# 神经网络图优化与量化

#### 6.2.1 赌是计算图

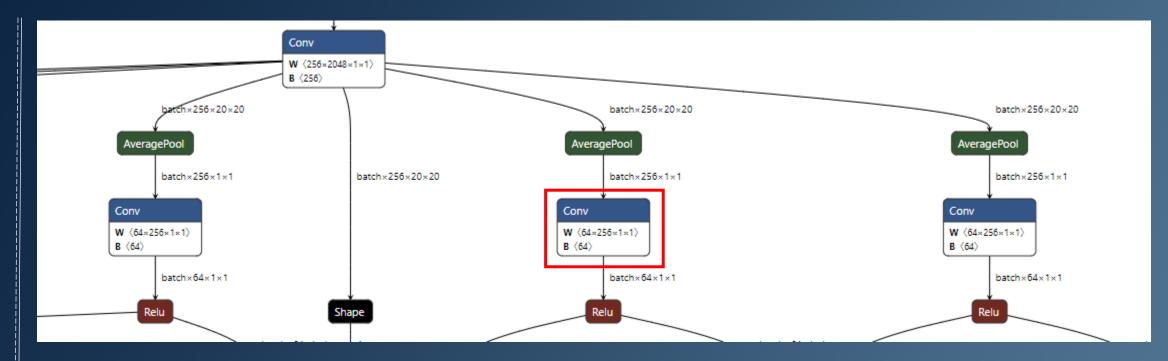
What is a Computational Graph.

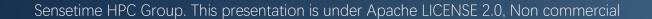
C = {N, E, I, O} 一个计算图可以表示为一个由节点、边集、输入边、输出边组成的四元组。

- 计算图是一个有向联通无环图,其中节点也被称作为算子。
- 算子必定有边相连、输入边、输出边不为空。
- 计算图中可以有重边。

### 6.2.1 算子

What is a Computational Graph.





#### 6.2.1 算子

#### What is a Computational Graph.

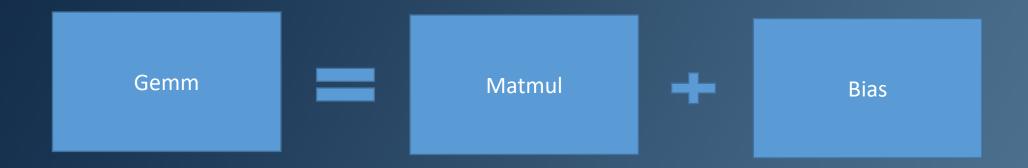
```
Operator Since version
        13, 6, 1
Abs
                                                 Constant 13, 12, 11, 9, 1
                                                 ConstantOfShape 9
Acos
Acosh
                                                 Conv
                                                         11, 1
Add 14, 13, 7, 6, 1
                                                 ConvInteger
                                                                  10
And 7, 1
                                                 ConvTranspose
                                                                  11, 1
ArgMax 13, 12, 11, 1
                                                 Cos
ArgMin 13, 12, 11, 1
                                                 Cosh
Asin
                                                 CumSum 14, 11
Asinh
                                                 DepthToSpace
                                                                13, 11, 1
Atan
                                                 DequantizeLinear 13, 10
Atanh
                                                         11
                                                 Det
AveragePool
            11, 10, 7, 1
                                                 Div
                                                         14, 13, 7, 6, 1
BatchNormalization
                         15, 14, 9, 7, 6, 1
                                                 Dropout 13, 12, 10, 7, 6, 1
```

https://github.com/onnx/onnx/blob/main/docs/Operators.md

#### 6.2.1 算子

What is a Computational Graph.

算子是神经网络的最小调度单位,但很遗憾的是,它并不是原子的:一个复杂的算子可以被更细粒度的算子所表示:



我们总是以算子为单位去支持你的网络。

在你的网络中你应该尽量避免使用特殊算子。

Graph Fusion.

```
declspec(noinline) void MatMul(
       ELEMENT TYPE** input, ELEMENT TYPE** weight,
       ELEMENT_TYPE** output, const unsigned int num_of_elements) {
       for (unsigned int i = 0; i < num_of_elements; i++)
                 for (unsigned int j = 0; j < num_of_elements; j++)
                          for (unsigned int k = 0; k < num of elements; k++)
                                    output[i][j] += input[i][k] * weight[k][j];
declspec(noinline) void BiasAdd(
       ELEMENT TYPE** input, ELEMENT TYPE* bias,
       ELEMENT_TYPE** output, const unsigned int num_of_elements) {
       for (unsigned int i = 0; i < num of elements; i++)
                 for (unsigned int j = 0; j < num_of_elements; j++)
                          output[i][j] += bias[i];
```

Graph Fusion.

