This is a sample of the report, but applicable for all homework.

[113062575] [徐義鈞] This is for double verification.

Don't copy the problem statement, just write the answer.

Please write down the question number in unit of sub-question.

Please write down the sub-question number even if you don't know how to solve it.

Part1

(1.3.1)

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Net                                      [1, 10]                   --
├─Sequential: 1-1                        [1, 6, 28, 28]            --
│    └─Conv2d: 2-1                       [1, 6, 28, 28]            150
│    └─ReLU: 2-2                         [1, 6, 28, 28]            --
├─Sequential: 1-2                        [1, 6, 14, 14]            --
│    └─MaxPool2d: 2-3                    [1, 6, 14, 14]            --
├─Sequential: 1-3                        [1, 16, 10, 10]           --
│    └─Conv2d: 2-4                       [1, 16, 10, 10]           2,400
│    └─ReLU: 2-5                         [1, 16, 10, 10]           --
├─Sequential: 1-4                        [1, 16, 5, 5]             --
│    └─MaxPool2d: 2-6                    [1, 16, 5, 5]             --
├─Sequential: 1-5                        [1, 120, 1, 1]            --
│    └─Conv2d: 2-7                       [1, 120, 1, 1]            48,000
│    └─ReLU: 2-8                         [1, 120, 1, 1]            --
├─Sequential: 1-6                        [1, 84]                   --
│    └─Linear: 2-9                       [1, 84]                   10,080
│    └─ReLU: 2-10                        [1, 84]                   --
├─Sequential: 1-7                        [1, 10]                   --
│    └─Linear: 2-11                      [1, 10]                   840
==========================================================================================
Total params: 61,470
Trainable params: 61,470
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 0.42
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.05
Params size (MB): 0.25
```

Estimated Total Size (MB): 0.30

===

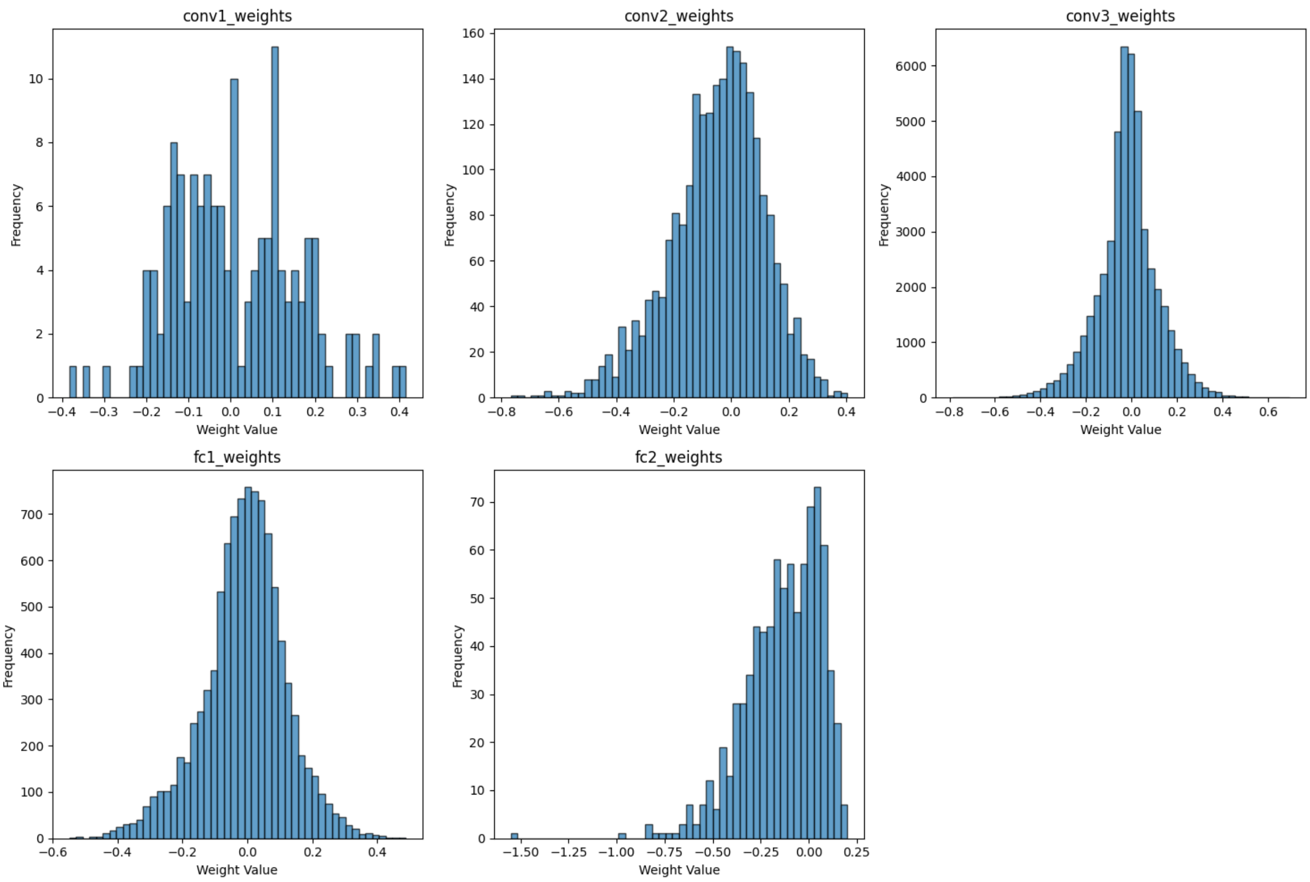
