Coherent Comment Generation for Chinese Articles with a Graph-to-Sequence Model

使用Graph-to-Sequence模型为中文文章生成连贯的评论

ACL 2019

Multi-head Self-attention Based Vertex Encoder(2017 NIPS)

- Embedding module

$$\epsilon_i = e_i + p_i$$

- Self-attention module

$$Attention(Q, K, V) = softmax(QK^T)V$$
$$MultiHead(Q, K, V) = [head_1; \cdots; head_h]W^o$$
$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

RNN decoder With Attention(2015 ICLR)

$$t_i = RNN(t_{i-1}, e_{i-1})$$
$$c_i = \sum \alpha_j \times g_j$$
$$\alpha_j = \frac{exp(\delta(t_i, g_j)}{\sum exp(\delta(t_i, g_k))}$$
$$y_i = softmax(W_o(tanh(W([t_i; c_i]) + b)))$$
$$p_{copy} = \sigma(W_{copy}[t_i; c_i])$$
$$p = (1 - p_{copy}) \times y + p_{copy} \times \alpha$$

Title: *Have you seen the movie intitled as ``the most hilarious Marvel movie?*

s_1: *Click on the ``IPTV4K ultra HD" to subscribe.*

s_2: *fantastic contents are waiting for you to share .*

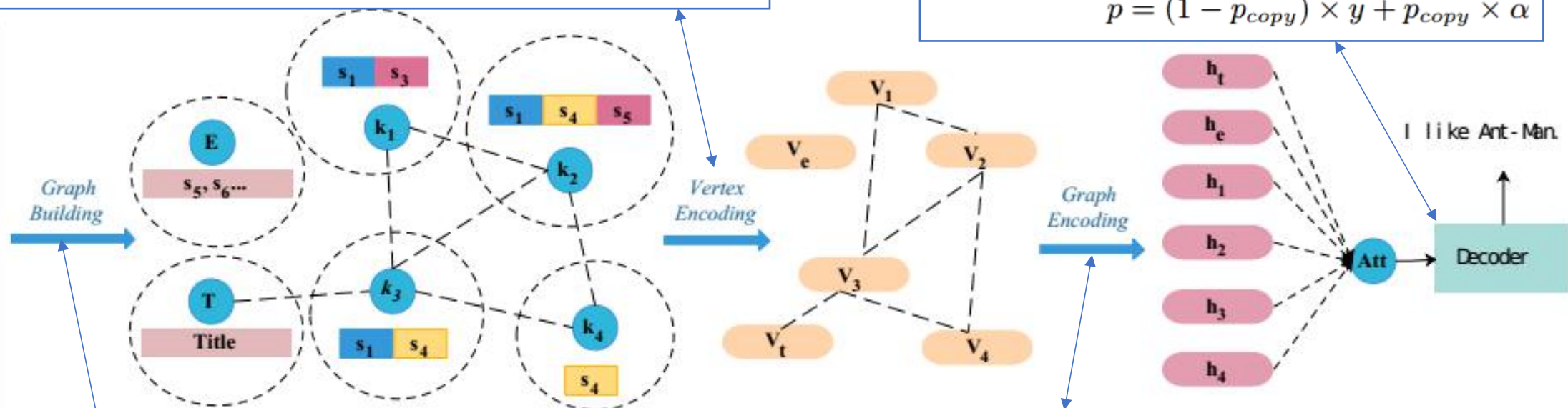
s_3

s_4

s_5

s_6

...