在Matmul + Bias + Relu的子网中,如果不融合算子,output将至少被写入3次并且启动3个算子的速度也不是很快。



Graph Fusion.



E: Task Emission

R: Read

C: Computing

W: Write

Graph Fusion.

```
declspec(noinline) void MatMul(
       ELEMENT_TYPE** input, ELEMENT_TYPE** weight, ELEMENT_TYPE* bias,
       ELEMENT_TYPE** output, const unsigned int num_of_elements) {
       for (unsigned int i = 0; i < num_of_elements; i++){
                 for (unsigned int j = 0; j < num of elements; j++){
                          int accumulator = 0;
                          for (unsigned int k = 0; k < num_of_elements; k++){
                                    accumulator += input[i][k] * weight[k][j];
                          output[i][j] = accumulator + bias[j] > 0 ? accumulator + bias[j]: 0;
```

Graph Fusion.



- 6.2.3.1 激活函数融合
- 6.2.3.2 移除 Batchnorm 与 Dropout
- 6.2.3.3 常量折叠
- 6.2.3.4 矩阵乘融合
- 6.2.3.5 Conv Add 融合



Widely - used Graph Optimization



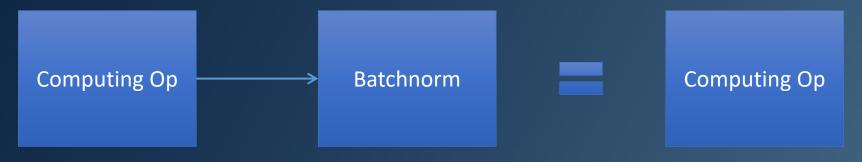
常见计算算子:Conv. ConvTranpose, Gemm

常见激活函数:Relu, Clip(Relu6), PRelu, Tanh, Sigmoid, Swish

output[i][j] = activation\_fn(accumulator + bias[j]);







计算算子: 
$$Y = WX + B$$

Batchnorm : 
$$Y' = gamma * \frac{Y - mean}{var} + beta$$

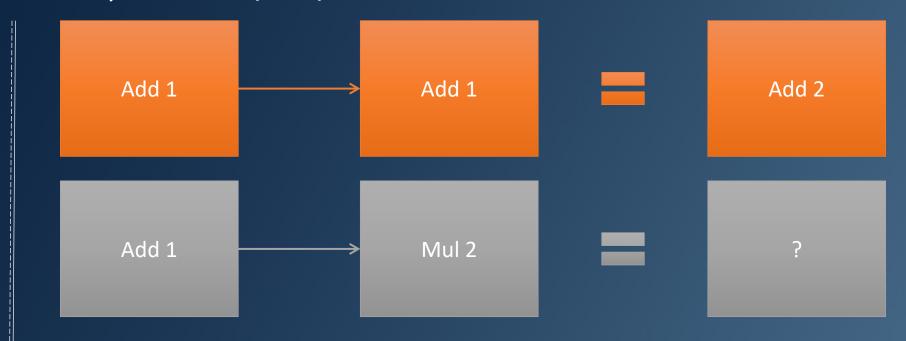
$$\mathsf{Merged}: Y' = \operatorname{gamma} * \frac{WX + B - \operatorname{mean}}{\operatorname{var}} + \operatorname{beta} = \frac{\operatorname{gamma}}{\operatorname{var}} WX + \frac{\operatorname{gamma}}{\operatorname{var}} (B - \operatorname{mean}) + \operatorname{beta}$$



```
alpha = bn op.parameters[0].value
beta = bn_op.parameters[1].value
                                                       Computing Op
mean = bn_op.parameters[2].value
      = bn op.parameters[3].value
var
if computing op.type == 'Conv':
         # calculate new weight and bias
         scale = alpha / np.sqrt(var + epsilon)
         w = w * scale.reshape([-1, 1, 1, 1])
         b = alpha * (b - mean) / np.sqrt(var + epsilon) + beta
elif computing op.type == 'Gemm':
         # calculate new weight and bias
         scale = alpha / np.sqrt(var + epsilon)
         if computing op.attributes.get('transB', 0): w = w * scale.reshape([-1, 1])
         else: w = w * scale.reshape([1, -1])
         b = alpha * (b - mean) / np.sqrt(var + epsilon) + beta
```