(1.3.2)

	type	input activation size	output activation size	activation function
conv1	convolution	1*32*32	6*28*28	ReLU
maxpool2	pooling	6*28*28	6*14*14	
conv3	convolution	6*14*14	16*10*10	ReLU
maxpool4	pooling	16*10*10	16*5*5	
conv5	convolution	16*5*5	120*1*1	ReLU
fc6	fully-connected	120	84	ReLU
output	fully-connected	84	10	

(1.3.3)

可以，藉由修改input / ouput activation size 即可正常運作。但是會使參數量顯著提升，影響模型效能，對於影像識別的表現可能會下降。

(2.1.1)



(2.2.1)

我使用symmetric quantization，具體計算為:max(abs(weights)) / 255

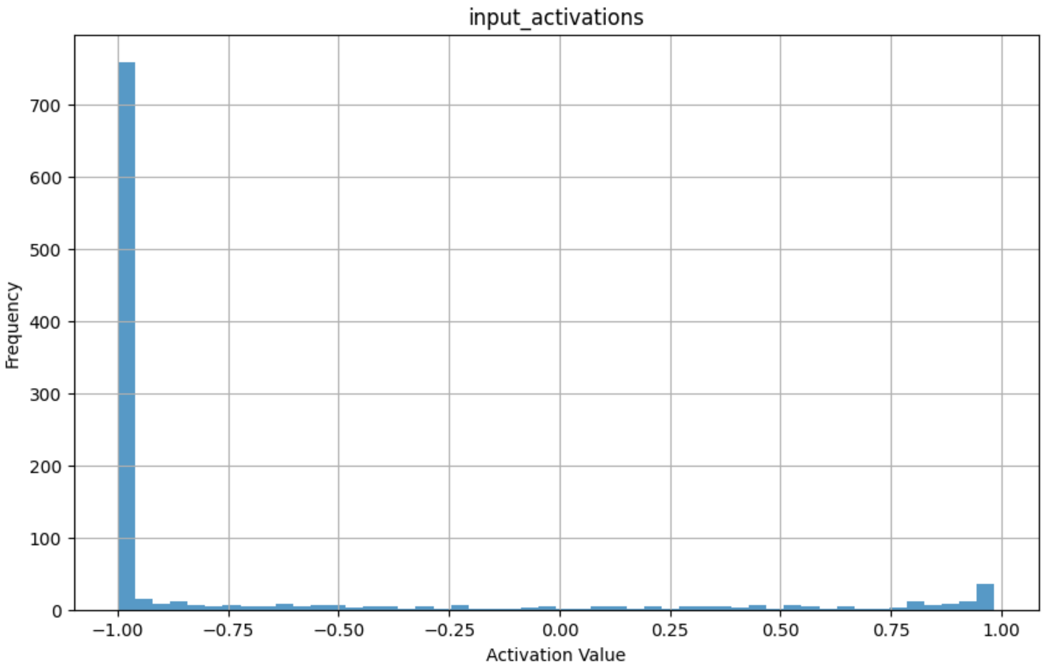
(2.2.2)

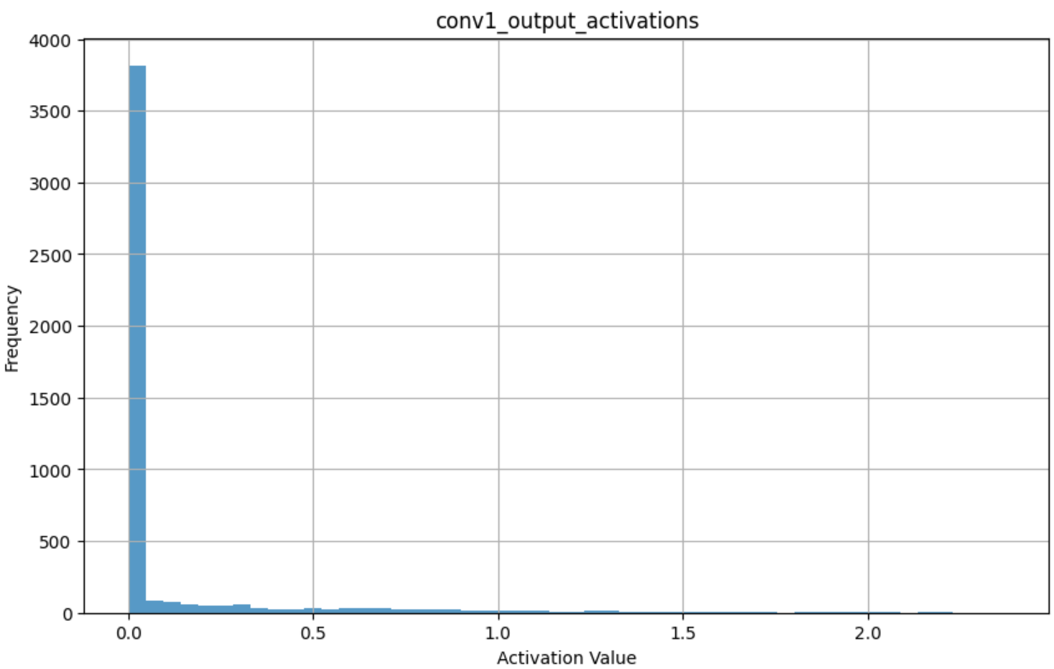
Accuracy of the network on the test images: 98.69%

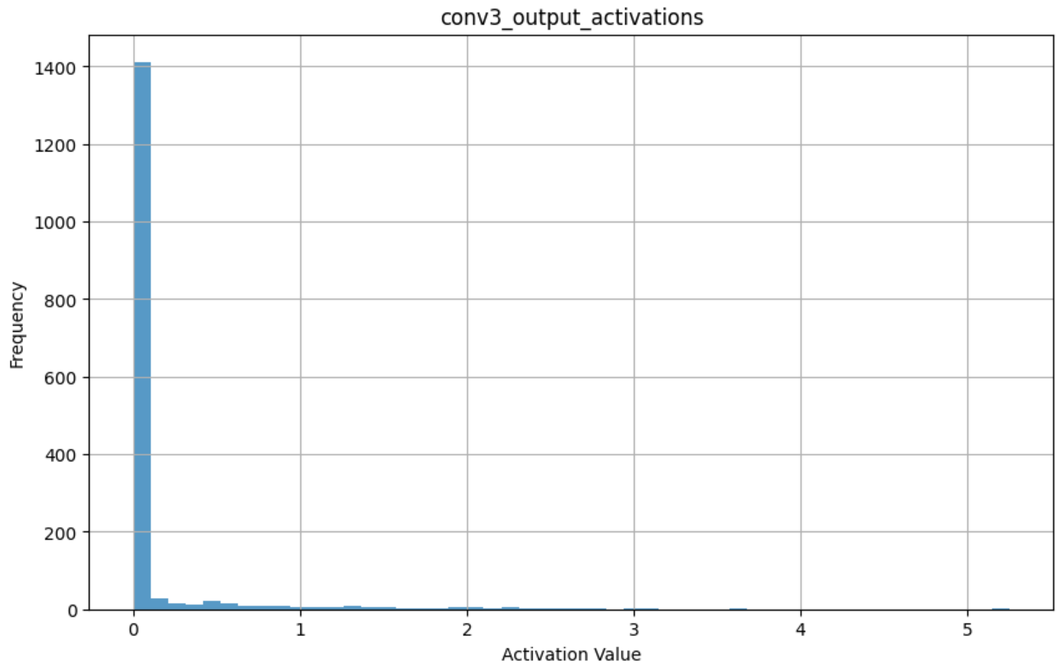
Accuracy of the network after quantizing all weights: 98.68%

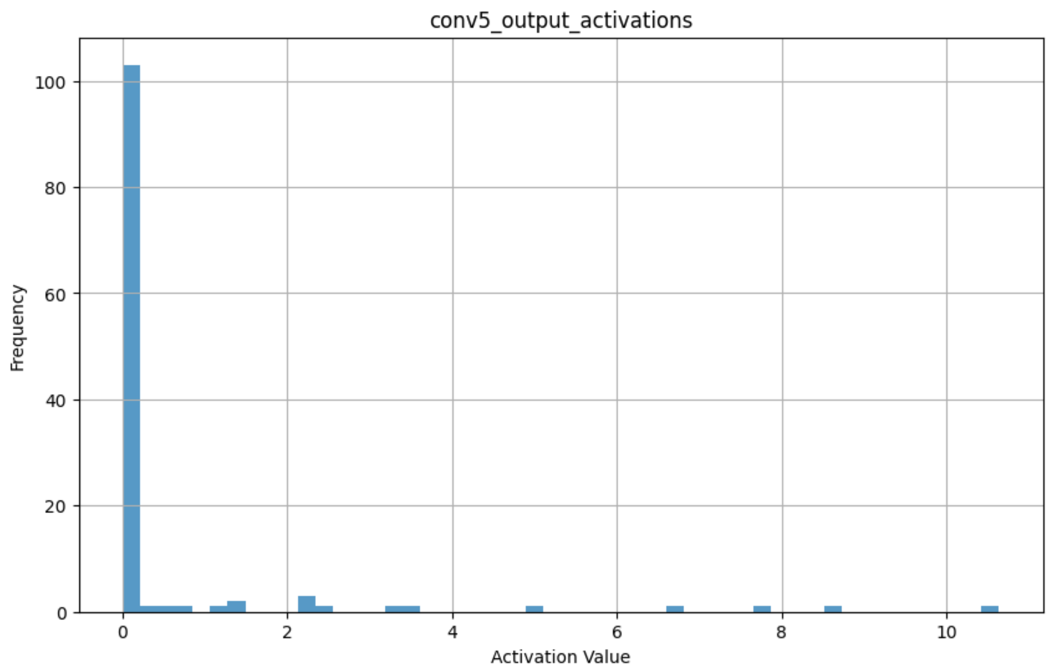
Accuracy degradation is 0.01%

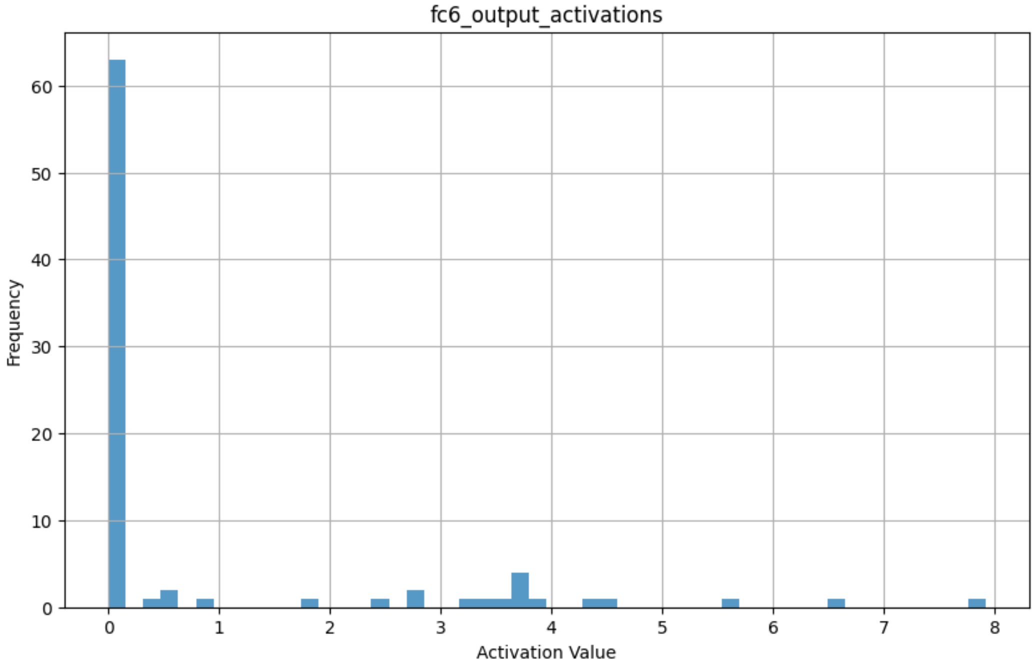
(2.3.1)

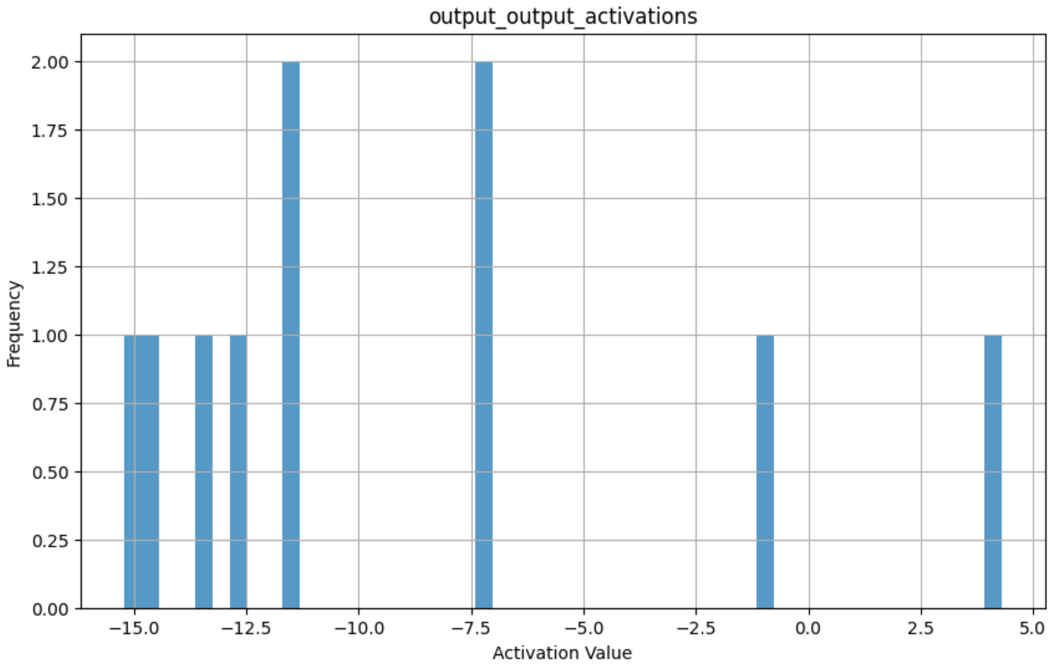





conv3_output_activations
Frequency
Activation Value
0
200
400
600
800
1000
1200
1400
0
1
2
3
4
5


conv5_output_activations
Frequency
