Rateless Codes for Straggler Mitigation in Distributed Computing

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Coded Computing

- What computing jobs can be coded such as any k out of n tasks are sufficient to complete the job?
- Example: Matrix-Vector Multiplication



Distributed Matrix Vector Multiplication

- o Large Matrices do not fit in memory on a single machine
- $\circ~$ Typically stored in a distributed fashion



Distributed Matrix Vector Multiplication

 $\circ~$ Each submatrix is multiplied with a vector and the results are

aggregated to obtain the final product



Coded Distributed Matrix Vector Multiplication

 Matrix is encoded by pre-multiplying with a generator matrix before storage



Coded Distributed Matrix Vector Multiplication

Result of matrix-vector multiplication needs to be decoded to

obtain the final product



Distributed Matrix Vector Multiplication

 \circ Generator matrix E is chosen so that any 2 of (b'_1, b'_2, b'_3) are

sufficient to obtain b



Properties of the Encoding Matrix

- \circ Encoding step: A'=EA
 - Size of $A = m \times n$
 - Size of $E = (3m/2) \times m$
 - Size of $A' = (3m/2) \times n$



Properties of the Encoding Matrix

 \circ If any 2 of (E₁, E₂, E₃) can be aggregated to form an invertible matrix then the matrix vector product Ax can be decoded

from any 2 of $(A'_{2}x, A'_{3}x, A'_{3}x)$



















Latency Reduction with coding

 $\,\circ\,$ Without coding we have to wait for all servers to complete



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Latency Reduction with coding

 $\,\circ\,$ With coding we only need to wait for the fastest 2 servers



Generalized Coded Computing

 In general the matrix vector multiplication can be distributed over 'N' workers



Generalized Coded Computing

 The goal of coding is to reconstruct the matrix vector product b = Ax from the outputs of any 'k' out of 'N' workers (protects against 'N-k' stragglers)



Generalized Coded Computing

• The encoding scheme consists of splitting matrix A into 'k' submatrices and generating N coded symbols using a standard MDS erasure code:



 Since the encoding scheme is linear, decoding can be achieved using standard MDS decoding from the outputs of any k workers

Drawbacks of the MDS Coded approach

Neglects partial work done by workers



Drawbacks of the MDS Coded approach

• Increases computation load at each individual server



Rateless Erasure Codes

- Erasure codes that can handle a limitless amount of erasures (packet losses)
- Motivated by unreliable communication protocols such as UDP
- Data is communicated at a rapid rate without waiting for acknowledgement from the receiver
- This leads to a high number of packet drops unknown to the sender
- The goal is to reconstruct the original message, with minimal overhead, in the presence of an unbounded number of packet drops, without resending the lost packets
- Rateless Erasure Codes were originally developed by Digital Fountain Inc. (now acquired by Qualcomm) and are used in several wireless communication standards

Mutlipoint-to-Point Transmission

- Waiting for acknowledgements from the receiver leads to time wastage
- If each node communicates the same message then the receiver may receive duplicate messages which is inefficient
- If the message is split across the nodes then erasures lead to loss of data
- Solution: Rateless Erasure Coding (LT/Raptor Codes)



System Model



LT Codes (Encoding)

- Determine the degree 'd' of an encoding symbol from a given degree distribution ρ(d)
- Choose 'd' distinct information symbols uniformly at random
- Generate an encoded symbol which is the sum of the 'd' information symbols
- Any number of encoded symbols can be generated

LT Codes (Encoding)

Original Rows



Encoding Computations



 Each encoded matrix row is a linear combination of a random subset of original matrix rows

$$\mathbf{a}_{\mathbf{e},j} = \sum_{i \in \mathcal{S}_d} \, \mathbf{a}_i$$

- The encoded matrix rows are distributed equally across all workers
- We generate 'αm' encoded rows from 'm' original rows (α>1 controls the amount of redundancy)

LT Codes (Decoding)

- Identify a symbol with degree 1
- Map that to the corresponding information symbol
- Remove the recovered information symbol from all other encoded symbols containing it
- Repeat until all symbols are successfully decoded

LT Codes (Decoding)



Decode degree 1 encoded symbols Subtract decoded symbols from encoded products

Decoding Computations



- Workers compute encoded row vector products of the form <a_e,i'x>
- Master collects a total of m' row vector products from across *all* workers (even the slow ones)
- Collected row vector products have the form:

$$egin{aligned} &< \mathbf{a}_{\mathbf{e},j}, x > = < \sum_{i \in \mathcal{S}_d} \, \mathbf{a}_i > \ &= \sum_{i \in \mathcal{S}_d} \, < \mathbf{a}_i, x > \ &= \sum_{i \in \mathcal{S}_d} \, b_i \end{aligned}$$

- LT decoding can be applied to the collected symbols to recover $b = [b_1, b_2, ..., b_m]^T$
- Successful decoding occurs with high probability for m' = m(1+ ϵ) where ϵ -> o as m -> ∞

Degree Distribution for LT Codes

The 'd' in $\mathbf{a}_{e,j} = \sum_{i \in S_d} \mathbf{a}_i$ is chosen according to the Robust soliton distribution

• Partial Work of all workers is Utilised

Reduction in Latency and computation overhead

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Simulations

Decoding overhead (difference between m' and m) for different settings of LT code parameters

Simulations

Simulations are for multiplying a 10000 x 10000 matrix with a 10000 x 1 vector across 10 workers assuming a shifted exponential delay

Experimental Results

Results are for multiplying a 10000 x 10000 matrix with a 10000 x 1 vector across 10 Amazon EC2 workers

Conclusions and Future Work

- Benefits of LT Codes:
 - Efficient utilization of partial work across all workers (both fast and slow)
 - Lower latency and computation overhead at all workers along with better tolerance to worker failures
- Future Directions:
 - Extending to unreliable communication channels between master and workers (erasures/errors in addition to straggling)
 - Extending to other distributed computing tasks beyond matrix-vector multiplication (distributed machine learning)
 - Handling sparsity and other kinds of structure in data (For eg. Low rank matrices)

References

- Mallick, Ankur, Malhar Chaudhari, and Gauri Joshi. "Rateless Codes for Near-Perfect Load Balancing in Distributed Matrix-Vector Multiplication." *arXiv preprint arXiv:1804.10331* (2018) (<u>https://arxiv.org/abs/1804.10331</u>)
- Luby, Michael. "LT codes." IEEE, 2002. (<u>https://www.researchgate.net/profile/Michael_Luby/publication/2214</u> <u>98536_LT_codes/links/59274994a6fdcc4443507e45/LT-codes.pdf</u>)