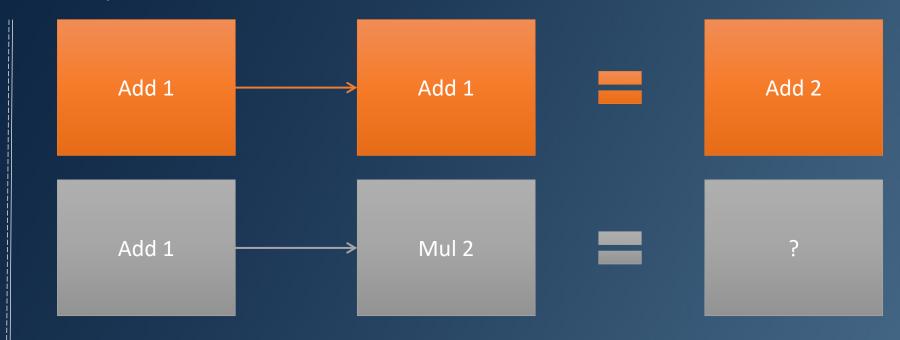
Widely - used Graph Optimization



Add1 : Y = X + 1

Add2: Y' = Y + 1

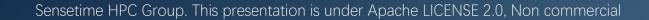
Merged: Y' = X + 2



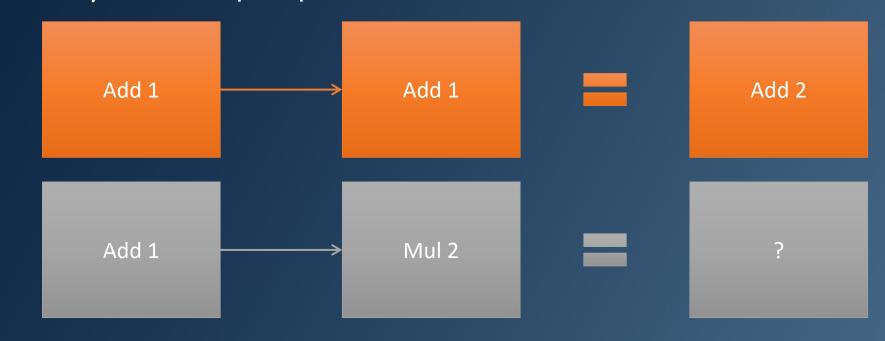
Add1 : 
$$Y = X + 1$$

$$Mul2 : Y' = Y * 2$$

Merged : 
$$Y' = (X + 1) * 2 = X * 2 + 2$$



Widely - used Graph Optimization

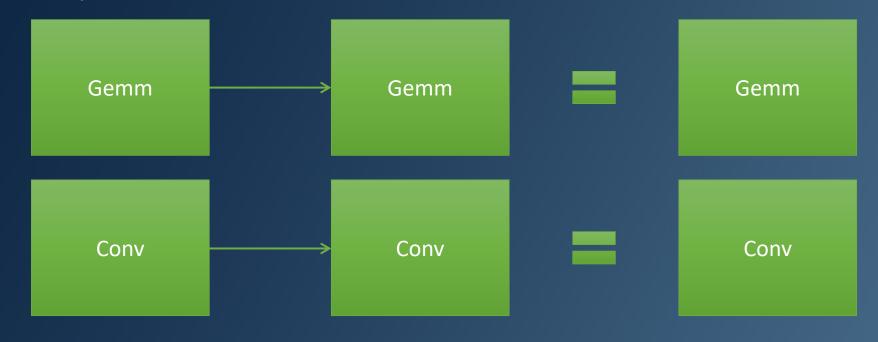


Add1 : 
$$Y = X + 1$$

$$Mul2 : Y' = Y * 2$$

Merged : 
$$Y' = (X + 1) * 2 = X * 2 + 2$$
?

