Distributed Offline Load Balancing in MapReduce Networks

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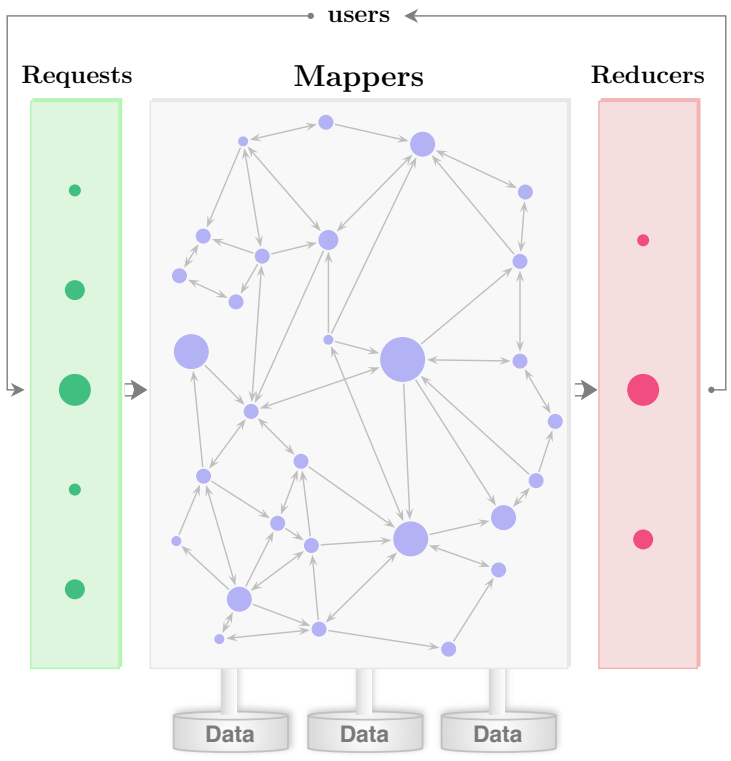
Outline

- Motivation - Introduction
- Notation and mathematical preliminaries
- Average consensus in digraphs
- Ratio consensus
- Examples
- Concluding remarks and future directions

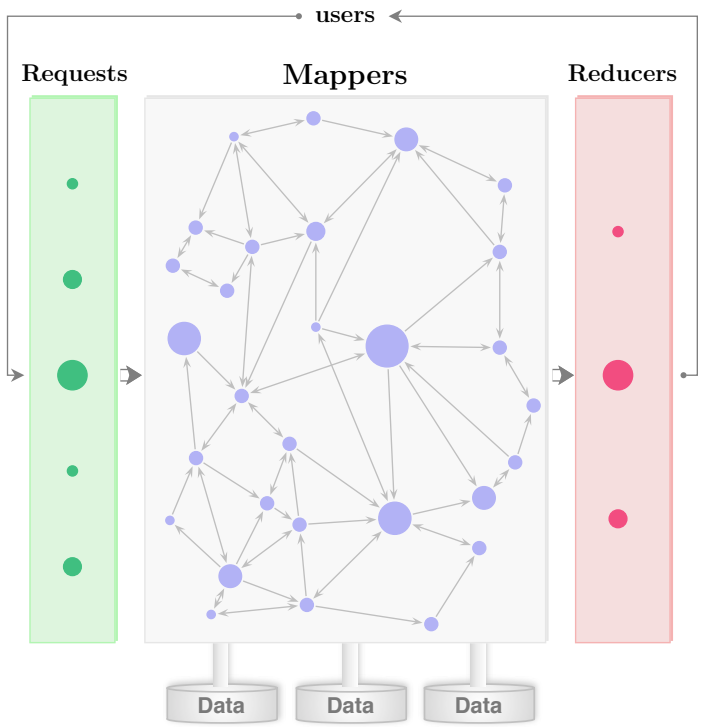
- Cloud computing enables quick application deployment over a *large pool of commodities* with *little capital investment*
- fast emerging Cloud application: big data computing
- modern applications in this domain employ: MapReduce paradigm, e.g.,
  - **Google** uses MapReduce for web search indexing, Google News and Google Maps
  - **Facebook** uses MapReduce for data warehousing operations
- MapReduce - designed to achieve high-job completion speedups through parallelism

Introduction
What is the MapReduce paradigm? (1)

- Input data divided into smaller chunks
- Input data transformed into key/value pairs
- Processing distributed to a network of processing elements
- Input data processed by two successively executed phases:
  1. Map phase: input data chunks processed independently by mappers - produce a new list of key/value pairs
  2. Reduce phase: pairs with common keys generated in the *map* phase are merged into a final list of key/values pairs



Introduction
What is the MapReduce paradigm? (2)