Stanford Core NLP
Text-Rank

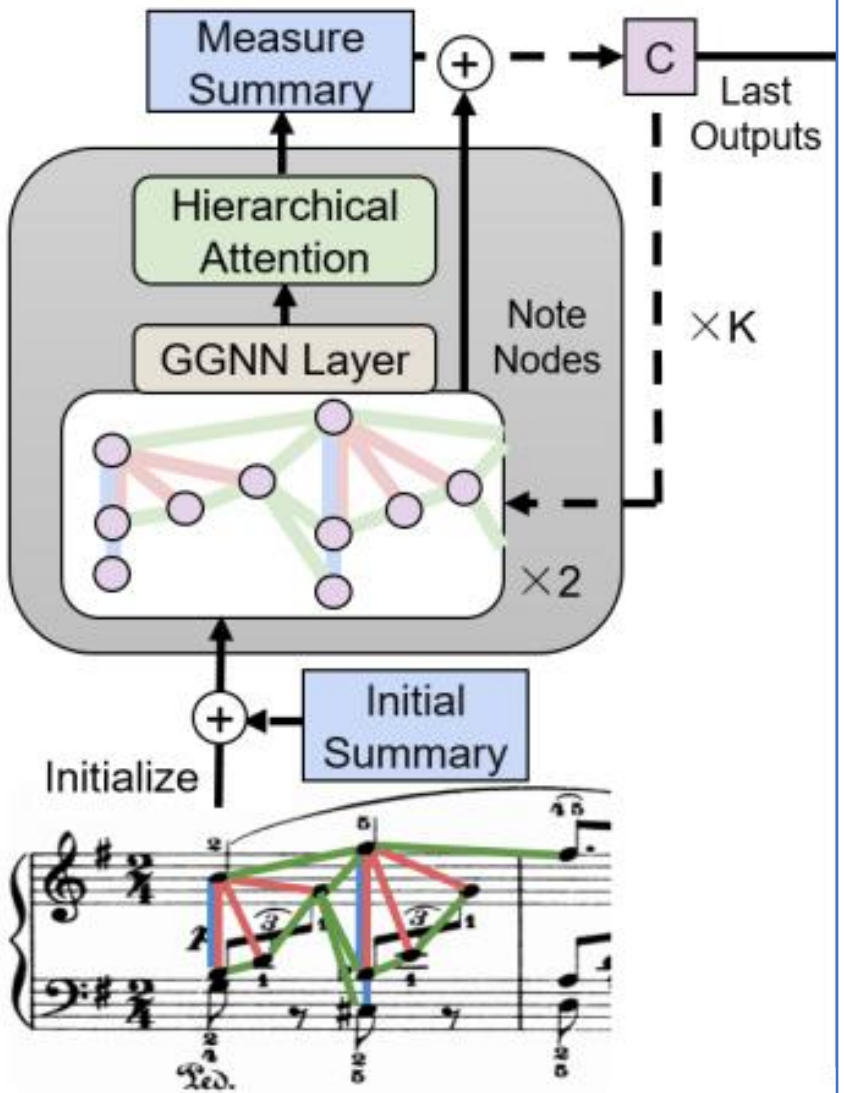
Spectral Based GCN(2016)

$$H^{l+1} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^l W^l)$$
$$\tilde{A} = A + I_N$$
$$g^{l+1} = H^{l+1} + H^l$$
$$g^{out} = tanh(W_o g^K)$$

Graph Neural Network for Music Score Data and Modeling Expressive Piano Performance

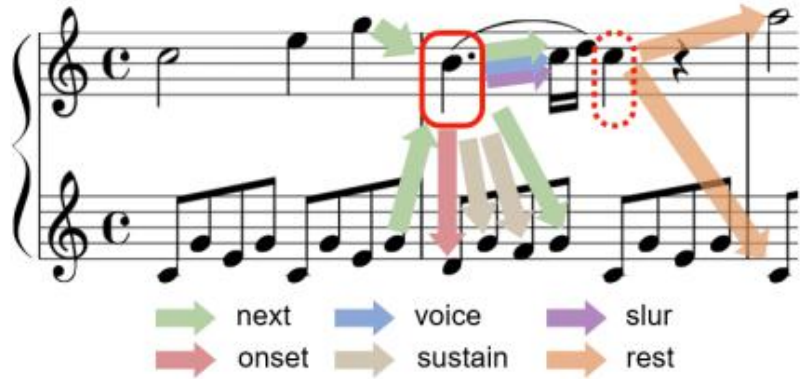
图神经网络用于乐谱数据和钢琴演奏表现力的建模

ICML 2019



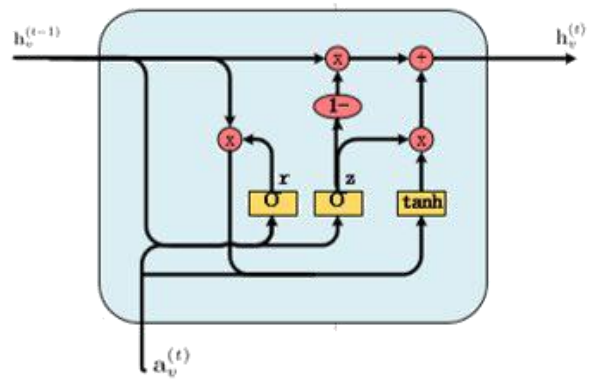
Score Encoder

Note-level Gated GNN (2016 ICLR)