Activation Value
0
20
40
60
80
100
0
2
4
6
8
10





(2.4.1)

SI, $SWconv1$, and $SOconv1$ 這三者的計算方式概念都一樣，以SI為例：max(abs(inputactivations)) / 255，其他兩者依此類推。

(2.4.2)

$$Oconv1q = \frac{\mathrm{SWconv1} * \mathrm{SI}}{\mathrm{SOconv1}} * (Wconv1q * Iq)$$

$$M_1 = \frac{\mathrm{SWconv1} * \mathrm{SI}}{\mathrm{SOconv1}}$$

(2.4.3)

$Oconv3q = \frac{\text{SWconv3} * \text{SOconv1}}{\text{SOconv3}} * (Wconv3q * Oconv1q)$

(2.4.4)

$Mn = \frac{\text{SWn} * \text{SI}}{\text{SOn}}$, $if\ n = 1$

$= \frac{\text{SWn} * \text{SOn}-1}{\text{SOn}}$, otherwise

(2.4.6)
使用floor在硬體層面比較容易實作，相比於round還需要去設計硬體考慮carry-in carry-out

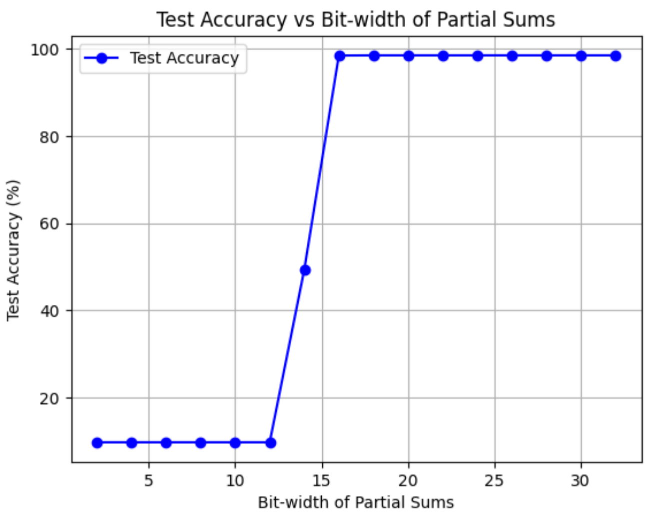
(2.4.7)
由於output_scale為小於1的浮點數，x * output_scale為浮點數乘法運算較難實現。
而 round(1/output_scale) 為整數，則x/round(1/output_scale)為整數除法運算，硬體上較容易實現

(2.5.1)
$S\beta = SW * SOn\text{-}1$

(3.1.1)
QAT訓練時就考量quantization，模型學會在該條件下調整權重減少quantization error，故相比於PTQ訓練後才去做quantization，能有更高的accuracy

(3.1.2)
quant：將 floating-point 的 weight 轉成 quantized values (e.g.,8-bit integer values)
