Generative modeling remains challenging for large scale discrete structured data like sequences, trees or graphs. The most commonly used model for such data structures is the autoregressive one. However, how to balance between the expressiveness and the computational tractability for the autoregressive models is still a hot research question.

In this talk, we first introduce a scalable autoregressive model BiGG [1] for generating graph structures, where it can reduce the inference cost from $O(n^2)$ to $O(n\log n)$ for a graph with $n$ nodes while still maintaining the full autoregressive capability. Then in the second part we show how this idea could be applied for the self-attention module in Transformers to reduce its asymptotic computation and memory cost, especially for long sequences, while still maintaining the full attention in the unidirectional language modeling scenario. This variant named Combiner [2] can achieve state-of-the-art performance in tasks including ImageNet generative modeling.

References:

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