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# “Short-Dot”: Computing Large Linear Transforms Distributedly Using Coded Short Dot Products Supplement

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## 1 Analysis of expected computation time for exponential tail models

We now provide a probabilistic analysis of the computational time required by Short-Dot and compare it with uncoded parallel processing, repetition and MDS codes as shown in Fig. 1.

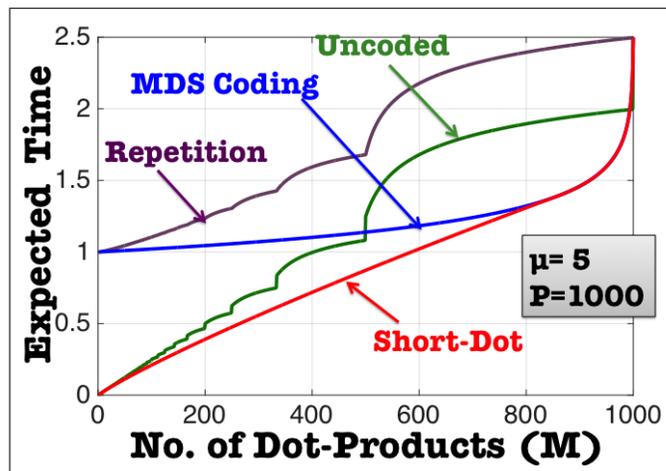


Figure 1: Comparison of theoretical computation time: Short-Dot outperforms MDS Codes when  $M \ll P$  and Uncoded when  $M \approx P$ , and is universally faster over the entire range of  $M$ . For the choice of straggling parameters, repetition performs worse than all other strategies.

We assume that the time required by a processor to compute a single dot-product follows an exponential distribution and is independent of other parallel processors.

Let us assume, the time required to compute a single dot-product of length  $N$ , follow the distribution:-

$$\Pr(T_N \leq t) = F(t) = 1 - \exp\left(-\mu \left(\frac{t}{N} - 1\right)\right) \quad \forall t \geq N \quad (1)$$

Here,  $\mu$  is a straggling parameter, that determines the "unpredictable latency" in computation time. We also assume, that if the length of the dot-product reduces by a factor of  $\tau$ , *i.e.*, if the length of the dot-product to be computed changes to  $N/\tau$  from  $N$ , the probability distribution of the computational time varies as:-

$$\Pr(T \leq t) = F(\tau t) = 1 - \exp\left(-\mu \left(\frac{\tau t}{N} - 1\right)\right) \quad \forall t \geq N/\tau \quad (2)$$

Thus, if length of the dot-product is  $s$  where  $s$  is the sparsity of the vector, the computation time would follow the distribution  $F(\frac{Nt}{s})$ . Now we derive the expected computation time using our proposed strategy and compare it with existing strategies in the regimes where the number of dot-products  $M$  is linear and sub-linear in  $P$ .

Table 1 shows the order-sense expected computation time in the regimes where  $M$  is linear and sub-linear in  $P$ .

### 1.1 Proposed Strategy – Short-Dot:

The computation time over each of the  $P$  processors behaves as independent, identically distributed exponential random variables following the distribution:-

$$\Pr(T \leq t) = F\left(\frac{Nt}{s}\right) = 1 - \exp\left(-\mu\left(\frac{t}{s} - 1\right)\right) \quad \forall t \geq s \quad (3)$$

Now, the expected computation time is the expected value of the  $K$ -th order statistic of these  $P$  independent, identically distributed exponential random variables, which is given by:-

$$E(T) = s \left(1 + \frac{\log(\frac{P}{P-K})}{\mu}\right) = \frac{(P-K+M)N}{P} \left(1 + \frac{\log(\frac{P}{P-K})}{\mu}\right) \quad (4)$$

Here we use the result that the  $K$ -th order statistic of  $P$  exponential random variables that are independent and identically distributed as  $\sim \exp(-T) \forall T \geq 0$  is given by  $\sum_{i=1}^P \frac{1}{i} - \sum_{i=1}^{P-K} \frac{1}{i}$ . For large  $P$  and  $K < P$ , this can be approximated as  $\log(P) - \log(P-K)$ .