- Different mappers and different reducers can be executed in parallel.
- Scalability achieved by distributing the workload
  1) within the network of mappers
  2) within the network of reducers;

Motivation
Stragglers and previous approaches

- Stragglers: take $\geq$ 1.5 times the median task in that phase, due to
  - contention for resources
  - heterogeneity (e.g., disk loss rate)
  - mapReduce artifacts
- Current schemes:
  - replicate the execution of data processed by stragglers using back-up [Dean & Ghemawat, 2004], [Zaharia *et al*, 2008]
  - combine specialized solutions based on root-cause analysis of outliers, network-aware placements, and duplication [Ananthanarayanan *et al*, 2010]
  - rely on centralized solutions to map tasks or data to nodes prior to application execution [Xie *et al*, 2010], [Verma *et al*, 2011]

Q: How can we deal with stragglers in a distributed fashion?

Contribution

- **Target:**
  - divide the set of input data into *variable-sized* chunks
  - assign each chunk with a mapper process $\rightarrow$ all mappers commence and complete processing with no/small differences
  - we address the problem of stragglers due to data processing load imbalances in heterogeneous networks

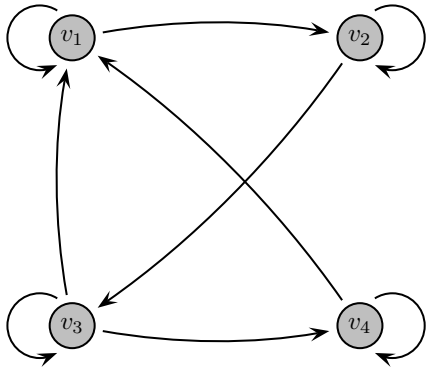
- **Propose:** a distributed algorithm, robustified ratio consensus
  - such that each mapper finishes its allocated workload at approximately the same time as the other mappers
  - allows mappers on heterogeneous nodes to operate asynchronously
  - operates in directed networks
  - mappers converge to proportional workload balancing between them
  - required limited local information exchanges

Contribution

Advantages over other methods (e.g., [Gonzalez-Ruiz *et al*, 2009])

- Lifted the assumption: cluster nodes need to be homogeneous and have the same resource capacity
  - allow for heterogeneous nodes
  - load distributed according to nodes' capacities (in terms of CPU, memory, disk space, etc.)
  - network topology might be weighted due to different bandwidth capabilities or time-varying delays
- Lifted the assumption: link-level delay needs to be either negligible or synchronous
  - our algorithm exhibits asymptotic converge in the presence of bounded delays
- Lifted the assumption: network is undirected
  - we consider directed graphs (digraphs)
  - In practice, network topology might become loosely directed because of delays, packet losses and asymmetric links
  - directed graph structure reduces overhead communication and can admit faster convergence

- Distributed systems conveniently captured by digraphs
  1. Components represented by vertices (nodes)
  2. Communication and sensing links represented by edges



- Consider a network with nodes $(v_1, v_2, \ldots, v_N)$ (in this case it is the network of mappers)
- Nodes can receive information according to (possibly directed) communication links
- Each node v_j has some initial value $\pi_j[0]$ of the amount of resources that it intends to contribute towards the map phase and a maximum capacity $\pi_j^{\max}$ that can provide

Graph Notation

- *Digraph* $\mathcal{G} = (\mathcal{V}, \mathcal{E})$
  - Nodes (system components) $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$
  - Edges (directed communication links) $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ where $(v_j, v_i) \in \mathcal{E}$ iff node v_j can receive information from node v_i
  - In-neighbors $\mathcal{N}_j^- = \{v_i \mid (v_j, v_i) \in \mathcal{E}\}$; in-degree $\mathcal{D}_j^- = |\mathcal{N}_j^-|$
  - Out-neighbors $\mathcal{N}_j^+ = \{v_l \mid (v_l, v_j) \in \mathcal{E}\}$; out-degree $\mathcal{D}_j^+ = |\mathcal{N}_j^+|$
- *Adjacency matrix A:* $A(j, i) = 1$ if $(v_j, v_i) \in \mathcal{E}$; $A(j, i) = 0$ otherwise
- *Undirected graph:* $(v_j, v_i) \in \mathcal{E}$ iff $(v_i, v_j) \in \mathcal{E}$ (bidirectional links)
  In undirected graphs, we have (for each node j)
  $\mathcal{N}_j^+ = \mathcal{N}_j^-$ and $\mathcal{D}_j^+ = \mathcal{D}_j^- = \mathcal{D}_j$; also, $A = A^T$
- *(Strongly) connected (di)graph* if for any $i, j \in \mathcal{V}$, $j \neq i$, there exists a (directed) path connecting them, i.e.,

$$v_i = v_{i_0} \to v_{i_1}, \; v_{i_1} \to v_{i_2}, \; \ldots, \; v_{i_{t-1}} \to v_{i_t} = v_j$$