- next 下一个
- rest 休止
- onset 起始
- sustain 持续
- voice 声音
- slur 模糊

- GRU



$$\mathbf{a}_v^{(t)} = \mathbf{A}_v^\intercal \left[\mathbf{h}_1^{(t-1)\intercal} \ldots \mathbf{h}_{|\mathcal{V}|}^{(t-1)\intercal}\right]$$

$$\mathbf{z}_v^{(t)} = \sigma\left(\mathbf{W}^z \mathbf{a}_v^{(t)} + \mathbf{U}^z \mathbf{h}_v^{(t-1)}\right)$$

$$\mathbf{r}_v^{(t)} = \sigma\left(\mathbf{W}^r \mathbf{a}_v^{(t)} + \mathbf{U}^r \mathbf{h}_v^{(t-1)}\right)$$

$$\tilde{\mathbf{h}}_v^{(t)} = \tanh\left(\mathbf{W}\mathbf{a}_v^{(t)} + \mathbf{U}\left(\mathbf{r}_v^t \otimes \mathbf{h}_v^{(t-1)}\right)\right)$$

$$\mathbf{h}_v^{(t)} = \left(1 - \mathbf{z}_v^t\right) \otimes \mathbf{h}_v^{(t-1)} + \mathbf{z}_v^t \otimes \tilde{\mathbf{h}}_v^{(t)}$$

Hierarchical Attention RNN (2015)

$$\mathbf{u}_v = \tanh(\mathbf{W}_a \mathbf{h}_v + \mathbf{b}_a)$$

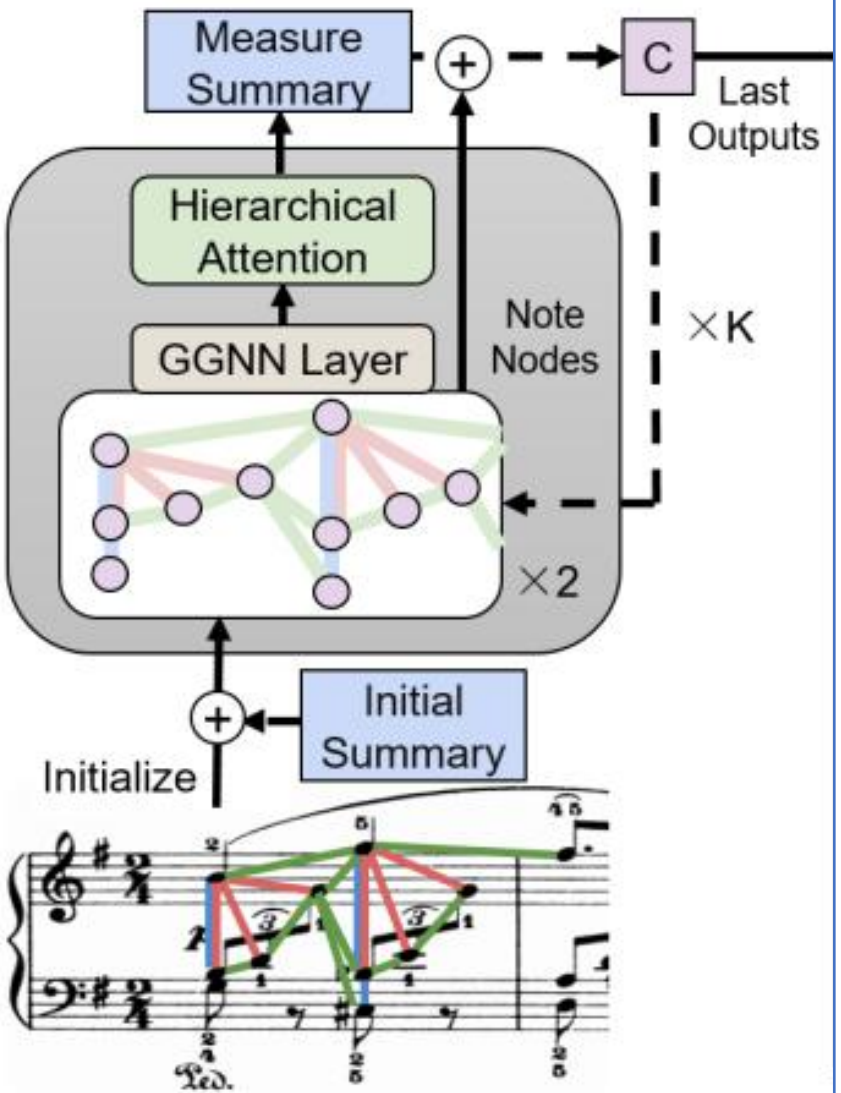
$$\mathbf{u}_v^i = \mathbf{u}_{t,i:(i+1)d}$$

$$\mathbf{h}_v^i = \mathbf{h}_{v,i:(i+1)d}$$

$$\boldsymbol{\alpha}_v^i = \frac{\exp(\mathbf{u}_v^{i\intercal} \mathbf{u}_c^i)}{\sum_t \exp(\mathbf{u}_v^{i\intercal} \mathbf{u}_c^i)}$$

