

Attention mechanism

Motivation

- LSTMs help with memory, but it's still hard.
- For encoder/decoder models, the fixed-length embedding is problematic.

we can choose the output of decoder to be large, but still finite

Encoder-decoder

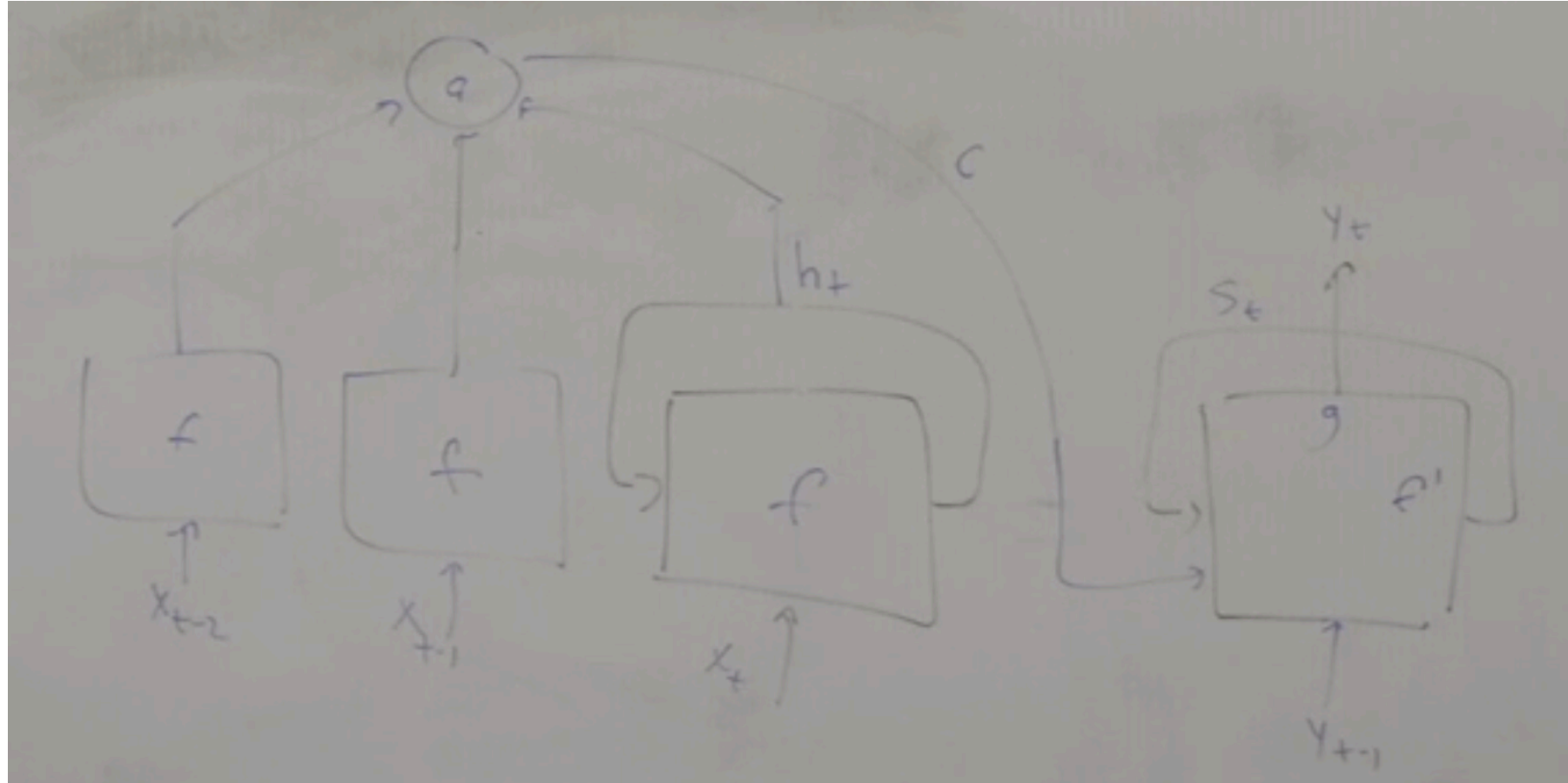
$$h_t = f(x_t, h_{t-1})$$