dequant：將 quantized values 轉回 floating-point 以供後續的layer運算。

Part2
(2.1.1)

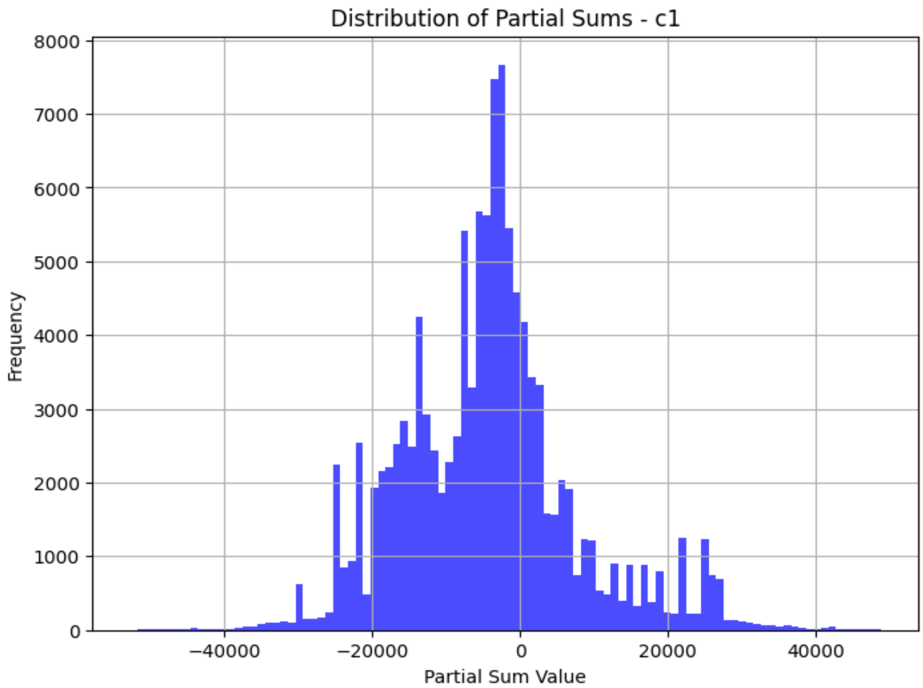


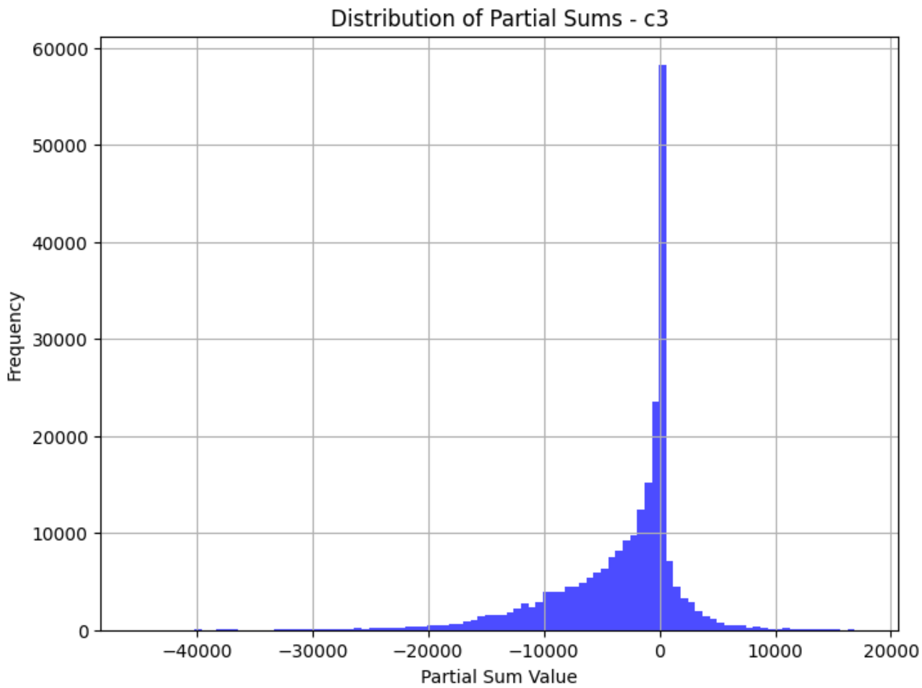
(2.1.2)

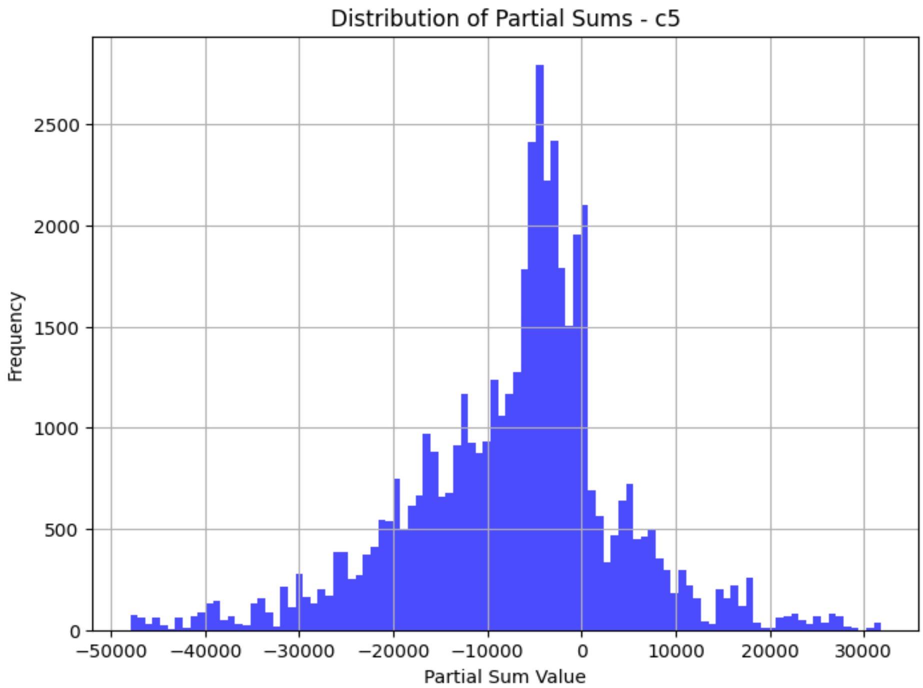
```
bit-width range: (-512, 511)
Accuracy: 9.74%
bit: 12
bit-width range: (-2048, 2047)
Accuracy: 9.74%
bit: 14
bit-width range: (-8192, 8191)
Accuracy: 49.34%
bit: 16
bit-width range: (-32768, 32767)
Accuracy: 98.49%
bit: 18
bit-width range: (-131072, 131071)
Accuracy: 98.53%
bit: 20
bit-width range: (-524288, 524287)
Accuracy: 98.53%
bit: 22
bit-width range: (-2097152, 2097151)
Accuracy: 98.53%
bit: 24
bit-width range: (-8388608, 8388607)
Accuracy: 98.53%
bit: 26
bit-width range: (-33554432, 33554431)
Accuracy: 98.53%
bit: 28
bit-width range: (-134217728, 134217727)
Accuracy: 98.53%
bit: 30
bit-width range: (-536870912, 536870911)
Accuracy: 98.53%
bit: 32
bit-width range: (-2147483648, 2147483647)
Accuracy: 98.53%
```

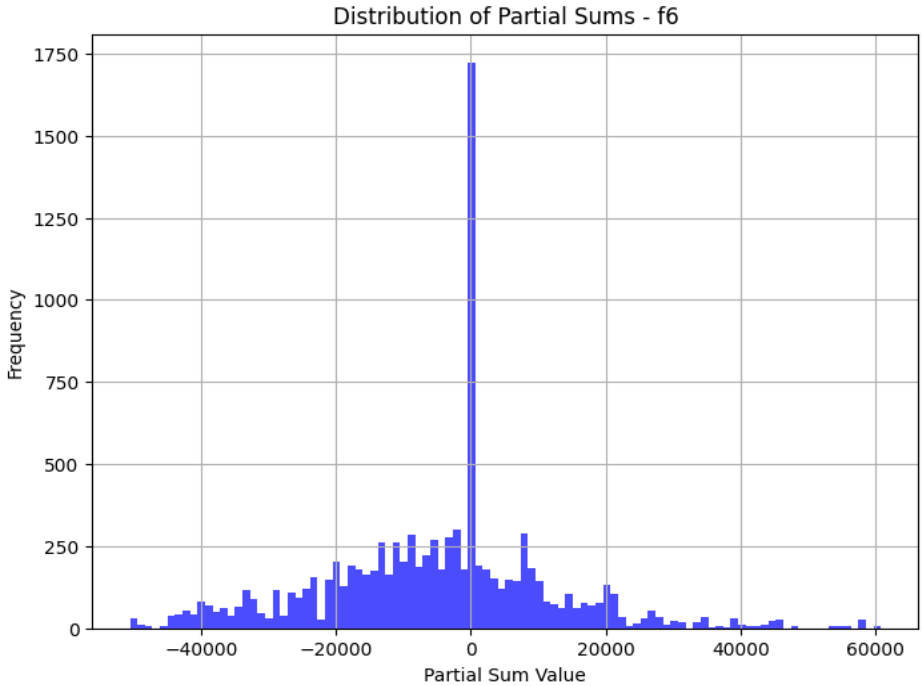
smallest bit-width of partial sums that maintains the same accuracy = 18