Note that, the expected computation time is minimized when  $P-K = \Theta(M)$ , and is given by:-

$$E(T) = \mathcal{O}\left(\frac{MN}{P} \left(1 + \frac{\log(P/M)}{\mu}\right)\right) \quad (5)$$

If  $M$  is linear in  $P$ , the expected time is  $\mathcal{O}(\frac{MN}{P})$ . If  $M$  is sub-linear in  $P$ , the expected time is  $\mathcal{O}\left(\frac{MN \log(P/M)}{P}\right)$ . Note that,  $s = \frac{(P-K+M)N}{P}$  is actually an upper bound on the length of each dot-product, using Short-Dot. Thus the expression obtained in (5) is an upper bound for the actual computation time. Thus we use  $\mathcal{O}(\cdot)$  instead of  $\Theta(\cdot)$ .

Table 1: Probabilistic Computation Times

Method	$E(T)$	$M$ linear in $P$	$M$ sub-linear in $P$
Only one Processor	$MN \left(1 + \frac{1}{\mu}\right)$	$\Theta(MN)$	$\Theta(MN)$
Uncoded <sup>1</sup>	$\frac{MN}{P} \left(1 + \frac{\log(P)}{\mu}\right)$	$\Theta\left(\frac{MN}{P} \log(P)\right)$	$\Theta\left(\frac{MN}{P} \log(P)\right)$
Repetition <sup>1</sup>	$N \left(1 + \frac{M \log(M)}{P\mu}\right)$	$\Theta\left(\frac{MN}{P} \log(P)\right)$	$\Theta(N)$
MDS	$N \left(1 + \frac{\log(\frac{P}{P-M})}{\mu}\right)$	$\Theta(N)$	$\Theta(N)$
Short-Dot	$\frac{N(P-K+M)}{P} \left(1 + \frac{\log(\frac{P}{P-K})}{\mu}\right)$	$\mathcal{O}\left(\frac{MN}{P}\right)$	$\mathcal{O}\left(\frac{MN}{P} \log\left(\frac{P}{M}\right)\right)$

<sup>1</sup> A more accurate analysis taking integer effects into account is also presented.

### 1.2 Existing Strategies

**One Single Processor:** For one single processor to compute all  $M$  dot-products of length  $N$ , the computation time is distributed as

$$\Pr(T \leq t) = F(t/M) = 1 - \exp\left(-\mu\left(\frac{t}{NM} - 1\right)\right) \quad \forall t \geq NM \quad (6)$$

Thus, the expected computation time can be easily derived to be

$$E(T) = MN \left(1 + \frac{1}{\mu}\right) \quad (7)$$

**Uncoded - Divide into  $P$  parts and wait for all:** Now, consider an uncoded strategy where the computation is simply divided into  $P$  dot-products and sent to  $P$  processors. We assume that each processor is sent only one dot-product at a time. We wait for all the processors to finish computation. Note that, integer effects arise when  $M$  does not exactly divide  $P$ . Some rows can be divided among  $\lceil \frac{P}{M} \rceil$  processors, while the remaining are divided among  $\lfloor \frac{P}{M} \rfloor$  processors. Let  $m_1$  and  $m_2$  denote the number of rows that get  $\lceil \frac{P}{M} \rceil$  processors and  $\lfloor \frac{P}{M} \rfloor$  processors respectively. Clearly the values can be obtained by solving:-

$$\begin{bmatrix} 1 & 1 \\ \lceil \frac{P}{M} \rceil & \lfloor \frac{P}{M} \rfloor \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} = \begin{bmatrix} M \\ P \end{bmatrix} \quad (8)$$

