# Asynchronous coordinate update methods

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## **Problem Set-up**

Let  $\mathbb{T}: \mathbb{R}^n \to \mathbb{R}^n$  be  $\theta$ -average with  $\mathbb{T} = \mathbb{I} - \theta S$ .

Partition  $x = (x_1, ..., x_m) \in \mathbb{R}^n$  and:

$$\mathbb{T}(x) = \begin{bmatrix} (\mathbb{T}(x))_1 \\ \vdots \\ (\mathbb{T}(x))_i \\ \vdots \\ (\mathbb{T}(x))_m \end{bmatrix} \quad \mathbb{T}_i(x) = \begin{bmatrix} x_1 \\ \vdots \\ x_{i-1} \\ (\mathbb{T}(x))_i \\ x_{i+1} \\ \vdots \\ x_m \end{bmatrix} \quad \mathbb{S}_i(x) = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ (\mathbb{S}(x))_i \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

We can perform a standard synchronous or asynchronous implementation of

$$x^{k+1} = \mathbb{T}(x^k) \qquad \qquad x^{k+1} = x^k - \eta \mathbf{S} x^k,$$

On multiple agents or CPUS.



## **Coordinate Update Methods**

Our main goal is to **decompose a large problem into smaller subproblems** and are thus useful for solving large-sized problems.

> $x^{k+1} = x^k - \eta \nabla f(x_k)_{i(k)}$ Partition x=(x<sub>1</sub>,..., x<sub>m</sub>)  $\in \mathbb{R}^n$



Variables can be updated in cyclic, **random** or greedy orders.



We can use multiple computational agents to speed up the algorithm

3:

4:



Concurrently

xAgent 25:Write 
$$s[i] = \eta S[i](x)$$
xmAgent m6:end while7:Synchronize: wait for all agent8:while not all indices processed9:Claim index i not yet claime0:Write  $x[i] = x[i] - s[i]$ 11:end while12:Synchronize: wait for all agent13:end while

Synchronous parallel FPI

- 1: while not converged do
- while not all indices processed do 2:
  - Claim index i not yet claimed **Read** x

Write 
$$s[i] = \eta S[i](x)$$

do

ed

#### **Asynchronous FPI**

An algorithm is asynchronous parallel if it avoids synchronization barriers.

1:	while not converged do
2:	Select <i>i</i> from Uniform $\{1, 2,, m\}$
3:	Read $x$
4:	Compute $s[i] = \eta S[i](x)$
5:	Write $x[i] = x[i] - s[i]$
6: end while	

completely Now, agents run uncoordinated, the cost and of synchronization is eliminated.



## Synchronous vs Asynchronous - Cost

#### sync-parallel computing

As the number of computing agents grows, the cost of synchrony becomes significant.

Faster agents must wait idly for the slower ones.

The synchronization barrier is itself an algorithm with a cost



#### async-parallel computing

Requires exclusive memory access to avoid race condition.

Communication congestion can become a factor.





## **Asynchronous Parallelism**



When an agent performs Step 5, other agents may have updated x, rendering x used to compute Step 4 outdated. In this case, we say x is stale

$$x^{k+1} = x^k - \eta \mathbf{S}_{i(k)} \hat{x}^k$$

where  $\hat{x}_k$  contains information older than  $x_k$ 

Convergence of Asynchronous Methods

**Exclusive Memory Access** 



Convergence of Asynchronous Methods

**Exclusive Memory Access** 

We can account for staleness if we enforce exclusive access in Step 5. An agent has exclusive access to x in **shared memory** if no other agent can read from or write to x simultaneously

#### 1: while not converged do

- 2: Select *i* from Uniform  $\{1, 2, \ldots, m\}$
- 3: Read x

4: Compute 
$$s[i] = \eta S[i](x)$$

5: Exclusively **Read** x[i]

6: Exclusively Write 
$$x[i] = x[i] - s[i]$$

7: end while

- AC-FPI removes explicit synchronization barriers, though it still requires exclusive access in writing to x[i].
- When there are much more blocks than agents, i.e., p ≪ m, it is rare for an agent to wait for the release of a block's exclusive access; hence, most, albeit not all, idle time is eliminated.