- Average Consensus: All nodes calculate (in a distributed manner) the average $\frac{1}{N}\sum_{\ell=1}^{N} x_\ell[0]$ of initial values
- Consider linear iterations of the form

$$x_j[k+1] = p_{jj}x_j[k] + \sum_{i\in\mathcal{N}_j^-} p_{ji}x_i[k] \ , \ \forall j \in \{1,2,...,N\}$$

  where p_{ji} are constant weights and $x_j[0]$ is the initial value of node j
- Can be written in compact form as

$$\begin{aligned} x[k+1] &= Px[k] \\ x[0] &= [x_1[0]\ x_2[0]\ \dots\ x_N[0]]^T \end{aligned}$$

- Weight matrix P such that $P(j,i) = p_{ji}$
  Note: $P(j,i) = 0$ if $(j,i) \notin \mathcal{E}$

Conditions for Asymptotic Average Consensus

- Necessary and sufficient conditions on P for asymptotic average consensus [Xiao & Boyd, 2004]
  1. P has a simple eigenvalue at 1 with left eigenvector $\mathbf{1}^T = [1\ 1\ \ldots\ 1]$ and right eigenvector $\mathbf{1} = [1\ 1\ \ldots\ 1]^T$
  2. All other eigenvalues of P have magnitude strictly smaller than 1
- As $k \to \infty$, $P^k \to \frac{1}{N}\mathbf{1}\mathbf{1}^T$ which implies that

$$\lim_{k\to\infty} x[k] = \frac{1}{N}\mathbf{1}\mathbf{1}^T x[0] = \left(\frac{\sum_{\ell=1}^{N} x_\ell[0]}{N}\right)\mathbf{1} \equiv \overline{x}\mathbf{1}$$

- Nonnegative $p_{ji} \Longrightarrow P$ is primitive bistochastic

How to distributively reach the average in digraphs?

Average Consensus in Digraphs

- In undirected graphs nodes have a number of ways to distributively choose their weights so as to form a bistochastic matrix
- Digraphs not as easy to handle, even in a centralized manner (because in general $\mathcal{D}_j^+ \neq \mathcal{D}_j^-$)
- Approaches:
  - Distributed algorithms to obtain weights that form bistochastic matrices [Gharesifard & Cortés, 2012], [T.C. & C.N.H., 2013]
  - Distributed approaches that introduce additional state variables and use broadcast gossip [Franceschelli *et al*, 2011], [Cai & Ishii, 2011] and reach the average consensus *asymptotically*
  - Run two coupled iterations simultaneously (ratio consensus) [Benezit *et al*, 2010], [A.D. Domíngez-García & C.N.H., 2010], [C.N.H. & T.C., 2011] that reach the average consensus *asymptotically*

Average Consensus using Ratio Consensus

Pair of Simultaneous Linear Iterations

- Run two iterations [Benezit *et al*, 2010], [D-G & H, 2010]

$$\begin{array}{rcl} \pi[k+1] & = & P_c\pi[k] \\ \pi[0] & = & [\pi_1[0]\dots\pi_N[0]]^T \end{array} \quad \Bigg| \quad \begin{array}{rcl} x[k+1] & = & P_c x[k] \\ x[0] & = & \mathbf{1} \end{array}$$

- Matrix P_c st $P_c(l,j) = \frac{1}{1+\mathcal{D}_j^+}$ for $v_l \in \mathcal{N}_j^+$ (zero otherwise)
- Since P_c is primitive column stochastic, we know that as $k \to \infty$, $P_c^k \to \mathbf{v}\mathbf{1}^T$ for a *strictly positive* vector $\mathbf{v}$ such that $\mathbf{v} = P_c\mathbf{v}$ ($\mathbf{v}$ is *normalized* so that its entries sum to unity)
- This implies that

$$\begin{array}{rcl} \lim_{k\to\infty} \pi[k] & = & \mathbf{v}\mathbf{1}^T\pi[0] = \left(\sum_{\ell=1}^N \pi_\ell[0]\right)\mathbf{v} \\ \lim_{k\to\infty} x[k] & = & \mathbf{v}\mathbf{1}^T x[0] = N\mathbf{v} \end{array}$$

- For all nodes $j \in \{1,2,\dots,N\}$, ratio converges

$$\frac{\pi_j[k]}{x_j[k]} \to \frac{v_j\sum_{\ell=1}^N \pi_\ell[0]}{v_j N} = \frac{\sum_{\ell=1}^N \pi_\ell[0]}{N} \equiv \overline{\pi}$$

