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# Supplemental Materials for: Exploring Hidden Dimensions in Parallelizing Convolutional Neural Networks

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## 1. Node and Edge Eliminations

We define node and edge eliminations in Algorithm 1.

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**Algorithm 1** Node and edge eliminations.

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1: function NODEELIMINATION( $\mathcal{G}$ )
2:   if exist a node  $l_j$  with a single in-edge  $e_1 = (l_i, l_j)$ 
   and a single out-edge  $e_2 = (l_j, l_k)$  then
3:      $e' = (l_i, l_k)$ 
4:      $\mathcal{G}' = \mathcal{G} - l_j - e_1 - e_2 + e'$ 
5:     return  $\mathcal{G}'$ 
6:   else
7:     return  $\mathcal{G}$ 
8:   end if
9: end function
10:
11: function EDGEELIMINATION( $\mathcal{G}$ )
12:   if exist two edges  $e_1 = (l_i, l_j)$  and  $e_2 = (l_i, l_j)$ 
   then
13:      $e' = (l_i, l_j)$ 
14:      $\mathcal{G}' = \mathcal{G} - e_1 - e_2 + e'$ 
15:     return  $\mathcal{G}'$ 
16:   else
17:     return  $\mathcal{G}$ 
18:   end if
19: end function
20:

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**Theorem 1.** Assume  $\mathcal{G}' = \text{NodeElimination}(\mathcal{G})$  and  $l_j$  is the eliminated layer. If  $\mathcal{S}_o'$  is an optimal strategy for  $\mathcal{G}'$ , then  $\mathcal{S}_o = \mathcal{S}_o' + \hat{c}_j$  is an optimal strategy for  $\mathcal{G}$ , where

$$\hat{c}_j = \arg \min_{c_j} \{t_C(n_j, c_j) + t_S(n_j, c_j) + t_X(e_1, c_i, c_j) + t_X(e_2, c_j, c_k)\} \quad (1)$$

*Proof.* It is equivalent to prove that  $t_O(\mathcal{G}, \mathcal{S}_1) \geq t_O(\mathcal{G}, \mathcal{S}_o)$  for any other strategy  $\mathcal{S}_1$ . We assume layer  $l_i$  has parallelization configuration  $c_{i1} \in \mathcal{S}_1$ . We prove this inequality by using the following path.

$$t_O(\mathcal{G}, \mathcal{S}_1) \geq t_O(\mathcal{G}', \mathcal{S}_1) \quad (2)$$

$$\geq t_O(\mathcal{G}', \mathcal{S}_o') \quad (3)$$

$$= t_O(\mathcal{G}, \mathcal{S}_o) \quad (4)$$

**Proof of Equation 2.** The difference between  $t_O(\mathcal{G}, \mathcal{S}_1)$  and  $t_O(\mathcal{G}', \mathcal{S}_1)$  is

$$\begin{aligned} & t_O(\mathcal{G}, \mathcal{S}_1) - t_O(\mathcal{G}', \mathcal{S}_1) \\ &= t_C(l_j, c_{j1}) + t_S(l_j, c_{j1}) + t_X(e_1, c_{i1}, c_{j1}) \\ & \quad + t_X(e_2, c_{j1}, c_{k1}) - t_X(e', c_{i1}, c_{k1}) \end{aligned} \quad (5)$$

This is because all other layers except  $l_j$  use the same configurations in  $t_O(\mathcal{G}, \mathcal{S}_1)$  and  $t_O(\mathcal{G}', \mathcal{S}_1)$ , and therefore all cost functions non-related to  $l_j$  are eliminated in the subtraction. The remaining parts are  $l_j$ ,  $e_1$ , and  $e_2$ , which no longer exist in  $\mathcal{G}'$  after node elimination, and  $e'$  that is added to  $\mathcal{G}'$ . Recall that  $t_X(e', \cdot, \cdot)$  is defined as follows.

$$\begin{aligned} t_X(e', c_i, c_k) &= \min_{c_j} \{t_C(l_j, c_j) + t_S(l_j, c_j) \\ & \quad + t_X(e_1, c_i, c_j) + t_X(e_2, c_j, c_k)\} \end{aligned} \quad (6)$$

Combining Equation 5 and 6, we have  $t_O(\mathcal{G}, \mathcal{S}_1) \geq t_O(\mathcal{G}', \mathcal{S}_1)$ .

**Proof of Equation 3.** Since  $\mathcal{S}_o'$  is an optimal strategy for  $\mathcal{G}'$ , the inequality holds by definition.

**Proof of Equation 4.** Similarly, the difference between  $t_O(\mathcal{G}', \mathcal{S}_o')$  and  $t_O(\mathcal{G}, \mathcal{S}_o)$  is

$$\begin{aligned} & t_O(\mathcal{G}, \mathcal{S}_o) - t_O(\mathcal{G}', \mathcal{S}_o') \\ &= t_C(l_j, \hat{c}_j) + t_S(l_j, \hat{c}_j) + t_X(e_1, c_i, \hat{c}_j) \\ & \quad + t_X(e_2, \hat{c}_j, c_k) - t_X(e', c_i, c_k) \end{aligned} \quad (7)$$

This is because  $\mathcal{S}_o = \mathcal{S}_o' + \hat{c}_j$ , and therefore all cost functions non-related to  $l_j$  are eliminated. We can prove Equation 4 by bringing Equation 1 into Equation 7.  $\square$

**Theorem 2.** Assume  $\mathcal{G}' = \text{EdgeElimination}(\mathcal{G})$ , and  $\mathcal{S}_o'$  is an optimal strategy for  $\mathcal{G}'$ , then  $\mathcal{S}_o = \mathcal{S}_o'$  is an optimal strategy for  $\mathcal{G}$ .

*Proof.* We can use the same path to prove this theorem.

**Proof of Equation 2.** The difference between  $t_O(\mathcal{G}, \mathcal{S}_1)$  and  $t_O(\mathcal{G}', \mathcal{S}_1)$  is

$$\begin{aligned} & t_O(\mathcal{G}, \mathcal{S}_1) - t_O(\mathcal{G}', \mathcal{S}_1) \\ &= t_X(e_1, c_{i1}, c_{j1}) + t_X(e_2, c_{i1}, c_{j1}) - t_X(e', c_{i1}, c_{j1}) \end{aligned} \quad (8)$$

Recall that  $t_x(e', \cdot, \cdot)$  is defined as follows.

$$t_x(e', c_i, c_j) = t_x(e_1, c_i, c_j) + t_x(e_2, c_i, c_j) \quad (9)$$

Combining Equation 8 and 9, we have  $t_o(\mathcal{G}, \mathcal{S}_1) = t_o(\mathcal{G}', \mathcal{S}_1)$ .

**Proof of Equation 3.** The inequality holds since  $\mathcal{S}_o'$  is an optimal strategy for  $\mathcal{G}'$ .

**Proof of Equation 4.** The difference between  $t_o(\mathcal{G}', \mathcal{S}_o')$  and  $t_o(\mathcal{G}, \mathcal{S}_o)$  is

$$\begin{aligned} & t_o(\mathcal{G}, \mathcal{S}_o) - t_o(\mathcal{G}', \mathcal{S}_o') \\ &= t_x(e_1, c_i, c_j) + t_x(e_2, c_i, c_j) - t_x(e', c_i, c_j) \quad (10) \\ &= 0 \end{aligned}$$

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