## Asynchronous fixed-point iteration - iterate

- $x^0$  is the state of x before the start of the algorithm.
- The kth interate is  $x^k = (x_1^k, ..., x_m^k)$
- **Iteration count increment**: The iteration counter increases by 1 whenever an agent completes an update of x in the global memory.
- State of x<sub>k</sub>[j] (no updates in progress): When the iteration counter reaches k , if no agent is writing to x[j] , then x<sub>k</sub>[j] reflects the current state of x[j] at that moment.
- State of x<sub>k</sub>[j] (updates in progress): When the iteration counter reaches k, if an agent is actively updating x[j], then x<sub>k</sub>[j] represents the state of x[j] right before the agent began its current update.



#### **Delay notation of staleness**

Write i(k) for the index of the kth update, consider a coordinate-by-coordinate notion of staleness:

$$\hat{x}^{k} = \left(x_{1}^{k-d_{1}(k)}, \dots, x_{m}^{k-d_{m}(k)}\right) \qquad d(k) = (d_{1}(k), \dots, d_{m}(k)) \in \mathbb{N}_{+}^{m}$$

Mathematical definition of the AC-FPI:

$$x^{k+1} = x^k - \eta \mathbf{S}_{i(k)} \hat{x}^k \longrightarrow x^{k+1} = x^k - \eta \mathbf{S}_{i(k)} x^{k-d(k)}$$

AC-FPI is a stochastic algorithm realized by the random variables i(0), i(1), . . . and d(0), d(1), . . .

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#### Convergence of Asynchronous Methods

**Exclusive Memory Access** 



## **Convergence of AC-FPI – ARock assumptions**

The AC-FPI update  $x^{k+1} = x^k - \eta S_{i(k)} x^{k-d(k)}$  models can be analyzed with the **ARock** assumptions:

- $i(0), i(1), \dots$  are IID with uniform probability.
- i(k) and  $d(\ell)$  are independent for k = 0, 1, ... and  $\ell \le k$
- $d(0), d(1), \dots$  is a stochastic process with nonincreasing  $Q_0, Q_1, \dots \in [0, 1]$  such that for every  $k = 0, 1, \dots, d(0)$

Prob 
$$[\max_{i=1,...,m} d_i(k) \ge \ell \mid d(k-1),..., d(0), i(k-1),..., i(0)] \le Q_\ell,$$
  
$$\sum_{\ell=1}^{\infty} \ell (Q_\ell)^{1/2} < \infty$$



#### Theorem

Assume  $S: \mathbb{R}^n \to \mathbb{R}^n$  is (1/2)-cocoersive or, equivalently, that  $\mathbb{T} = \mathbb{I} - \theta S$  is  $\theta$ -averaged with  $\theta \in (0,1)$ . Assume Fix  $\mathbb{T} \neq \emptyset$ . Under the **ARock** assumptions, the AC-FPI with any starting point  $x^0 \in \mathbb{R}^n$  and step size  $\eta$  obeying

$$0 < \eta < \left(1 + \frac{2}{\sqrt{m}} \sum_{\ell=1}^{\infty} Q_{\ell}^{1/2}\right)^{-1}$$

Converges to one fixed point with probability 1

$$x^k \to x^\star$$
 for some  $x^\star \in \operatorname{Fix} \mathbb{T}$ 

Furthermore, with probability 1,

dist 
$$(x^k, \operatorname{Fix} \mathbb{T}) \to 0$$



## **Discussion of assumptions**

Exclusive Access: Step 4 requires exclusive access. Otherwise, we would not be able to use the notation

 $\boldsymbol{d}(k) = (d_1(k), \dots, d_m(k)) \in \mathbb{N}^m_+$ 

Independence:

- i(k) and d(k) are independent for k= 0,1,.... This is realistic if the computational costs of the blocks are uniform.
- Sequence i(0), i(1),... Is assumed to be IID.
  - If the blocks have non-uniform computational costs, the choice of index affects the iteration count the update is assigned to and the IID assumption is violated.