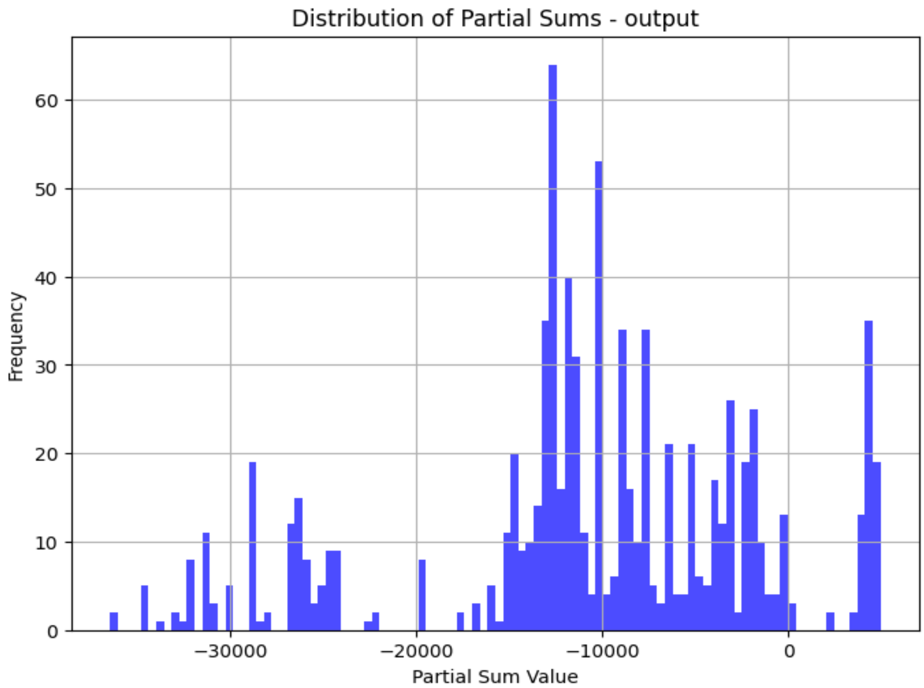
(2.2.1)


Distribution of Partial Sums - c1
Frequency
Partial Sum Value
8000
7000
6000
5000
4000
3000
2000
1000
0
−40000
−20000
0
20000
40000


Distribution of Partial Sums - c3
Frequency
Partial Sum Value
60000
50000
40000
30000
20000
10000
0
−40000
−30000
−20000
−10000
0
10000
20000


Distribution of Partial Sums - c5
Frequency
Partial Sum Value
2500
2000
1500
1000
500
0
−50000
−40000
−30000
−20000
−10000
0
10000
20000
30000


Distribution of Partial Sums - f6
Frequency
Partial Sum Value
1750
1500
1250
1000
750
500
250
0
−40000
−20000
0
20000
40000
60000



	min	max	standard deviation
C1	-52685	48834	11930.04150
C3	-45165	17499	5539.88138
C5	-47968	31846	11342.33533
F6	-50556	60838	16911.83450
Output	-36443	4971	9073.27535

(2.2.2)

	minimum bit-width
C1	18
C3	16
C5	16
F6	18
Output	16

Accuracy: 98.53%

我認為題目應該是指完全不能影響 accuracy，很不巧根據數據理論上只能都取 18 bit-width 但為了符合作業精神只考慮到小數第二位的話，結果是如此

(3.1.1)

根據程式碼 Batch Size = 4

```python
for n in range(N):
    for m in range(out_channels):
        for p in range(P):