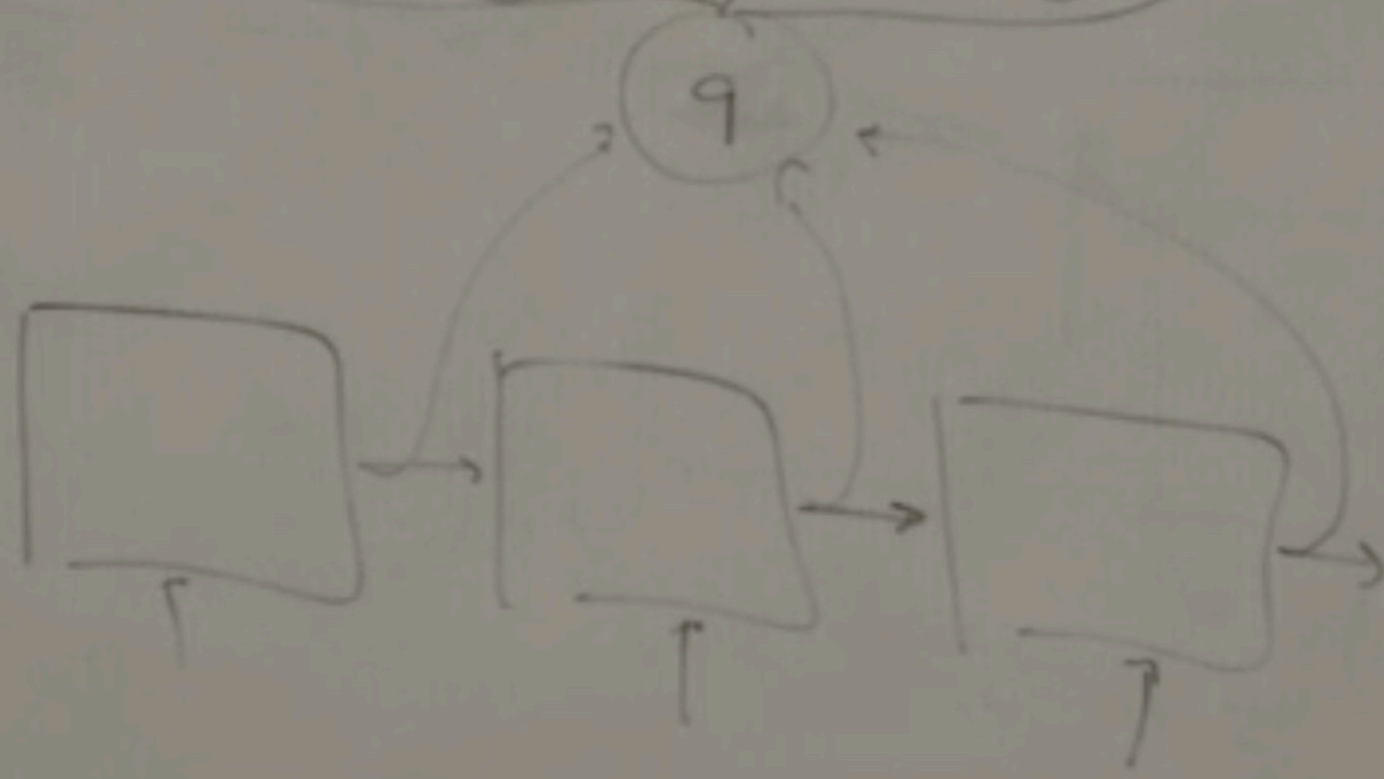
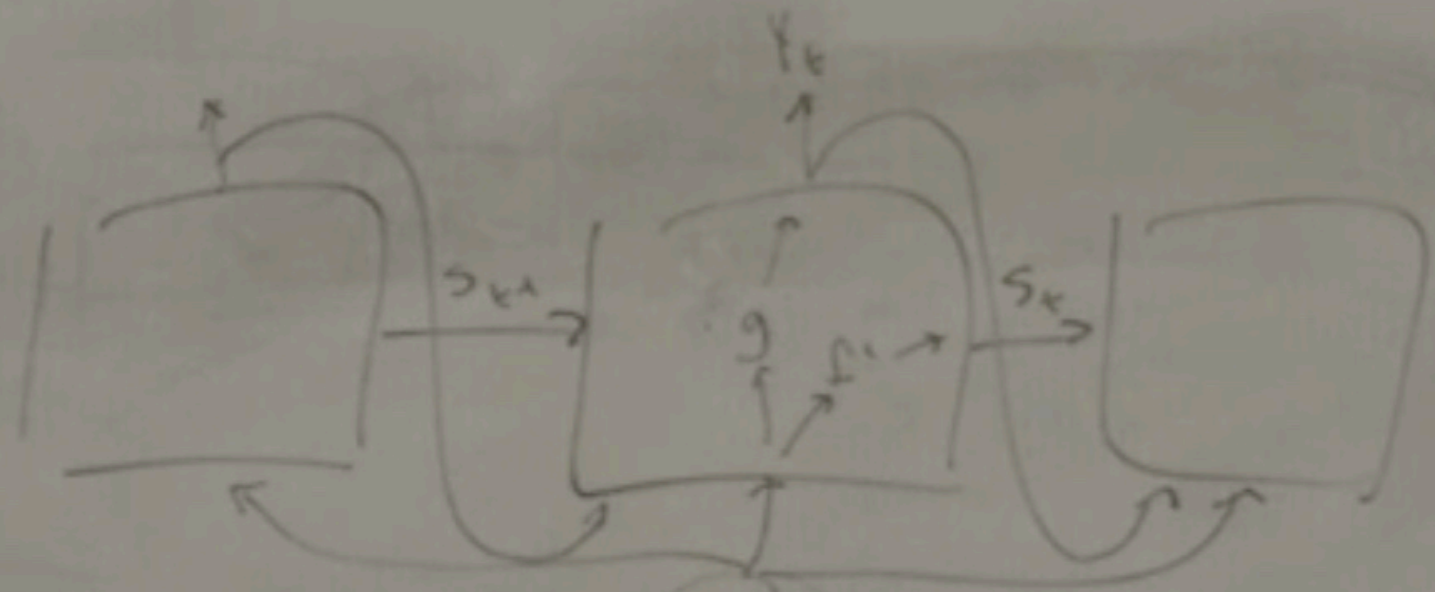
q — somehow aggregate all of the h_t (mean, median)