EMM... WE DO NOT HAVE AN OP TO RUN X\*2+2!



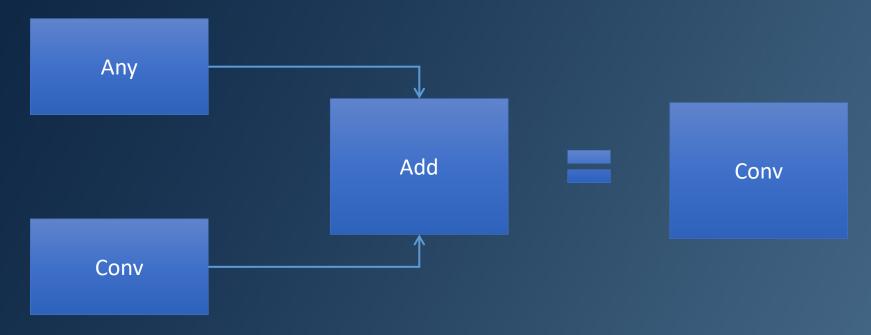
计算算子1: 
$$Y = W_1X + B_1$$

计算算子2: 
$$Y' = W_2Y + B_2$$

融合后: 
$$Y' = W_2(W_1X + B_1) + B_2$$

```
def svd_for_factorization(self, w: torch.Tensor):
    assert w.ndim == 2
    u, s, v = torch.svd(w)
    a = torch.matmul(u, torch.diag(torch.sqrt(s)))
    b = torch.matmul(torch.diag(torch.sqrt(s)), v.transpose(0, 1))
    print(a.max(), b.max(), w.max())
    return a, b
if operation.type == 'Gemm':
         w = operation.parameters[0].value
         w = w.transpose(0, 1)
         if self.method == 'svd':
           a, b = self.svd_for_factorization(w)
```