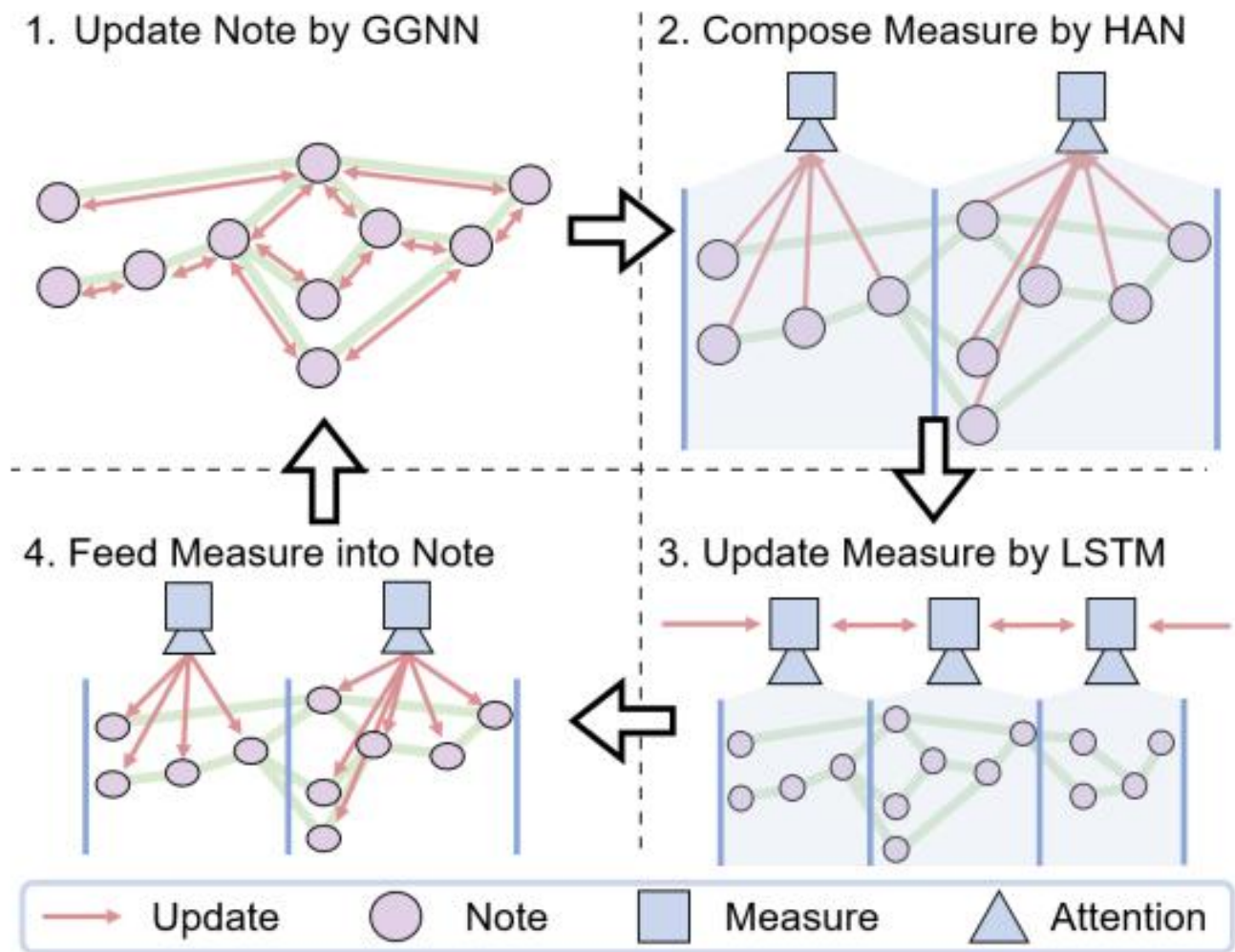
$$\mathbf{m}^i = \sum_v \boldsymbol{\alpha}_v^i * \mathbf{h}_v^i$$