Now, we have two groups of exponential variables - one group consisting of  $m_1 \lceil \frac{P}{M} \rceil$  independent and identically distributed exponential random variables of task size  $\frac{N}{\lceil \frac{P}{M} \rceil}$  and another group consisting of  $m_2 \lfloor \frac{P}{M} \rfloor$  independent and identically distributed exponential random variables of task size  $\frac{N}{\lfloor \frac{P}{M} \rfloor}$ . The two groups are independent of each other. Note that, for each of calculations we assume that  $N$  is large compared to  $P$  and is divisible by  $P, \lceil \frac{P}{M} \rceil, \lfloor \frac{P}{M} \rfloor$ , so that the integer effects with respect to  $N$  do not appear and the plots can be scaled with respect to  $N$  for ease of understanding.

The expected computation time is thus given by the expectation of the maximum of all these  $P = m_1 \lceil \frac{P}{M} \rceil + m_2 \lfloor \frac{P}{M} \rfloor$  exponential random variables.

$$\Pr(T \leq t) = \left( 1 - \exp \left( -\mu \left( \frac{\lceil \frac{P}{M} \rceil t}{N} - 1 \right) \right) \right)^{m_1 \lceil \frac{P}{M} \rceil} \times \left( 1 - \exp \left( -\mu \left( \frac{\lfloor \frac{P}{M} \rfloor t}{N} - 1 \right) \right) \right)^{m_2 \lfloor \frac{P}{M} \rfloor} \quad \forall t \geq \frac{N}{\lfloor \frac{P}{M} \rfloor} \quad (9)$$

The expectation is thus obtained as

$$E(T) = \int_0^\infty (1 - \Pr(T \leq t)) dt \quad (10)$$

This expression is computed using MATLAB and plotted in the plot of theoretical computation time (Refer Fig. 1). When  $M$  divides  $P$  exactly, the expressions are simpler. The computation time for each processor is distributed as

$$\Pr(T \leq t) = F(t/M) = 1 - \exp \left( -\mu \left( \frac{Pt}{MN} - 1 \right) \right) \quad \forall t \geq NM/P \quad (11)$$

The expected computation time is the maximum of  $P$  such independent and identically distributed random variables, as given by:-

$$E(T) = \frac{MN}{P} \left( 1 + \frac{\log(P)}{\mu} \right) \quad (12)$$

The expected time is  $\Theta \left( \frac{MN \log(P)}{P} \right)$  whether  $M$  is linear or sub-linear in  $P$ . Our strategy offers a speed-up of  $\Omega(\log(P))$  when  $M$  is linear in  $P$ .

**Repetition:** When a  $(P, M)$  repetition strategy is used, we separate the matrix into  $M$  rows and repeat each row  $P/M$  times, so as to obtain a total of  $P$  tasks. Note that, integer effects arise when  $M$  does not exactly divide  $P$ . Some rows are repeated  $\lceil \frac{P}{M} \rceil$  times, while the remaining are repeated  $\lfloor \frac{P}{M} \rfloor$  times. Let  $m_1$  and  $m_2$  denote the number of rows that are repeated  $\lceil \frac{P}{M} \rceil$  times and  $\lfloor \frac{P}{M} \rfloor$  times respectively. Clearly the values can be obtained by solving:-

$$\begin{bmatrix} 1 & 1 \\ \lceil \frac{P}{M} \rceil & \lfloor \frac{P}{M} \rfloor \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} = \begin{bmatrix} M \\ P \end{bmatrix} \quad (13)$$

Now, the minimum of  $\lceil \frac{P}{M} \rceil$  (or similarly  $\lfloor \frac{P}{M} \rfloor$ ) independent and identically distributed exponential random variables is also exponential with parameter scaled by  $\lceil \frac{P}{M} \rceil$  (or similarly  $\lfloor \frac{P}{M} \rfloor$ ). The expected computation time is thus given by the expectation of the maximum of  $m_1$  independent exponential variables with parameter scaled by  $\lceil \frac{P}{M} \rceil$  and  $m_2$  independent exponential variables with parameter scaled by  $\lfloor \frac{P}{M} \rfloor$ .