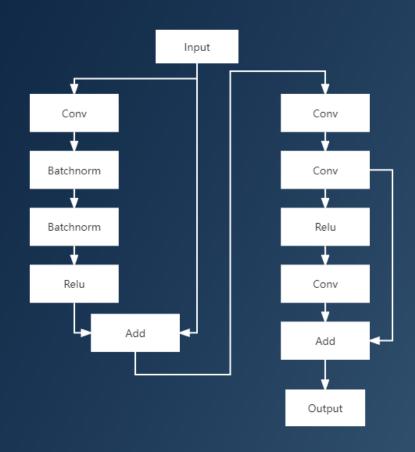


Conv : 
$$Y_1 = W_1 X_1 + B_1$$

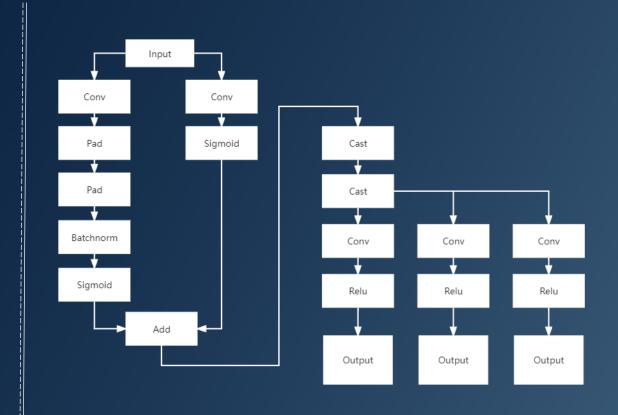
Any : 
$$Y_2$$

$$Y = Y_1 + Y_2$$

融合后: 
$$Y = W_1X_1 + (Y_2 + B_1)$$

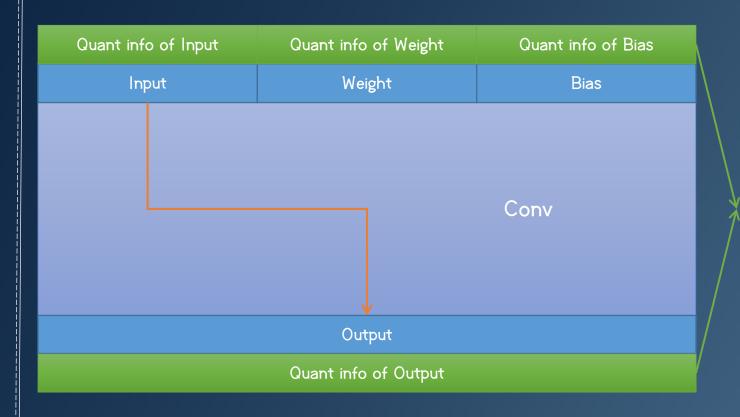








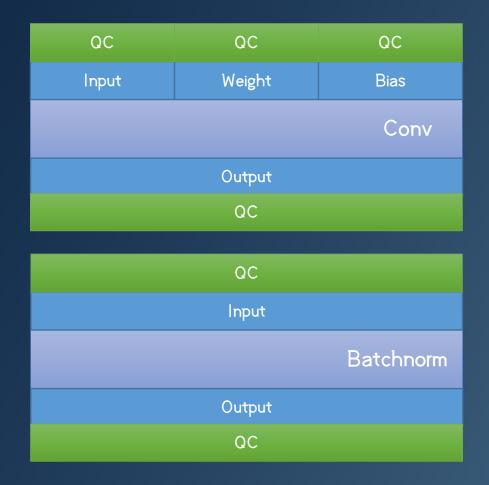
Union - Quantize



#### class TensorQuantizationConfig(Serializable):

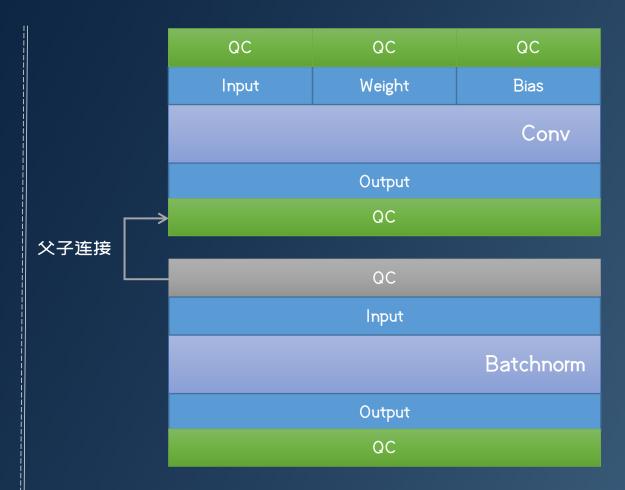
```
self._policy = policy
self._num_of_bits = num_of_bits
self._scale = scale
self._offset = offset
self.state = state
self._rounding = rounding
self._quant_min = quant_min
self._quant_max = quant_max
self._father_config = self # union - find
```

#### Union - Quantize





Union - Quantize



输入已经被量化, 定点信息停用

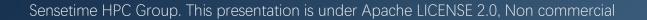


Union - Quantize

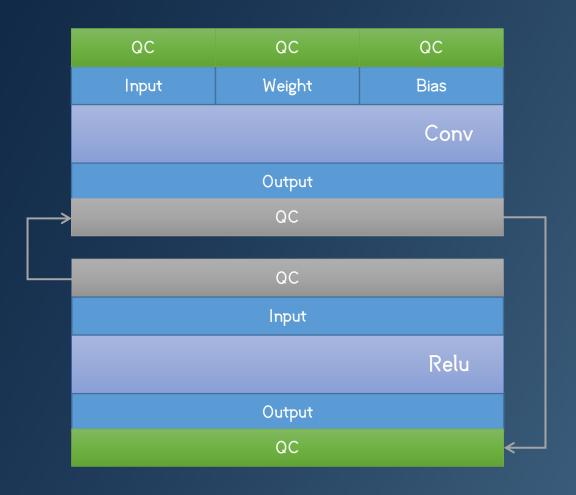


考虑到Conv与Batchnorm图融合 输出定点被停用

级联父子连接(并查集)



