Qwen-1.5-4/7/72B-Chat
- Metrics: best_subspan_em (LitM), EM, F1, Acc. (KGQA), Acc. (MMLU)
- Methods: Original (order-sensitive), PCW, Setbased prompting, PINE, RoToR

Efficiency

- Less computation:
- Overhead FLOPs ↓ 98% (72B)
- Faster:
- E2E Latency ↓ 23-43 % on LitM
- Reduces OOD:
- Perplexity ↓; collision rate 0 %

Model	Benchmark	PINE	RoToR	Reduction					
(a) Overhead FLOPs, relative to original model									
I lama 2 1	MMLU, $N=4$	0.59×	0.55×	7.6%					
Llama-3.1- 8B-Instruct	LitM, $N = 10$	7.07×	4.81 ×	31.9%					
	LitM, $N = 30$	22.43×	$15.05 \times$	32.9%					
Llama-3.1-	KGQA, $N = 30$	1.27×	0.94×	26.0%					
70B-Instruct	KGQA, $N = 50$	1.82×	1.29 ×	29.0%					
Qwen1.5-	KGQA, $N = 30$	0.45×	0.01×	98.0%					
72B-Chat	KGQA, $N = 50$	0.58×	$0.03 \times$	94.8%					
(b) End-to-e	end latency (s)								
Llama-3.1-	LitM, $N=10$	57,352	44,219	22.9%					
70B-Instruct	LitM, $N=20$	87,091	58,680	32.6%					
I lama 2 1	MMLU, $N=4$	7,371	6,608	10.4%					
Llama-3.1- 8B-Instruct	LitM, $N = 10$	18,551	14,264	23.1%					
	LitM, $N = 30$	41,664	23,569	43.4%					
(c) Perplexi	ty & Collision rate, (on L	itM)							
Llama-3.1-	Perplexity $(N=20)$	6.91	6.65	_					
8B-Instruct	Collision rate ($N = 30$)	42.3%	0 (None)	_					

KGQA

	Llama-3.1-8B-Instr.			Llama-3.1-70B-Instr.			Qwen1.5-4B-Chat			Qwen1.5-7B-Chat			Qwen1.5-72B-Chat		
Method	Acc.	EM	F1	Acc.	EM	F1	Acc.	EM	F1	Acc.	EM	F1	Acc.	EM	F1
						N=	= 30								
Initial, no shuff	ling of	segmen	its												
Original	50.2	44.0	51.9	61.6	57.7	63.6	30.7	27.9	34.9	31.5	27.8	35.4	41.4	37.7	43.7
PINE	51.5	45.0	52.6	63.1	58.7	64.8	31.6	28.7	35.6	32.3	28.8	36.4	46.7	42.9	49.0
RoToR	53.1	46.5	54.1	63.6	59.1	65.2	32.0	29.0	35.7	34.3	29.8	37.7	47.5	43.2	49.2
RoToR-MonoT5	51.6	45.0	52.5		_		32.3	29.1	36.2	32.9	28.4	36.3		_	
RoToR-Freq.	52.6	46.1	53.7		_		32.3	29.2	36.0	33.7	29.5	37.2		_	
After shuffling	segmen	ts, aver	raged or	ver 3 se	eds										
Original	49.5	43.3	51.0	62.1	57.8	64.0	30.1	27.5	34.7	31.4	27.3	35.0	41.0	37.6	43.6
\hookrightarrow stdev. (\pm)	0.0	7 / 0.14 /	0.17	0.37 / 0.40 / 0.27		0.41 / 0.34 / 0.43		0.26 / 0.28 / 0.29			0.75 / 0.40 / 0.33				
PINE	51.8	45.2	52.8	63.3	58.8	64.9	31.5	28.7	35.6	32.3	28.8	35.7	46.9	43.3	49.2
\hookrightarrow stdev. (\pm)	0.0	5 / 0.07 /	0.16	0.1	3 / 0.04	0.10	0.20	0/0.18/	0.13	0.17	/ 0.20 /	0.13	0.18	3 / 0.20 /	0.20
RoToR	52.8	46.2	53.8	63.5	59.1	65.3	31.8	28.8	35.5	34.2	29.9	37.7	47.4	43.1	49.1
\hookrightarrow stdev. (\pm)	0.0	5 / 0.05 /	0.02	0.1				0.05 / 0.02 / 0.09		0.09 / 0.07 / 0.06		0.06 / 0.04 / 0.07			
RoToR-MonoT5	51.6	45.0	52.6		- 32.4 29.2 36.3				33.0 28.8 36.5			_			
\hookrightarrow stdev. (\pm)	0.1	2/0.06/	0.10	_			0.04 / 0.02 / 0.13			0.12 / 0.09 / 0.07			_		
RoToR-Freq.	52.5	45.9	53.5	_			32.3 29.3 36.0		33.8 29.6 37.4		_				
\hookrightarrow stdev. (\pm)	0.1	0/0.15/	0.11		_		0.13 / 0.16 / 0.09			0.04 / 0.00 / 0.09			_		
						N=	= 50								
Initial, no shuff	ling of	segmen	its												
Original	50.0	44.0	51.7	62.6	58.5	64.5	31.6	28.6	35.8	31.7	28.0	35.7	42.1	38.7	44.5
PINE	51.6	45.1	52.6	64.1	59.8	65.8	31.6	28.8	35.3	32.0	28.5	35.9	48.0	44.1	49.9
RoToR	52.9	46.0	53.6	64.6	60.0	66.2	32.7	29.6	36.2	34.3	30.1	38.0	48.4	44.3	50.3
RoToR-MonoT5	52.4	45.4	52.8		_		32.3	29.3	35.9	32.9	28.9	36.6		_	
RoToR-Freq.	53.1	46.4	53.7		_		32.3	29.2	36.1	33.5	29.5	37.2		_	
After shuffling	segmen	ts, aver	raged or	ver 3 se	eds										
Original	49.7	43.5	51.0	62.8	58.5	64.5	30.3	27.6	35.0	31.6	27.9	35.5	42.1	38.9	44.7
\hookrightarrow stdev. (\pm)	0.3	4/0.28/	0.46	0.29 / 0.28 / 0.05		0.26 / 0.24 / 0.35		0.40 / 0.56 / 0.42			0.30 / 0.40 / 0.35				
PINE	51.8	45.3	52.7	64.3	59.8	65.9	31.5	28.7	35.3	31.7	28.2	35.7	48.0	44.3	50.0
() atday ()	0.1	5/0.16/	0.19	0.1	6/0.15	0.14	0.17 / 0.20 / 0.21		0.18 / 0.16 / 0.14			0.02 / 0.04 / 0.05			
\hookrightarrow stdev. (\pm)				64.5 60.0 66.1		32.5 29.6 36.1		34.2 30.1 38.0			48.3 44.3 50.3				
` ,	52.7	45.9	53.5	64.5	60.0	00.1	32.5	29.6	30.1	34.2	30.1	38.0	48.3	44.3	50.3
\rightarrow stdev. (\pm) RoToR \rightarrow stdev. (\pm)		45.9 5 / 0.09 /		1	60.0)2 / 0.02 /			29.6 / 0.06 /			30.1 6 / 0.05 /			44.3 5 / 0.09 /	

