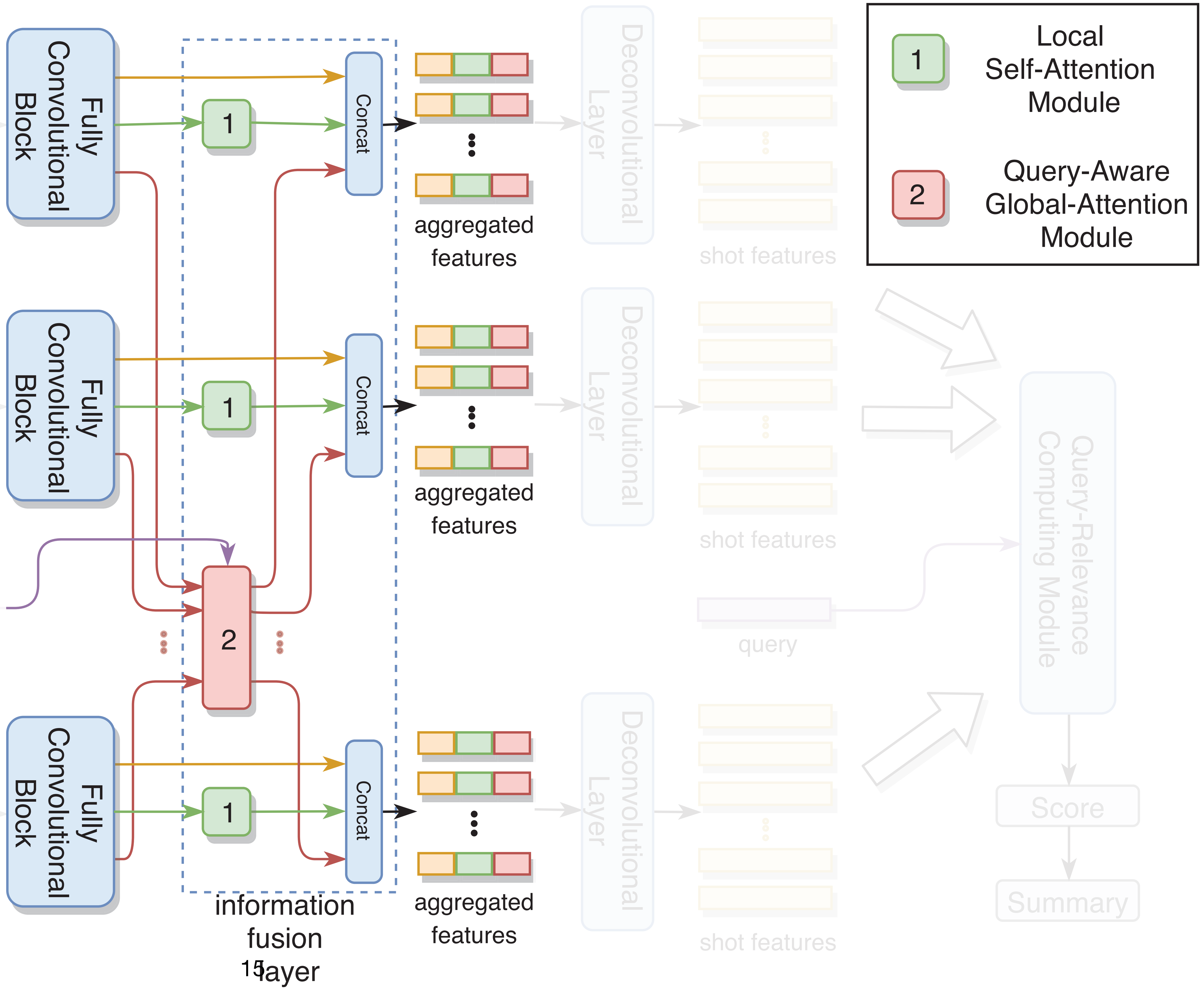
Proposed Method

Information Fusion Layer

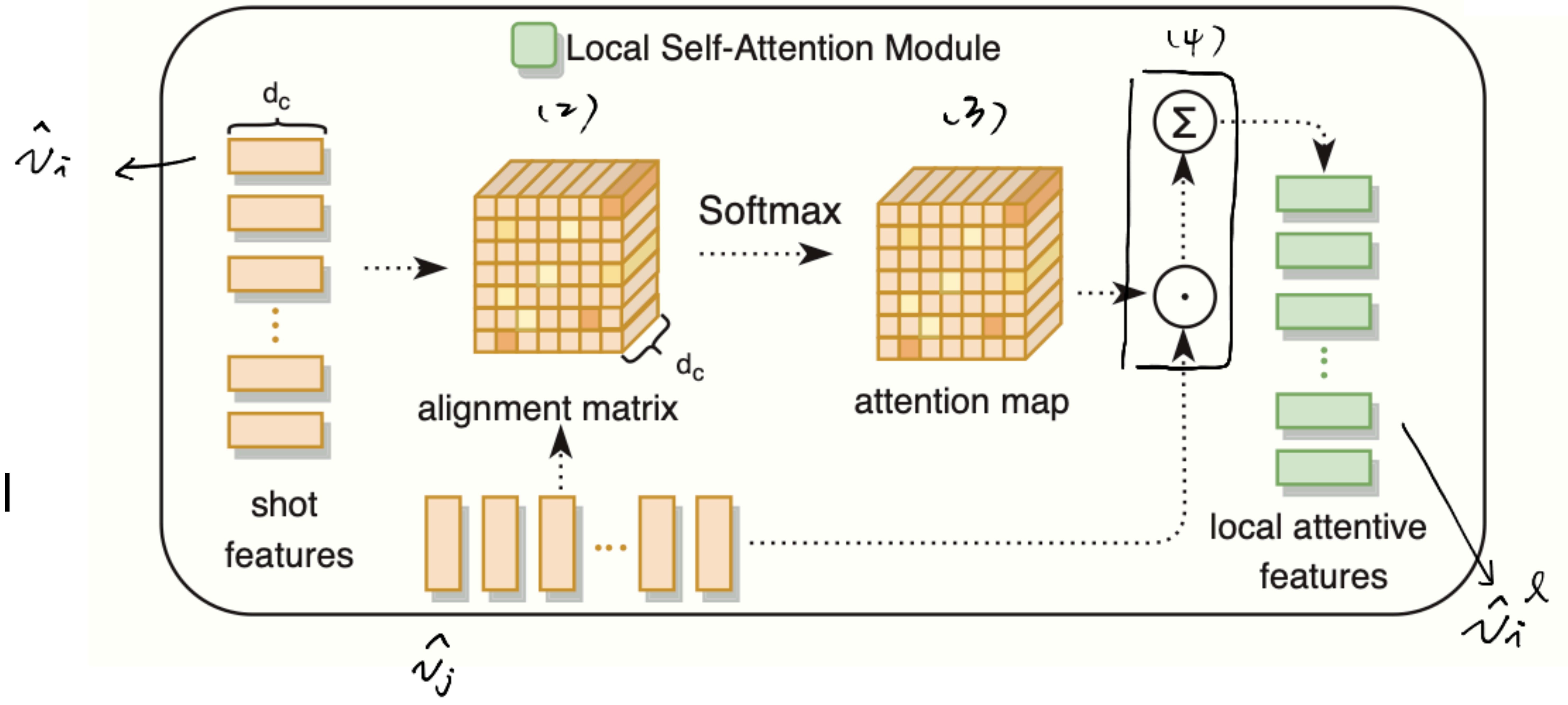
- Denote the output features of fully convolutional block as $(\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_t)$
  - t: length of output feature sequence
- **Input**: features from fully convolutional block
- **Output**: Sequence of concatenated vectors
  - {outputs from previous block, local attentive, query-aware global attentive}



Proposed Method

Local self-attention module

- Capture the semantic relations between all shots among a video segment.
- Given $(\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_t)$ to compute the alignment matrix. (shape: $t \times t \times d_c$)
- Module can learn the relative semantic relationship of different frames in the same segments.
- For different segments, the relation structure should be similar. Therefore, modules share all the trainable parameters, also reduces the amounts of parameters in our model.



(2) $f(\hat{v}_i, \hat{v}_j) = P \tanh(W_1\hat{v}_i + W_2\hat{v}_j + b) \in R^{d_c}$

- $P, W_1, W_2 \in R^{d_c \times d_c}$: trainable parameters
- $b \in R^{d_c}$: bias vector , d_c : dimension of $\hat{v}_i$

(3) $r_{ij} = \dfrac{\exp(f(\hat{v}_i, \hat{v}_j))}{\sum_{k=0}^{t} \exp(f(\hat{v}_i, \hat{v}_k))}$

(4) Local attentive video feature for i-th: $\hat{v}_i^l = \sum_{j=0}^{t} r_{ij} \odot \hat{v}_j$