**Dependence allowed:** 

- Independence of d(0), d(1) ... is not assumed.
  - It is likely that  $\hat{x}^k$  and  $\hat{x}^{k+1}$  are read at close points in time, and this makes d(k) and d(k+1) highly correlated.



Convergence of Asynchronous Methods

**Exclusive Memory Access** 



## **Exclusive Memory Access**



#### inconsistent read

inconsistent write

Exclusive access can be implemented with standard parallel computing techniques such as:

- Atomic operations
- Mutexes
- semaphore



An operation of a computational agent is atomic if:

- The whole operation is guaranteed to complete without interruption from other agents.
- An atomic operation consists of multiple steps, other agents will not observe intermediate results

```
% Create a DataQueue for communication
2 dq = parallel.pool.DataQueue;
3
4 % Define a callback to update the shared vector
5 afterEach(dq, @(data) assignin('base', 'sharedVector', ...
      evalin('base', 'sharedVector') + data));
  % Use parallel processing
  parfor i = 1:numIterations
      % Create a vector where only the i-th position is updated
10
      localUpdate = zeros(numIterations, 1);
11
      localUpdate(i) = 1; % Assign exclusive value for worker i
12
13
      % Send the local update to the DataQueue
14
      send(dq, localUpdate);
15
16
  end
```



Convergence of Asynchronous Methods

**Exclusive Memory Access** 



## Methods – Asynchronous coordinate gradient descent

Consider the problem

$$\min_{x \in \mathbb{R}^n} f\left(\sum_{i=1}^m A_{:,i} x_i - b\right) + \sum_{i=1}^m g_i\left(x_i\right), \qquad A = [A_{:,1} A_{:,2} \cdots A_{:,m}]$$

Every  $i_{th}$  agent has access to  $x_i^k$ ,  $Prox_{\alpha g_i}$ ,  $A_{:,i}$  and  $\nabla f$  for i = 1, ..., m. The RC-FPI with the FBS operator is:

$$x_{i(k)}^{k+1} = \operatorname{Prox}_{\alpha g_{i(k)}} \left( x_{i(k)}^{k} - \alpha A_{:,i(k)}^{\top} \nabla f\left(y^{k}\right) \right)$$
$$y^{k+1} = y^{k} + A_{:,i(k)} \left( x_{i(k)}^{k+1} - x_{i(k)}^{k} \right)$$

where we initialize  $y^0 = Ax^0 - b$ . The corresponding AC-FPI is

$$s_{i(k)}^{k} = \eta \left( \hat{x}_{i(k)}^{k} - \operatorname{Prox}_{\alpha g_{i(k)}} \left( \hat{x}_{i(k)}^{k} - \alpha A_{:,i(k)}^{\top} \nabla f \left( \hat{y}^{k} \right) \right) \right)$$
  

$$x_{i(k)}^{k+1} = x_{i(k)}^{k} - s_{i(k)}^{k}$$
  

$$y^{k+1} = y^{k} - A_{:,i(k)} s_{i(k)}^{k}$$



## Methods – Asynchronous coordinate gradient descent

Where:

$$\hat{x}_{i(k)}^{k} = x_{i(k)}^{k-d_{i(k)}(k)}, \quad \hat{y}^{k} = A_{:,1}x_{1}^{k-d_{1}(k)} + \dots + A_{:,m}x_{m}^{k-d_{m}(k)}$$

In a shared memory system, we can implement AC-FPI with:

Algorithm ACGD 1: Initialize x = 0, y = -b2:  $Pr_i = prox_{\alpha q_i}, G_f = gradient of f$ 3: while not converged do **Read** y4:  $s[i] = \eta \cdot (x[i] - Pr_i(x[i] - \alpha \cdot A[:,i]' \cdot G_f(y)))$ 5: 6:  $\operatorname{del}[i] = -A[:,i] \cdot s[i]$ 7: Acquire exclusive access to y8:  $y = y + \operatorname{del}[i]$ Release exclusive access to y9: x[i] = x[i] - s[i]10: 11: end while



## **Examples – Lasso Regression**

Now consider the lasso problem

 $\min_{\beta} \frac{1}{2} \|y - X\beta\|_{2}^{2} + \lambda \|\beta\|_{1}$ 









## Thank You!

Any Questions?