0.16 / 0.09 / 0.07

0.04 / 0.16 / 0.22

29.6 37.4

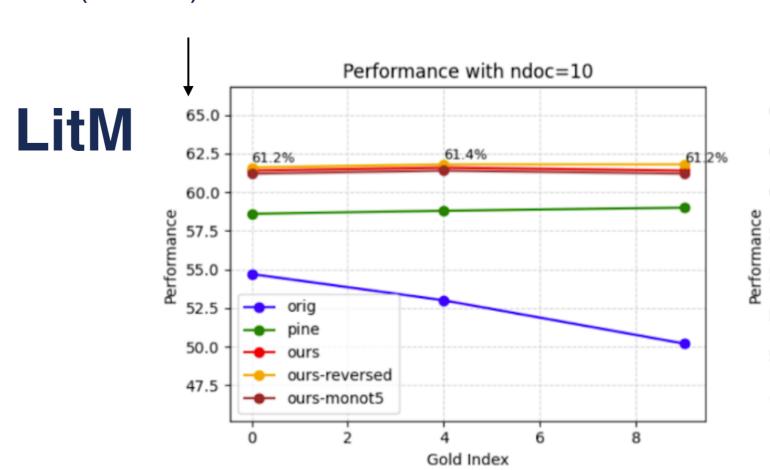
33.7

36.1

0.09 / 0.04 / 0.06

- Top-30 and Top-50 knowledge triples per query

- Test before / after shuffling segments to see robustness
- RoToR obtains lower stdev (better stability) + higher performance than PINE
- Trend persists for > 70B model variants
 - Single use of Order-invariant models fail, but selective routing restores ---accuracy & improves performance.
- On Llama-3.1-8B-Inst.
- Original model fluctuates performance, while ours (RoToR) maintains stable



MMLU

	Llan	1a-3.1-8	B-Instruct	Qv	ven1.5-	4B-Chat	Qv	ven1.5-	n1.5-7B-Chat	
Method	Init.	Rev.	Avg.	Init.	Rev.	Avg.	Init.	Rev.	Avg.	
Orig.	68.3	64.8	65.5 ± 1.0	53.6	51.9	52.6 ± 0.6	60.1	56.6	58.6 ± 0.9	
PCW	57.0	55.1	56.1 ± 1.1		_		_			
Set-Based Prompting	31.1	33.0	31.6 ± 0.8		_					
PINE	64.8	63.3	63.6 ± 0.7	50.5	49.3	49.4 ± 0.5	57.0	54.4	55.8 ± 0.9	
RoToR	63.2	62.6	62.8 ± 0.7	49.6	47.7	48.3 ± 0.7	56.5	55.8	56.2 ± 0.6	
\hookrightarrow + S.R.	68.5	65.1	65.7 ± 0.9	53.7	51.8	$\textbf{52.6} \pm \textbf{0.6}$	60.1	57.4	$\textbf{58.8} \pm \textbf{0.7}$	
RoToR - MonoT5	64.2	62.9	63.5 ± 0.5	49.7	47.6	48.7 ± 0.7	56.2	54.4	55.5 ± 0.7	
\hookrightarrow + S.R.	68.4	65.2	65.8 ± 0.9	53.8	51.9	$\textbf{52.6} \pm \textbf{0.6}$	60.1	57.3	$\textbf{58.7} \pm \textbf{0.8}$	
RoToR - Freq.	64.3	63.6	63.8 ± 0.6	49.9	47.6	48.7 ± 0.5	56.4	54.7	55.7 ± 0.7	
\hookrightarrow + S.R.	68.5	65.3	$\textbf{65.8} \pm \textbf{0.8}$	53.7	52.3	$\textbf{52.6} \pm \textbf{0.6}$	60.0	57.3	58.6 ± 0.8	
RoToR + S.R. (Oracle)	75.0	71.9	72.7 ± 1.0	61.8	60.1	$\textbf{61.1} \pm \textbf{1.0}$	68.1	66.2	67.2 ± 0.7	
Performance with ndoc=20						Performance with ndoc=30				