            for q in range(Q):
                x_out[n][m][p][q] = 0
                for r in range(kernel_size):
                    for s in range(kernel_size):
                        for c in range(C):
                            h = p * stride + r
                            w = q * stride + s
                            x_out[n][m][p][q] += x[n][c][h][w] * weights[m][c][r][s]

                            if(x_out[n][m][p][q] < psum_range[0]):
                                x_out[n][m][p][q] = psum_range[0]
                            elif(x_out[n][m][p][q] > psum_range[1]):
                                x_out[n][m][p][q] = psum_range[1]

                            if psum_record:
                                psum_record_list.append(x_out[n][m][p][q])
```

Conv2d 迴圈次數 N*M*P*Q*R*S*C

最內層 3 次 mul , 3 次 add

C1 = 4*6 *28 *28*5*5*1 = 470400

C3 = 4*16*10*10*5*5*6 = 960000

C5 = 4*120*1*1*5*5*16 = 192000

```python
for h in range(H):
    for c in range(C):
        x_out[h][c] = 0
        for w in range(W):
            x_out[h][c] += x[h][w] * weights[c][w]
            # clamp the partial sum to the specified range
            if x_out[h][c] < psum_range[0]:
                x_out[h][c] = psum_range[0]
            elif x_out[h][c] > psum_range[1]:
                x_out[h][c] = psum_range[1]

            if psum_record:
                psum_record_list.append(x_out[h][c])


if weightsBias is not None:
    x_out += weightsBias
```

Linear 迴圈次數 H*C*W

F6 = 4*84*120 = 40320

Output = 4*10*84 = 3360

最內層 1 次 mul, 1 次 add

H*C 個 elements 要加 bias

	Nmul	Nadd	Bmul	Smul	Badd	Sadd	Ew
C1	1411200	1411200	8	64	18	18	115718400
C3	2880000	2880000	8	64	18	18	236160000
C5	576000	576000	8	64	18	18	47232000
F6	40320	40320	8	64	18	18	3306240
Output	3360	3400	8	64	18	18	276240

Overall E_w = 402,692,880

(3.1.2)

	N_{mul}	N_{add}	B_{mul}	s_{mul}	B_{add}	s_{add}	E_w
C1	1411200	1411200	8	64	18	18	115718400
C3	2880000	2880000	8	64	16	16	230400000
C5	576000	576000	8	64	16	16	46080000
F6	40320	40320	8	64	18	18	3306240
Output	3360	3400	8	64	16	16	269440

Overall E_w = 395,774,080