$$\Pr(T \leq t) = \left( 1 - \exp\left(-\mu \left\lceil \frac{P}{M} \right\rceil \left(\frac{t}{N} - 1\right)\right)\right)^{m_1} \times \left( 1 - \exp\left(-\mu \left\lfloor \frac{P}{M} \right\rfloor \left(\frac{t}{N} - 1\right)\right)\right)^{m_2} \quad \forall t \geq N \quad (14)$$

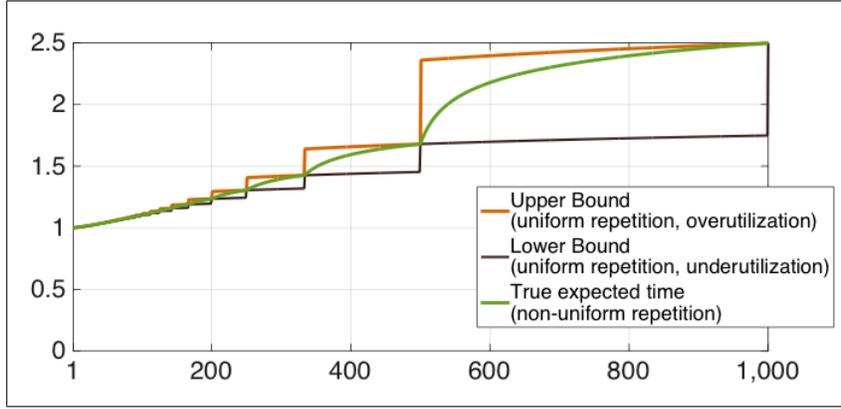


Figure 2: Theoretical Plot of expected computation time of repetition taking integer effects into account: straggling parameter  $\mu = 5$ , total processors  $P = 1000$  and number of dot-products  $M$  is varied from 1 to  $P$ .

The expectation is thus obtained as

$$E(T) = \int_0^{\infty} (1 - \Pr(T \leq t)) dt \quad (15)$$

This expression is computed using MATLAB in the plot of theoretical expected computation time (Fig. 1). When,  $M$  exactly divides  $P$ , the analysis is simpler, and both the two types of exponential distributions are identical. Following an analysis similar to [1], it simplifies to

$$E(T) = N \left( 1 + \frac{M \log(M)}{P\mu} \right) \quad (16)$$

When  $M$  is linear in  $P$ , the expected computation time is  $\Theta\left(\frac{MN}{P} \log(P)\right)$  while our strategy achieves  $\mathcal{O}(N)$  in this regime. When  $M$  is sub-linear in  $P$ , the expected computation time is  $\Theta(N)$  while our strategy Short-Dot achieves  $\mathcal{O}\left(\frac{MN \log(P/M)}{P}\right)$  that offers speed-up by a factor diverging to infinity.

**MDS codes-based strategy:** The matrix is separated into  $M$  rows and coded into  $P$  rows using a  $(P, M)$  MDS code. Thus, each processor effectively computes a dot-product of length  $N$ . We have to wait for any  $M$  processors to finish. Assuming the computation of each processor is independent, following an analysis similar to [1], we obtain that,

$$E(T) = N \left( 1 + \frac{\log(P)}{\mu} - \frac{\log(P - M)}{\mu} \right) \quad (17)$$

When  $M$  is linear in  $P$ , the expected computation time is  $\Theta(N)$  as compared to our strategy that achieves  $\mathcal{O}(MN/P)$ . However, in the regime where  $M$  is sub-linear in  $P$ , the expected computation time is also  $\Theta(N)$  while our strategy achieves  $\mathcal{O}\left(\frac{MN \log(P/M)}{P}\right)$ , and thus outperforms MDS codes by a factor that diverges to infinity for large  $P$ .