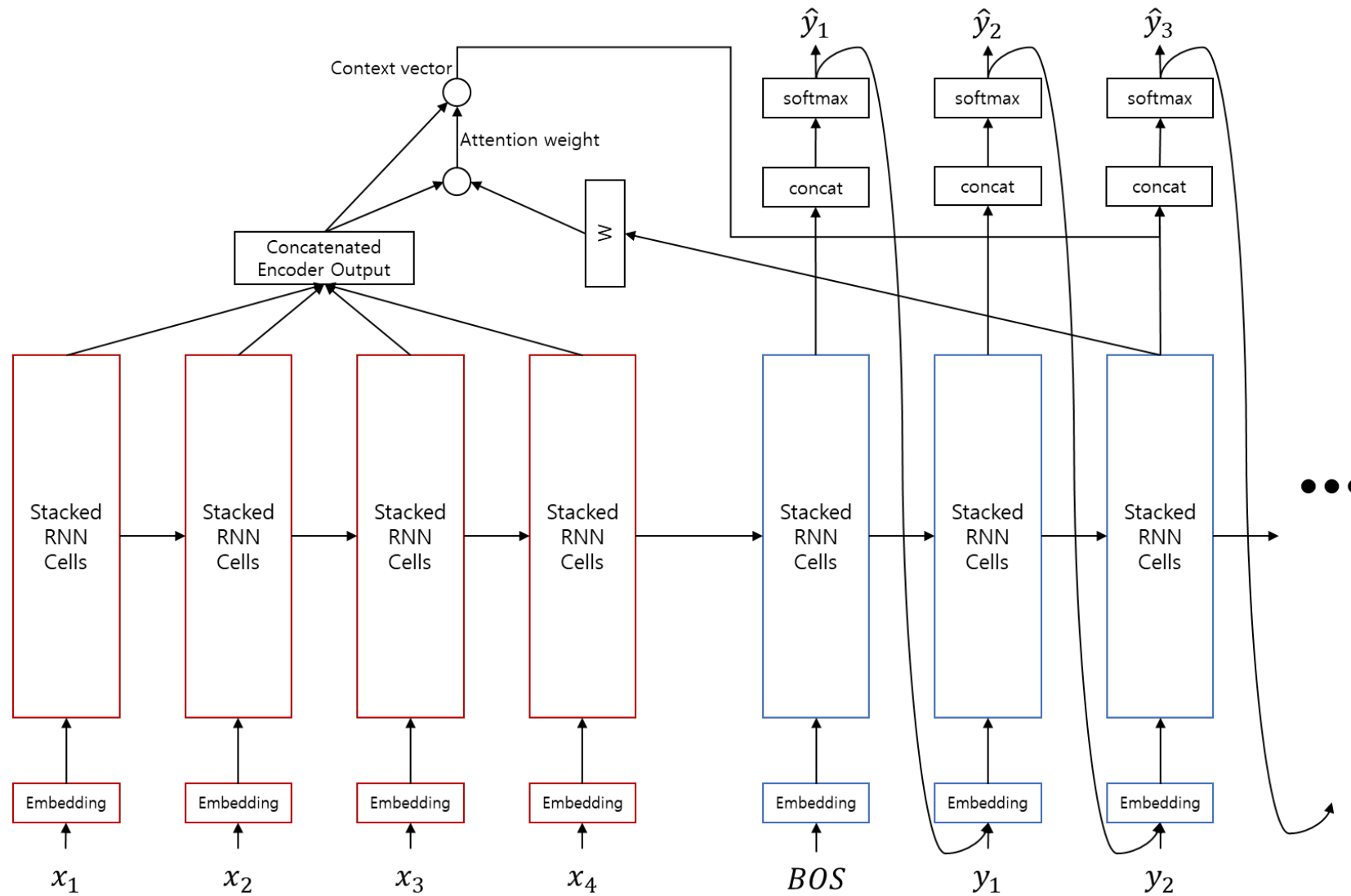


# Input Feeding

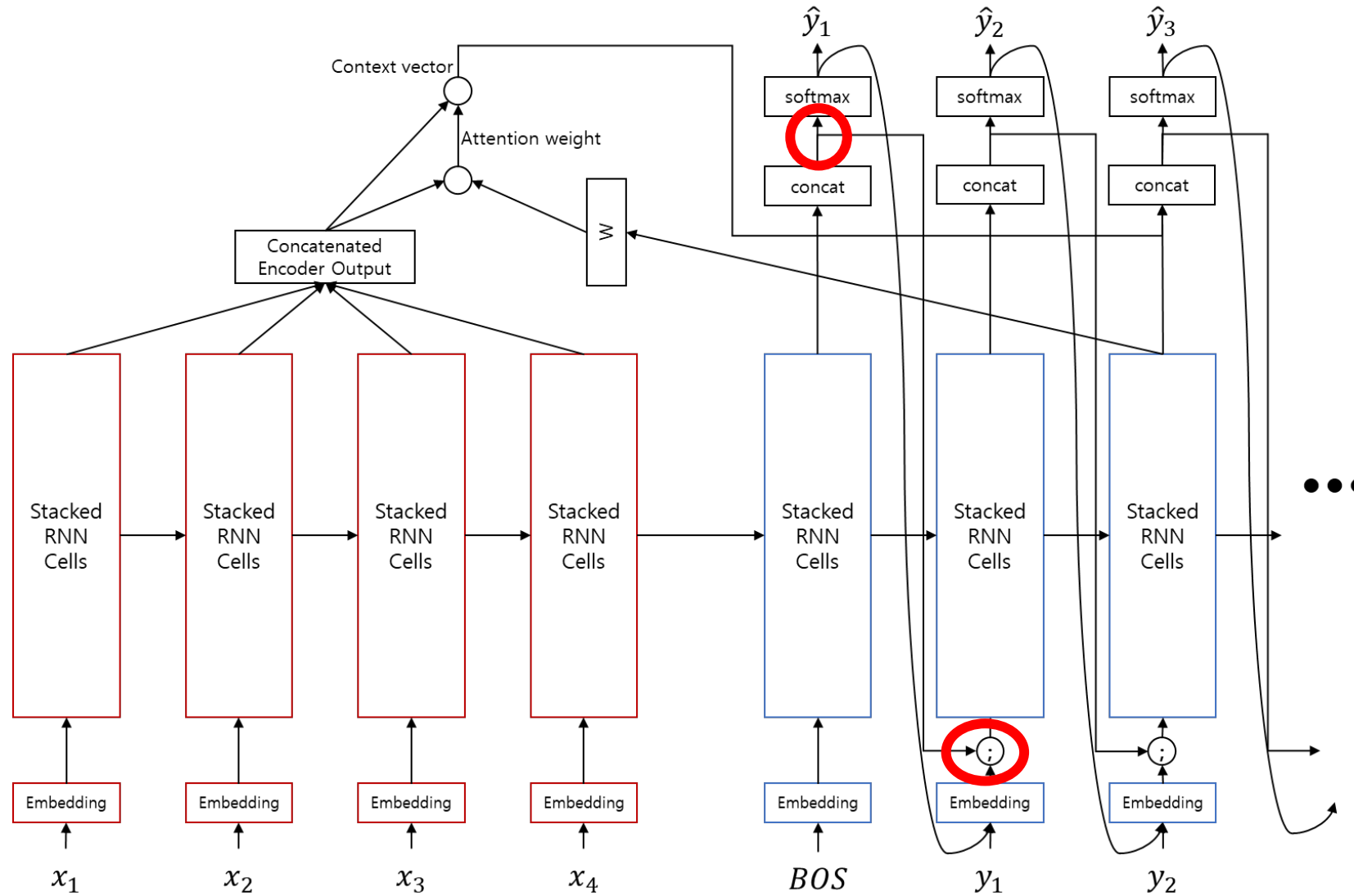
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# Motivation



# Input Feeding



# By Input Feeding,

- Sampling 과정에서 손실 되는 정보를 최소화
- Teacher Forcing으로 인한 학습/추론 사이의 괴리를 최소화

# Full Equations

$$\mathcal{D} = \{x^i, y^i\}_{i=1}^N$$

$$x^i = \{x_1^i, \dots, x_m^i\} \text{ and } y^i = \{y_0^i, y_1^i, \dots, y_n^i\},$$

where  $y_0 = \langle \text{BOS} \rangle$  and  $y_n = \langle \text{EOS} \rangle$ .

$$\hat{y}_{1:n} = f(x_{1:m} : \theta)$$

$$h_{1:m}^{\text{enc}} = \text{RNN}_{\text{enc}}(\text{emb}_{\text{enc}}(x_{1:m}), h_0^{\text{enc}}), \text{ where } h_0^{\text{enc}} = 0.$$

$$h_t^{\text{dec}} = \text{RNN}_{\text{dec}}([\text{emb}_{\text{dec}}(y_{t-1}); \tilde{h}_{t-1}^{\text{dec}}], h_{t-1}^{\text{dec}}),$$

where  $h_0^{\text{dec}} = h_m^{\text{enc}}$ .

$$w = \text{softmax}(h_t^{\text{dec}} \cdot W_a \cdot h_{1:m}^{\text{enc} \top})$$

$$c = w \cdot h_{1:m}^{\text{enc}},$$

