RUTGERS OF NEW JERSEY

### **DISTRIBUTED LINEAR REGRESSION**

Linear regression is an algorithm aiming to represent a data matrix *A*, labeled with a vector **y**, by a vector of attributes  $\mathbf{x}^*$  such that  $A\mathbf{x}^* \approx \mathbf{y}$ .

A possible solution is to run the following iterative computation

$$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} - \alpha^{(t)} A^T (A \mathbf{x}^{(t)} - \mathbf{y}).$$
(1)

Here  $\alpha^{(t)}$  is called the learning rate and  $\mathbf{x}^*$  is found when  $\mathbf{x}^{(t+1)} \approx \mathbf{x}^{(t)}$ .

In a distributed setting, one wants to divide the main computation into smaller tasks and distribute them to *n* worker machines that can perform these smaller tasks in parallel.



### Main challenges:

Secrecy: maintain the confidentiality of A, in an information theoretic sense.

*Stragglers:* Should M wait for the slow workers? [1]

### Assumptions:

*Communication cost* as proxy for latency. *Delays* are shifted exponential random variables [2],

 $F(delay = t) \triangleq 1 - e^{-\lambda(t-c)}, \text{ for } t \ge c.$ 

### Goal:

Design codes that ensure secrecy, mitigate any number of stragglers up to a given threshold and minimize the communication cost.

### **ONGOING WORK AND FUTURE DIRECTIONS**

♦ Heterogeneous system: Workers have different properties. ♦ Malicious workers: Workers might send wrong results to M.

*◊ Beyond linear regression:* Flexible straggler mitigation for gradient descent and stochastic gradient descent algorithms.





# **STAIRCASE CODES**

**Theorem 1 ([3])** The (n, k, z) Staircase code constructed as follows mitigates any number of stragglers n-d,  $k \leq d \leq n$ , and achieves minimum download cost given by

for all values of d.



# structed over GF(5).

Worker 1  $A_1 + A_2 + A_3 + R_1$  $A_5 + A_6 + R_2$  $R_1 + R_2 + R_3$  $A_3 + R_4$  $A_6 + R_5$  $R_3 + R_6$ 

# **CODES FOR STRAGGLER MITIGATION IN SECURE DISTRIBUTED** LINEAR REGRESSION

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# **IMPLEMENTATION ON AMAZON CLOUD**

Fig. 1: An example of distributed linear regression. The computation given in (1) is divided into two multiplications:  $A\mathbf{x}$  and  $A^T\mathbf{b}$ , with  $b \triangleq A\mathbf{x} - \mathbf{y}$ . Each worker multiplies his matrix by the vector sent to them and sends the result back to the Master.

download 
$$cost = \frac{d(k-z)}{d-z}$$

$$= \begin{bmatrix} \text{Vandermonde} \end{bmatrix} \begin{bmatrix} \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} & \mathbf{I} \\ \mathbf{I}$$

**Example:** An (n, k, z) = (4, 2, 1) Staircase code con-



*◊ Dynamic environment:* Workers can join and leave the system at any time. ♦ Delay analysis: Study the delay model for small amount of data.



## **SAVINGS IN WAITING TIME AT THE MASTER**



Figure 3: The savings brought by (n, n/2, 1) Staircase codes on Amazon EC2 instances compared to theoretical results for large amounts of data. The data is a matrix of size  $387000 \times 250$ . The savings obtained on Amazon match the theoretical expectations.

### REFERENCES

- [1] J. Dean and L. A. Barroso, "The tail at scale," *Communications of the ACM*, vol. 56, no. 2, pp. 74–80, 2013.
- [2] G. Liang and U. C. Kozat, "TOFEC: Achieving optimal throughput-delay trade-off of cloud storage using erasure codes," in IEEE International Conference on Computer Communications, 2014.

**Theorem 2 (Lower bound on savings in mean waiting time [4])** *The savings on mean waiting time*  $\mathbb{E}[T_{SC}]$  *of an* (n, k, z) system using Staircase codes compared to k-out-of-n classical codes is lower bounded by

Savings 
$$\geq 1 - \min_{d \in \{k,...,n\}} \left\{ \frac{(k-z)(\lambda c + H_n - H_{n-d})}{(d-z)(\lambda c + H_n - H_{n-k})} \right\}$$

where  $H_n$  is the  $n^{th}$  harmonic sum defined as  $H_n \triangleq \sum_{i=1}^n \frac{1}{i}$ , and  $H_0 \triangleq 0$ .



Figure 4: The savings brought by (4, 2, 1) Staircase codes on Amazon EC2 instances compared to theoretical results for small amounts of data. The data is a matrix of size  $42000 \times 250$ . The savings obtained on Amazon EC2 do not match theoretical expectations.

- [3] R. Bitar and S. El Rouayheb, "Staircase codes for secret sharing with optimal communication and read overheads," IEEE Transactions on Information Theory, Vol. 64, No. 2, February 2018.
- [4] **R. Bitar**, P. Parag, and S. El Rouayheb, "Minimizing Latency in Secure Distributed Computing via Staircase Codes," submitted to IEEE Transactions on Information Theory.