$$c = q(\{h_1, \dots, h_{T_x}\})$$

$$p(y_t | \{y_1, \dots, y_{t-1}\}, c) = g(y_{t-1}, s_t, c)$$

$$s_t = f'(s_{t-1}, y_{t-1}, c)$$





with attention

decoder: state output

$$s_i = f'(s_{i-1}, y_{i-1}, c_i)$$

compute a special weighted
sum of the input information

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

encoder: hidden state

α_{ij} describe the relationship between output i and input j

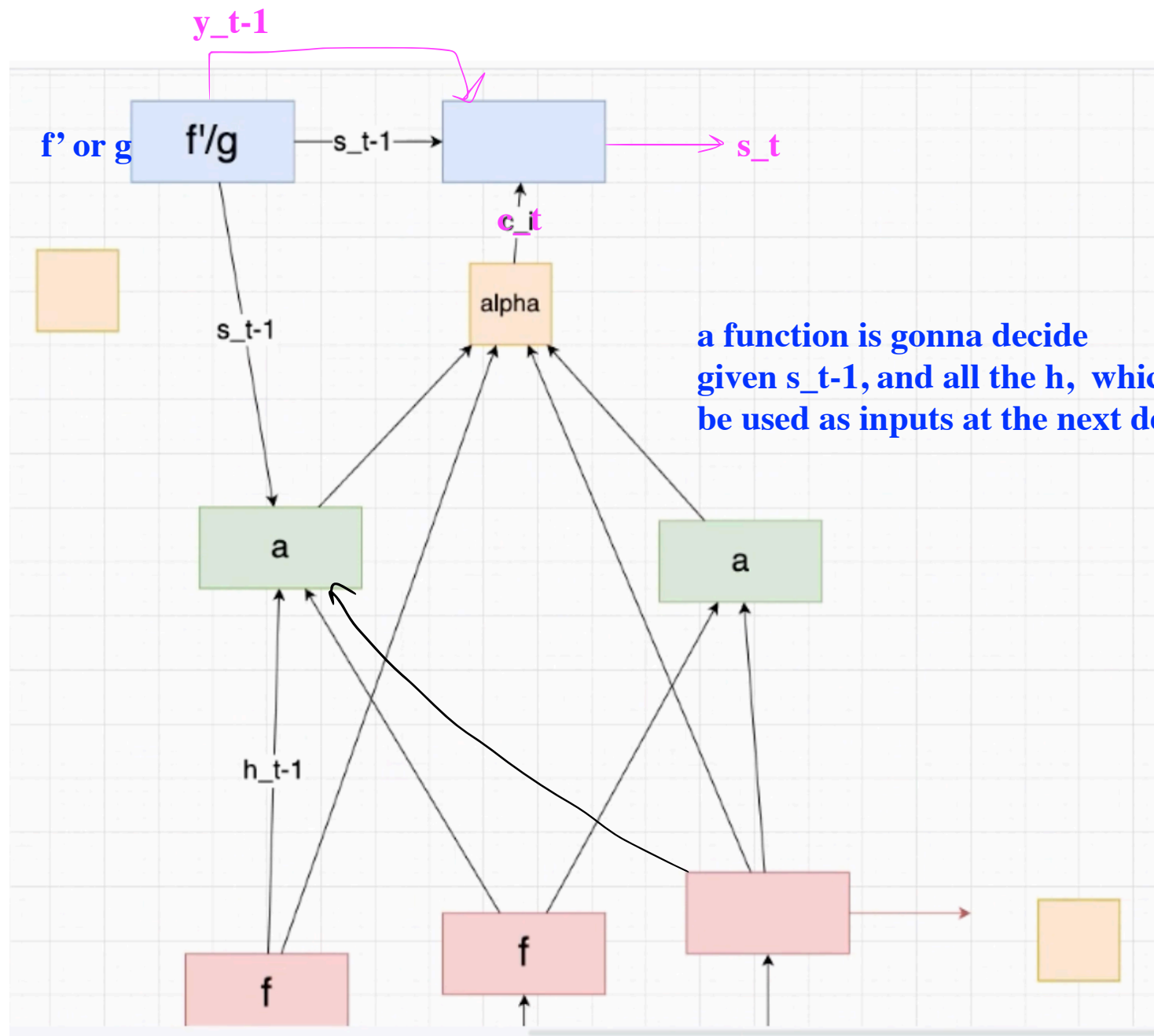
i for decoder, j for encoder

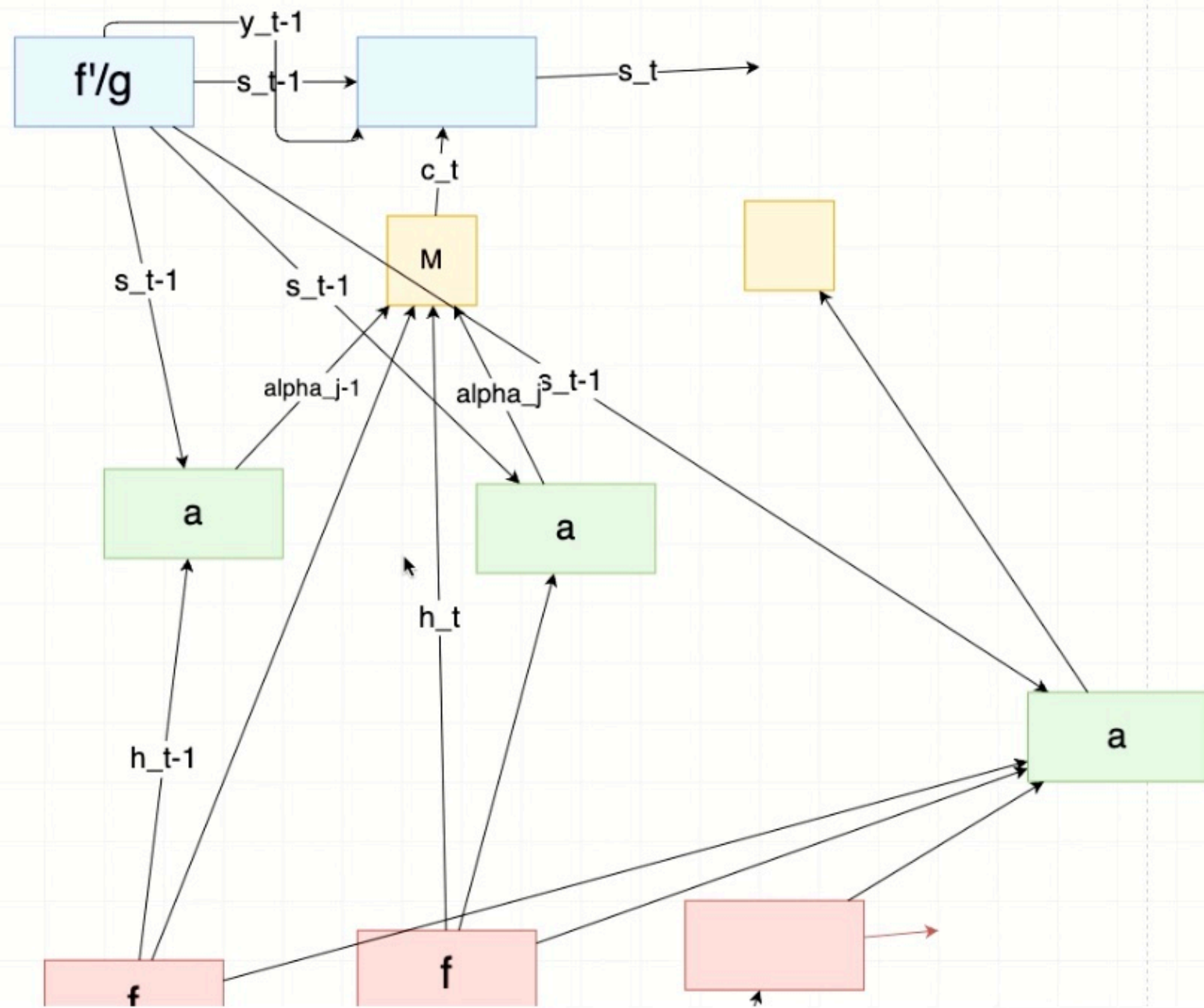