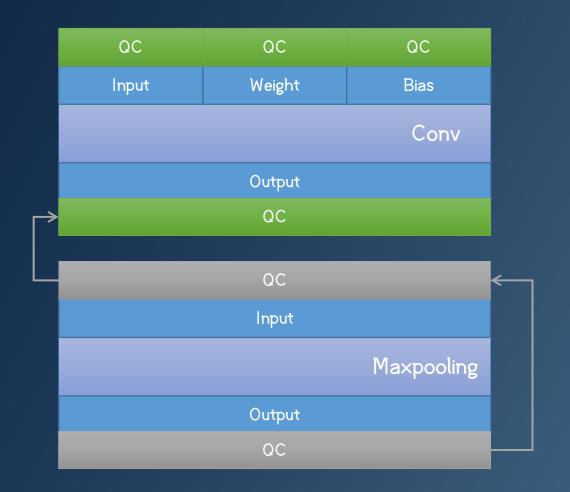
#### Union - Quantize



类似地, 激活函数联合定点

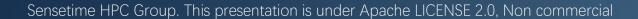


Union - Quantize

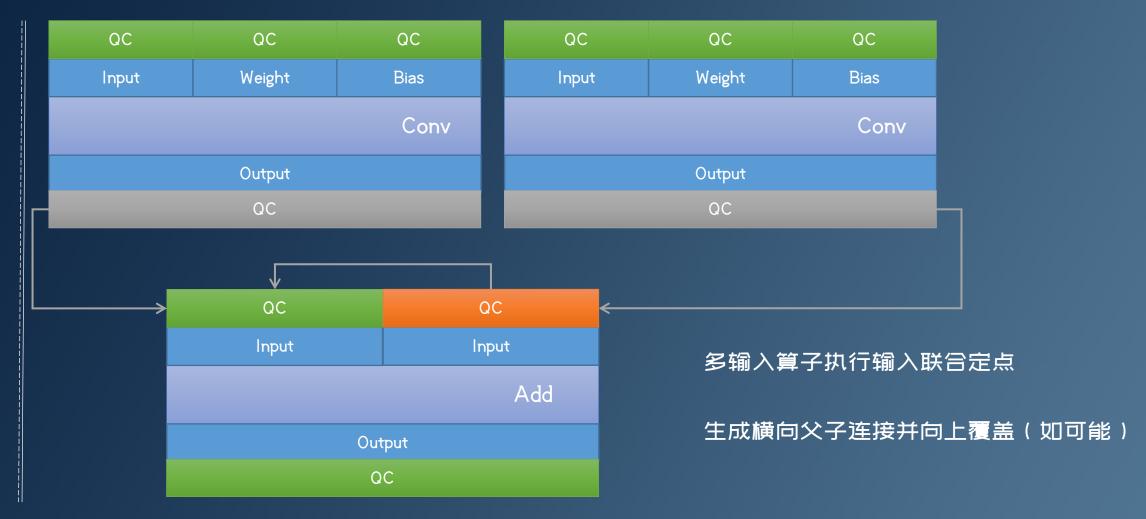


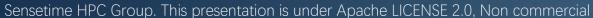
被动算子量化定点信息全部停用

向上生成级联父子连接

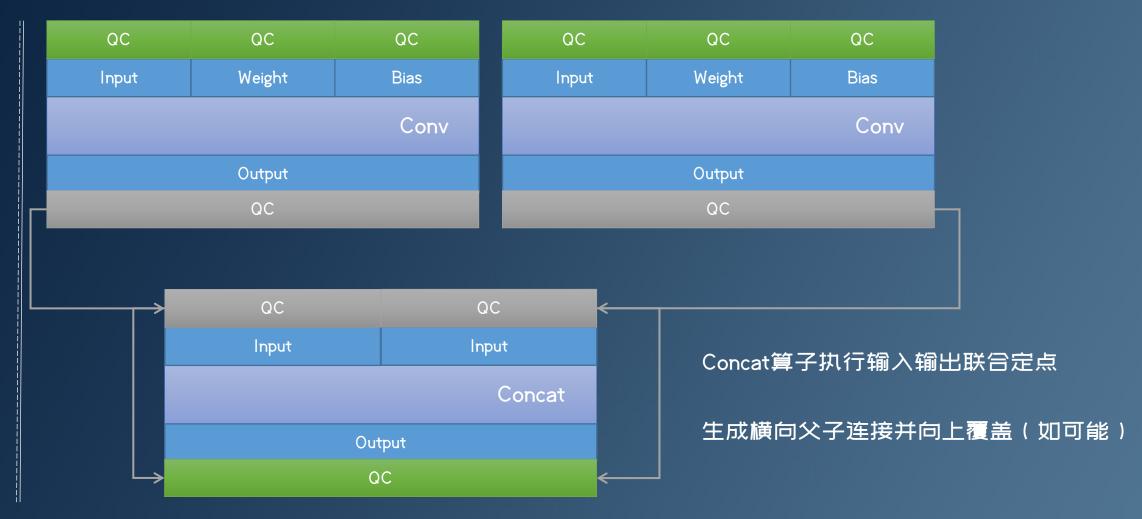


Union - Quantize



