

# From Weighted Mean to FlashAttention

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In this note, self-attention is approached from the view of weighted mean. Then from this insight, flash attention and ring attention are deciphered in a unified way.

## 1 The Self-Attention

The computation of self attention in it's simplest form can be described as:

$$O = softmax(QK^T)V \quad (1)$$

which can be further factorized to 3 stage:

$$S = QK^T \quad (2)$$

$$P = softmax(S) \quad (3)$$

$$O = PV \quad (4)$$

For the convenience of subsequent discussions, two extra matrices are defines beforehand.

$$W = exp(S) = P * rowsum(S) \quad (5)$$

$$W_{safe} = exp(S - rowmax(S)) = W * exp(-rowmax(S)) \quad (6)$$

## 2 Weighted Mean

Formally, the weighted mean of a non-empty finite tuple of data  $(x_1, x_2, \dots, x_n)$ , with the corresponding non-negative weights  $(w_1, w_2, \dots, w_n)$  is

$$\bar{x} = \frac{\sum_1^n w_k * x_k}{\sum_1^n w_k} \quad (7)$$

### 2.1 Online Weighted Mean

Weighted mean can be calculated in a streaming way, with the data and weight feed one by one (or block by block). And there are two algorithms (1, 2).

### 3 Weighted Mean and Self-Attention

Since the sum of each row of  $P$  is 1. Each row of  $O$  can be considered as a weighted mean of the rows of  $V$ , with the corresponding row of  $P$  as weights.

Mathematically, If the weights are scaled by a common factor, the weighted mean remains the same. Hence, each row of  $O$  can also be considered as a weighted mean of the rows of  $V$ , with the corresponding row of  $W$  or  $W_{safe}$  as weights.

### 4 Flash Attention: Online Weighted Mean

With numerical stability taken into consideration, each row of  $O$  can be regarded as a weighted mean of the rows of  $V$ , with the corresponding row of  $W_{safe}$  as weights. Resembling the two algorithms for online weighted mean, there are two algorithms (3, 4) for computing  $O$ , corresponding to flash attention 1 and flash attention 2 respectively.

### 5 Ring Attention: Hierarchy Weighted Mean

If we define

$$\bar{x}_{(i,j)} = \frac{\sum_i^j w_k * x_k}{\sum_i^j w_k} \quad (8)$$

$$d_{(i,j)} = \sum_i^j w_k \quad (9)$$

then the global weighted mean can be computed as a weighted mean of two local weighted mean

$$\bar{x} = \frac{d_{(1,m)}}{d_{(1,n)}} \bar{x}_{(1,m)} + \frac{d_{(m+1,n)}}{d_{(1,n)}} \bar{x}_{(m+1,n)} \quad (10)$$

The equation above assumes that the elements are split into two groups. However, it can be extrapolated to any group, the global weighted mean is a weighted mean of local weighted mean:

$$\bar{x} = \frac{d_{(1,m_1)}}{d_{(1,n)}} \bar{x}_{(1,m_1)} + \frac{d_{(m_1+1,m_2+1)}}{d_{(1,n)}} \bar{x}_{(m_1+1,m_2+1)} + \dots + \frac{d_{(m_k+1,n)}}{d_{(1,n)}} \bar{x}_{(m_k+1,n)} \quad (11)$$

This is the mathematics behind ring attention:  $K$  and  $V$  are split into blocks; each block attention results in a partial result, and the final result is a weighted mean of the partial results.

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**Algorithm 1** one pass weighted mean 1

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```
1:  $\bar{x}_0 = 0$ 
2:  $d_0 = 0$ 
3: for  $i = 1, 2, \dots, N$  do
4:    $d_i = d_{i-1} + w_i$ 
5:    $\bar{x}_i = \frac{d_{i-1}}{d_i} \bar{x}_{i-1} + \frac{w_i}{d_i} x_i$ 
6: end for
7:  $\bar{x} = \bar{x}_N$ 
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**Algorithm 2** one pass weighted mean 2

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```
1:  $\bar{x}_0 = 0$ 
2:  $d_0 = 0$ 
3: for  $i = 1, 2, \dots, N$  do
4:    $d_i = d_{i-1} + w_i$ 
5:    $\bar{x}_i = \bar{x}_{i-1} + w_i x_i$ 
6: end for
7:  $\bar{x} = \frac{\bar{x}_N}{d_N}$ 
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**Algorithm 3** flash attention 1

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```
1:  $m_0 = -\infty$ 
2:  $d'_0 = 0$ 
3:  $o'_0 = \text{row vector of } 0$ 
4: for  $i = 1, 2, \dots, N$  do
5:    $x_i = Q[k, :] K^T[:, i]$ 
6:    $m_i = \max(m_{i-1}, x_i)$ 
7:    $d'_i = d'_{i-1} e^{m_{i-1} - m_i} + e^{x_i - m_i}$ 
8:    $o'_i = \frac{d'_{i-1} e^{m_{i-1} - m_i}}{d'_i} o'_{i-1} + \frac{e^{x_i - m_i}}{d'_i} V[i, :]$ 
9: end for
10:  $O[k, :] = o'_N$ 
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**Algorithm 4** flash attention 2

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```
1:  $m_0 = -\infty$ 
2:  $d'_0 = 0$ 
3:  $o'_0 = \text{row vector of } 0$ 
4: for  $i = 1, 2, \dots, N$  do
5:    $x_i = Q[k, :] K^T[:, i]$ 
6:    $m_i = \max(m_{i-1}, x_i)$ 
7:    $d'_i = d'_{i-1} e^{m_{i-1} - m_i} + e^{x_i - m_i}$ 
8:    $o'_i = o'_{i-1} e^{m_{i-1} - m_i} + e^{x_i - m_i} V[i, :]$ 
9: end for
10:  $O[k, :] = \frac{o'_N}{d'_N}$ 
```

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