where  $W_a \in \mathbb{R}^{\text{hidden\_size} \times \text{hidden\_size}}$ .

$$\tilde{h}_t^{\text{dec}} = \tanh([h_t^{\text{dec}}; c] \cdot W_{\text{concat}})$$

$$\hat{y}_t = \text{softmax}(\tilde{h}_t^{\text{dec}} \cdot W_{\text{gen}}),$$

where  $W_{\text{concat}} \in \mathbb{R}^{(2 \times \text{hidden\_size}) \times \text{hidden\_size}}$  and  $W_{\text{gen}} \in \mathbb{R}^{\text{hidden\_size} \times |V|}$ .

$$\mathcal{L}(\theta) = - \sum_{i=1}^N \sum_{t=1}^n \log P(y_t^i | x^i, y_{<t}^i; \theta)$$

$$= - \sum_{i=1}^N \sum_{t=1}^n y_t^{i \top} \cdot \log \hat{y}_t^i$$

$$\theta \leftarrow \theta - \alpha \nabla_{\theta} \mathcal{L}(\theta)$$

# Wrap-up

## Encoder

- 문장을 받아 context vector로 압축
- Bi-directional RNN을 통해 구현

## Attention

- Key-value 함수
- 디코더의 hidden state를 인코더의 각 hidden state에 유사도 비교
- 좋은 query를 만들어내는 과정을 학습

## Decoder & Generator

- Conditional Language Model
  - Encoder로부터 정보를 받아 문장을 생성
- Cross Entropy(PPL)를 통해 최적화

## Input Feeding

- Sampling 과정에서 손실된 정보를 word embedding에 concatenate