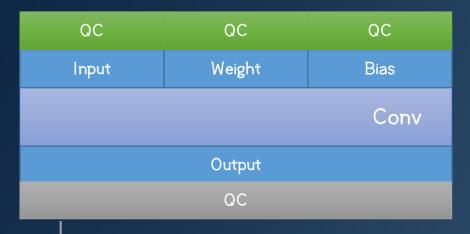


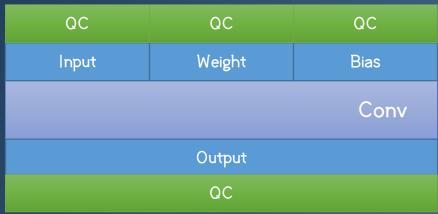
Union - Quantize

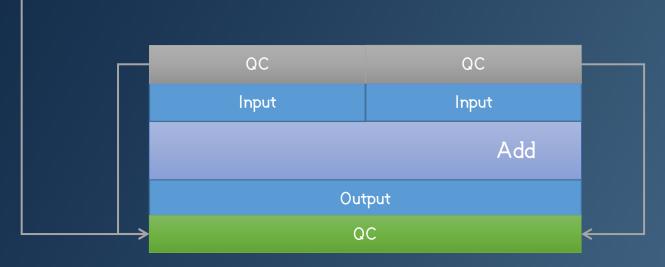




#### Union - Quantize

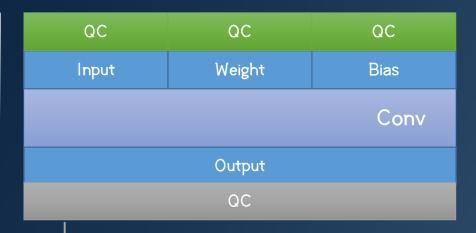


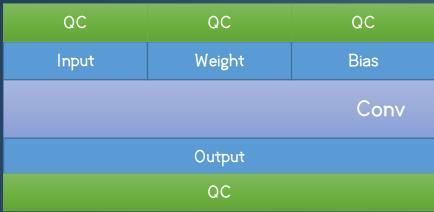


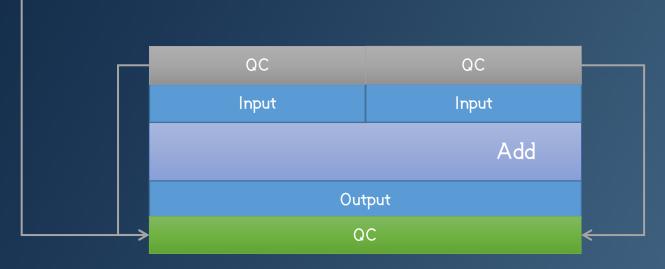


ConvAdd 联合定点(如可能)

