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LeaPformer: Enabling Linear Transformers for Autoregressive and Simultaneous Tasks via Learned Proportions

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Motivation

- Attention in transformers is bottlenecked in run-time and memory footprint when engaging with large sequences, but is still de-facto for sequence modeling!
- Efficient attention variants have been studied almost since the introduction of transformers, but remain niche or result in severe degradation to model accuracy.





Linear Attention

- Truly linear with no prerequisites? O(n) run-time and memory footprint!
 - Results in RNN-like recurrent behavior during inference!
 - Recurrent state is memory constraint during attention, much smaller than QK^T matrix! No need to cache key and value matrices!
 - Includes benefits like infinite LLM context, increased accessibility for edge devices, extreme speedups, etc.



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Linear Attention Preliminaries



Softmax Attention: $O(n^2)$ Run-time and Mem.

Linear Attention: *O*(*n*) Run-time and Mem.





Re-weighting Functions





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Limits of Explicit Positional Re-weighting

- Why are explicit positional re-weighting functions (SOTA is cosFormer) limited? Sequence length is needed, so autoregressive tasks become very difficult! Additionally, most simultaneous (i.e. streaming) tasks are impossible.
 - Autoregressive Language Modeling
 - Machine Translation (usually autoregressive) and Simultaneous Translation (T2T, S2T, etc.)







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Limits of Static Attention Concentrations

- Static patterns are not very generalizable across tasks! For example:
 - Cross-attention concentrations between English-to-German vs. English-to-Chinese
 - Bidirectional language modeling vs. hierarchical math problem solving



Static Attention Concentration Pattern



Proposed Approach: LeaPformers

- Replace explicit positional reweighting functions in sequences with sequence proportions. No theoretical dependence on explicit token positions!
- Replace static attention concentrations, with a learnable component based on proportions!

 $P_{q} = [P_{q,1}, P_{q,2}, \dots P_{q,N_{1}}], \quad 0 \le P_{q,i} \le 1$ $P_{k} = [P_{k,1}, P_{k,2}, \dots P_{k,N_{2}}], \quad 0 \le P_{k,j} \le 1$ $S(Q_{h,i}, K_{h,j}^{T}) = S_{q}(Q_{h,i})S_{k}(K_{h,j}^{T})\sigma(P_{q,i}, P_{k,j})$

$$P_q(Q_{h,i}) = P_{q,i} = LeaP_Q(Q_{h,i})$$
$$P_k(K_{h,j}) = P_{k,j} = LeaP_K(K_{h,j})$$
$$P_q(Q_h) = [LeaP_Q(Q_{h,1}), \dots, LeaP_Q(Q_{h,N_1})]$$
$$P_k(K_h) = [LeaP_K(K_{h,1}), \dots, LeaP_K(K_{h,N_2})]$$





Impact of Proposed Approach

- **LeaPformers** solve the aforementioned issues!
 - Proportion representations mean **no theoretical blockade** to autoregressive and simultaneous applications.
 - Combined with the desire to eliminate static representations, a learnable representation allows for dynamism in attention concentrations!
 - Architectural changes are minimal to maintain linear attention throughput in addition to improving accuracy.



Dynamic Attention Concentration Pattern



LeaPformer Architecture and Results

- Small accuracy loss, but up to 7.8x faster than softmax with 7.5x less memory!
- Roughly equal in accuracy to BigBird, but 3.3x faster and 3.1x less memory!
- Improves on cosFormer!
 More accurate on all tasks, only slightly slower.
 Adapts seamlessly to generation!





Want to find out more?

Find us at our poster session or send us an e-mail! (agostinv, chenliz)@oregonstate.edu