



Summary of related papers on Graph Transformer

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2022_SIGIR_LogiformerA Two-Branch Graph Transformer Network for Interpretable Logical Reasoning

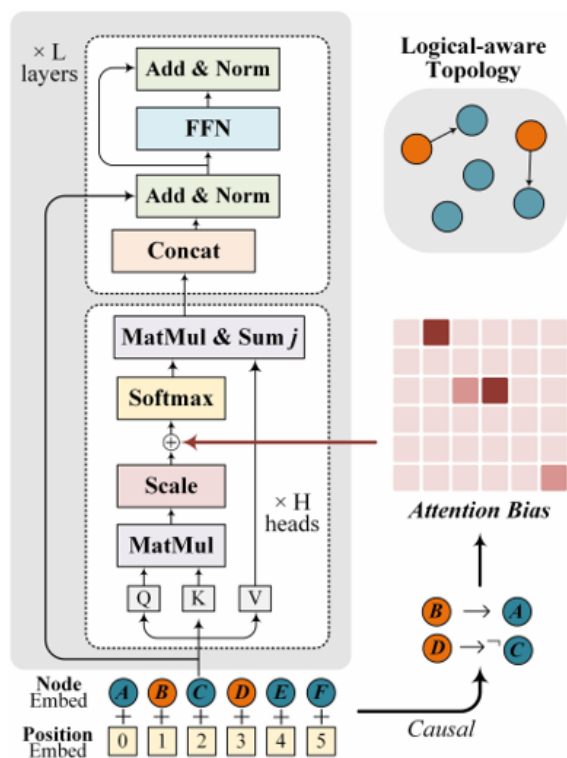


Figure 3: The illustration of logical-aware graph transformer. The inputs are the node sequence as well as the topology and the outputs are omitted.

$$\begin{aligned} Q &= V_i \cdot W^Q, \\ K &= V_i \cdot W^K, \\ V &= V_i \cdot W^V, \end{aligned} \quad (6)$$

$$A = \frac{QK^T}{\sqrt{d_k}}, \quad (7)$$

$$Att(Q, K, V) = \text{softmax}(A) \cdot V,$$

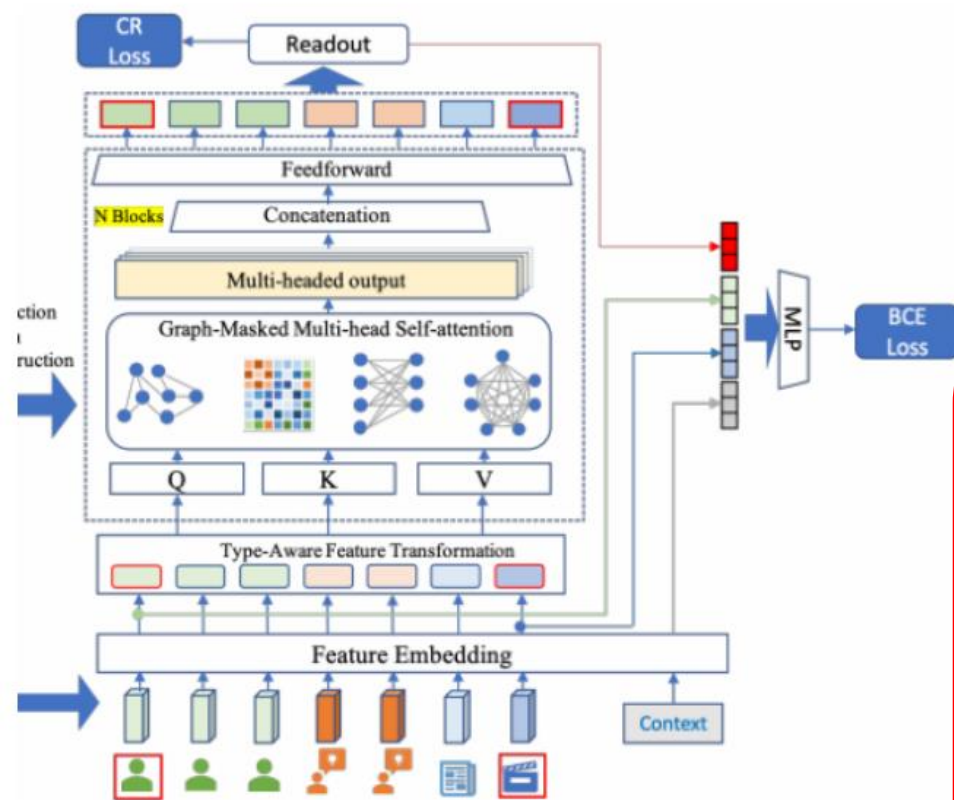
$$A' = \frac{QK^T}{\sqrt{d_k}} + M_{cas}. \quad (8)$$

$$Att_{MH}(Q, K, V) = [Head_1; \dots; Head_H] \cdot W^H, \quad (9)$$

$$V_{cas} = V_{cas}^{(L-1)} + V_{cas}^{(L)}, \quad (10)$$

$$V_{occ} \in \mathbb{R}^{K_{occ} \times d}$$

2022_SIGIR_Neighbour Interaction based Click-Through Rate Prediction via Graph-masked Transformer



Heterogeneous Node Feature Transformation layer:

$$\begin{aligned} \mathbf{x}_i &= \mathbf{W}_i \mathbf{f}_i && \text{User or item: } [\mathbf{f}_1, \dots, \mathbf{f}_k] \\ \mathbf{h}_i &= \text{Linear}^{t(i)}(\mathbf{x}_i). \end{aligned} \quad (1)$$

Graph-masked Multi-head Self-attention:

$$\begin{aligned} e_{ij} &= \frac{(\mathbf{Q}\mathbf{h}_i)^\top (\mathbf{K}\mathbf{h}_j)}{\sqrt{d}}, \\ \alpha_{ij} &= \frac{\exp(e_{ij})}{\sum_{k=1}^n \exp(e_{ik})}, \end{aligned} \quad (2)$$

$$\mathbf{z}_i = \sum_{j=1}^n \alpha_{ij} (\mathbf{V}\mathbf{h}_j),$$

$$e_{ij} = f_m\left(\frac{(\mathbf{Q}\mathbf{h}_i)^\top (\mathbf{K}\mathbf{h}_j)}{\sqrt{d}}, \mathbf{M}_{ij}\right), \quad (3)$$

$$f_m(x, \lambda) = \begin{cases} \lambda x & \lambda \neq 0 \\ -\infty & \lambda = 0. \end{cases} \quad (4)$$

$$\mathbf{z}_i = \text{FFN}(\mathbf{W}^O \text{Concat}(\mathbf{z}_i^1, \dots, \mathbf{z}_i^H)), \quad (5)$$

$$\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_{|\mathcal{N}_{uv}|}\}.$$

$$\mathbf{g}_{uv} = \text{Readout}(\mathbf{Z}), \quad (6)$$