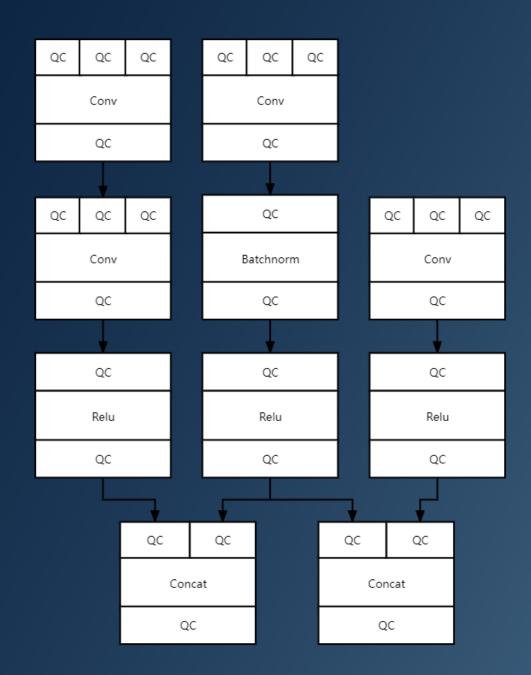
#### Union - Quantize







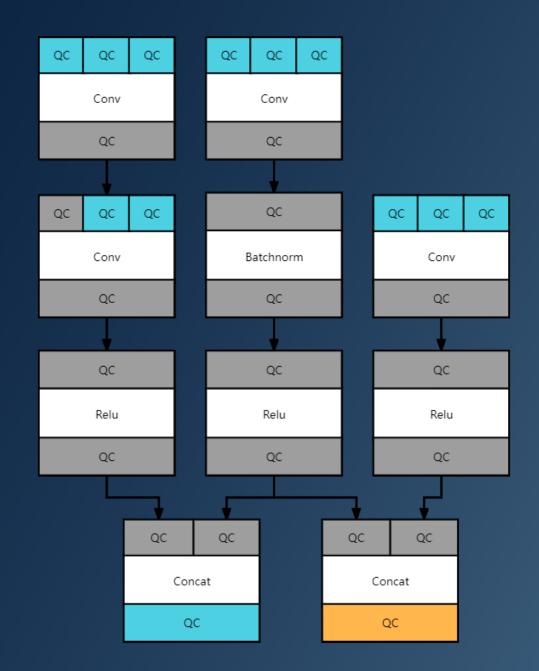
ConvAdd 联合定点(如可能)





- conv-conv融合
- conv-relu融合
- conv batchnorm融合
- concat联合定点

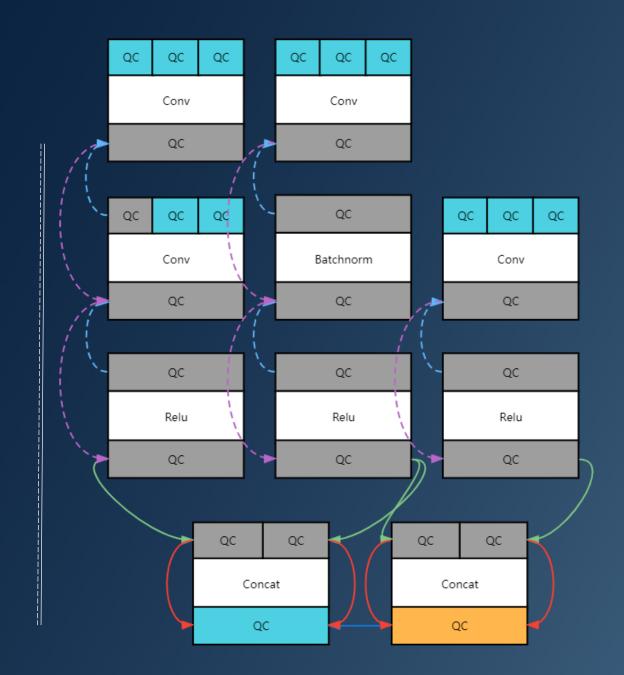
在如此规则下, 左图应当如何联合定点?





- conv-conv融合
- conv-relu融合
- conv batchnorm融合
- concat联合定点

在如此规则下,左图应当如何联合定点?



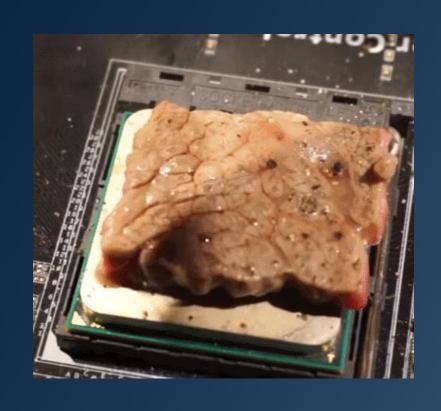


#### 已知硬件存在

- conv-conv融合
- conv-relu融合
- conv batchnorm融合
- concat联合定点

在如此规则下, 左图应当如何联合定点?

# 联系我们 https://github.com/openppl-public







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