just normalizing so that sum to 1

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

$$e_{ij} = a(s_{i-1}, h_j)$$

a 是一个公式 $\text{QKt}/\text{sqrt}(n)$



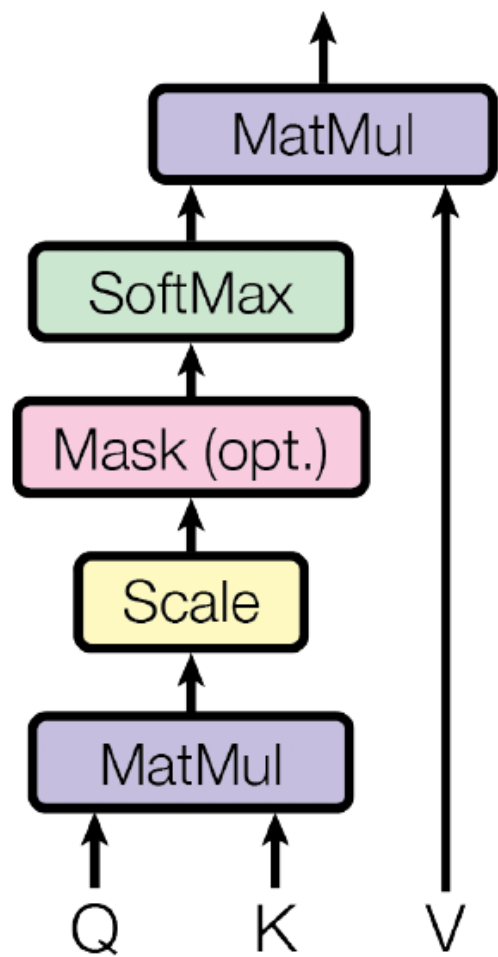


Broad idea of attention:

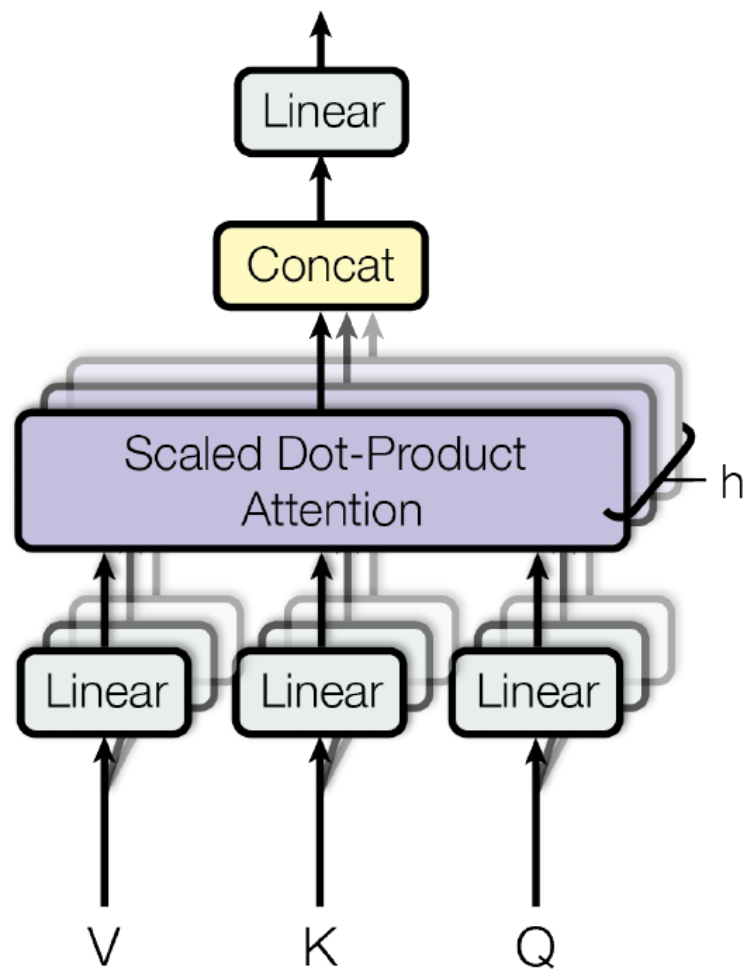
we compute how much to care about each input, specially given each output (with real information about that output which comes from the previous state(s_{t-1}))

this did two things for us when we sort of reduced that bottleneck of the big context sector by saying that we get compute the context independently for each output and it shortens the network (the shortest path between each output and each input has shrunk).

the output just need to decide to depend on that input and the path (the number of weights and activation function that information need to go through to get where it needs to go).



$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{n}} \right) \mathbf{V}$$



Resources

- [Neural Machine Translation by Jointly Learning to Align and Translate](#)
- [Attention Is All You Need](#)