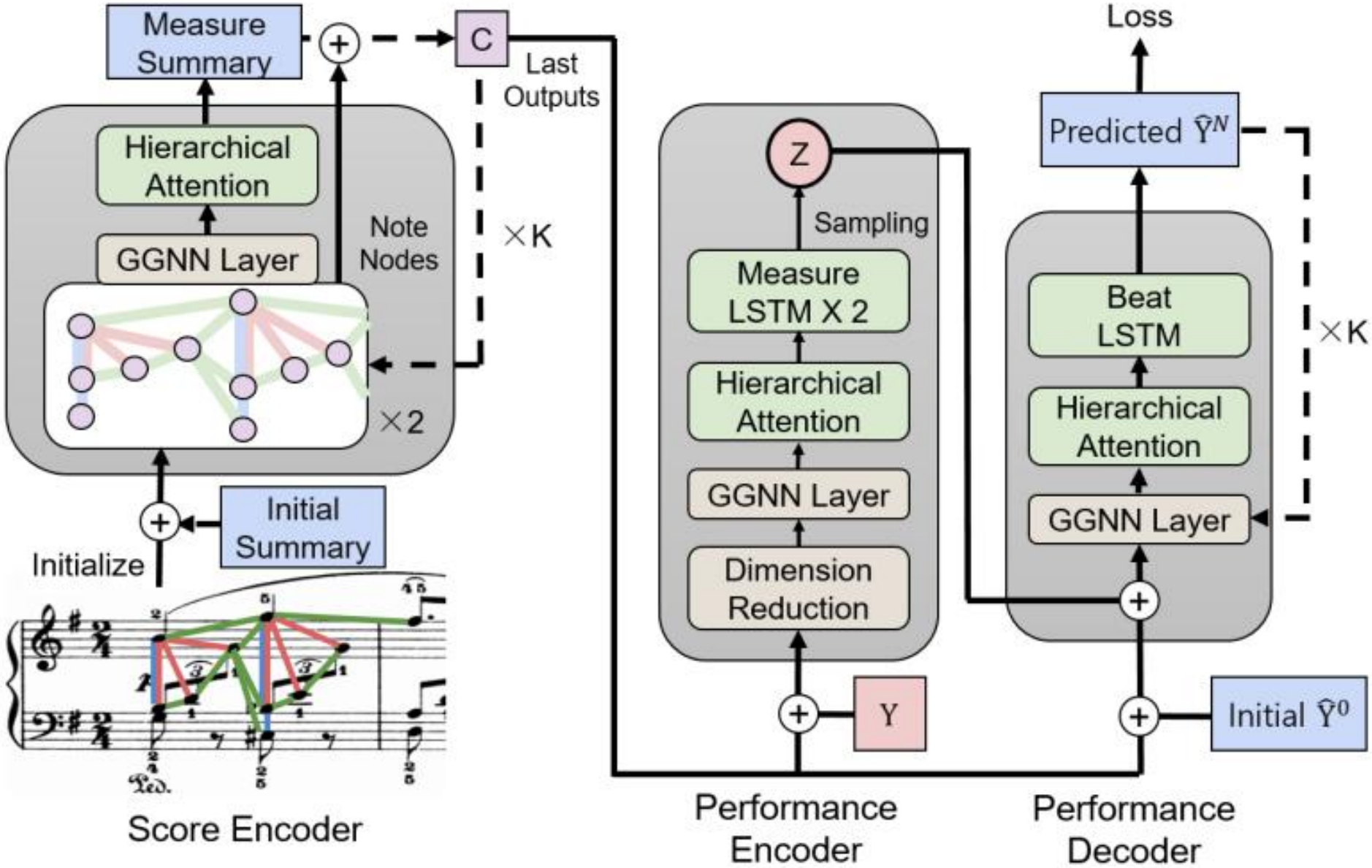
$$\mathbf{m} = \text{Concat}(\mathbf{m}^0, \ldots, \mathbf{m}^I)$$



Score Encoder

Iterative Sequential Graph Network




Measure Summary
C
Last Outputs
Hierarchical Attention
GGNN Layer
Note Nodes
×K
×2
Initial Summary
Initialize
Score Encoder
Loss
Predicted $\hat{Y}^N$
Z
Sampling
Measure LSTM X 2
Hierarchical Attention
GGNN Layer
Dimension Reduction
Y
Performance Encoder
Beat LSTM
Hierarchical Attention
GGNN Layer
×K
Initial $\hat{Y}^0$
Performance Decoder