Robustified Ratio Consensus
in the presence of bounded time-varying delays

- A transmission on link (v_j, v_i) (from node v_i to node v_j) at any time-step k can be delayed by 0, 1, ..., D steps (arriving at node v_j respectively at time-step $k+1$, $k+2$, ..., $k+D+1$)
- Unknown time-dependent delay function for each link (v_j, v_i)

$$delay_{(j,i)}[k] = d \ , \quad d \in \{0, 1, 2, ..., D\}$$

- $delay_{(j,j)}[k] = 0$ for all k and $v_j \in \mathcal{V}$
(own value is always available)
- Ratio consensus can be adopted to work in the presence of bounded time-varying delays [C.N.H. & T.C., 2011]
- Can also handle time-varying topologies (as long as nodes know their out-degrees) [C.N.H. & T.C., 2012]

- A new MapReduce job d needs to process a set of input data
- Total demand of resources required by d in the map phase is given by ρ_d.
- ρ_d can be approximately estimated via offline application profiling
- Problem to be solved:

$$\rho_d = \sum_{v_\ell \in \mathcal{V}} \pi_\ell[m],$$

such that

$$0 \leq \pi_j[m] \leq \pi_j^{\max}, \ \ \forall v_j \in \mathcal{V}$$

$$0 \leq \rho_d \leq \sum_{v_\ell \in \mathcal{V}} \pi_\ell^{\max} \triangleq \chi^{\max}$$

- A simple, feasible solution $\pi^\dagger$

$$\pi_j^\dagger = \frac{\rho_d}{\chi^{\max}} \pi_j^{\max}, \ \forall v_j \in \mathcal{V}$$

- Each node v_j updates its demanded amount $\pi_j[k]$ by combining it with the available (possibly delayed) demanded amount of its neighbors ($\pi_i[s]$ $s \in \mathbb{Z}, s \leq k,\ v_i \in \mathcal{N}_j^-$)

$$\pi_j[k+1] = \frac{1}{1+\mathcal{D}_j^+}\pi_j[k] + \sum_{v_i \in \mathcal{N}_j^-} \sum_{r=0}^{\bar{\tau}} \frac{1}{1+\mathcal{D}_i^+}\pi_i[k-r]I_{k-r,ji}[r]$$

where

$$I_{k,ji}(\tau) = \begin{cases} 1, & \text{if } \tau_{ji}[k] = \tau, \\ 0, & \text{otherwise.} \end{cases}$$

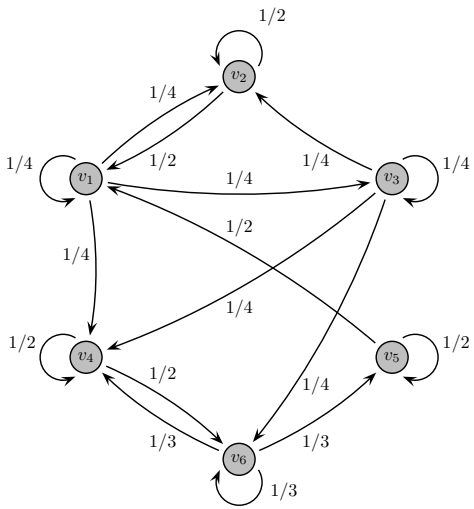
- Run two iterations, (with $y_j[0] = \pi_j[0]$ and $y_j[0] = \pi_j^{\max}$),

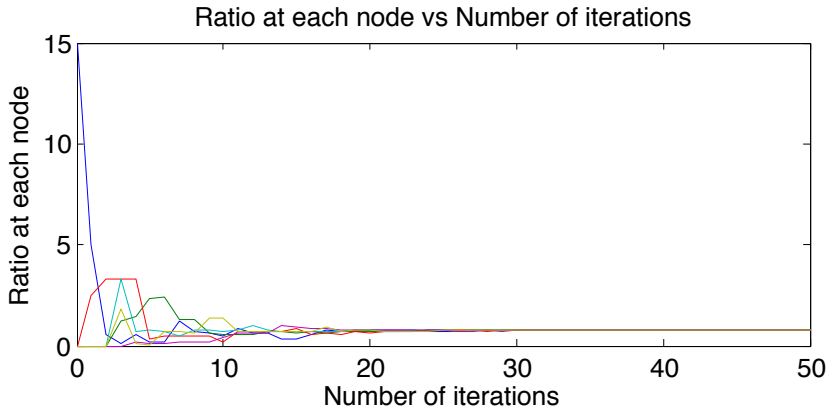
$$\lim_{k\to\infty} \mu_j[k] = \frac{\sum_{v_\ell \in \mathcal{V}} \pi_\ell[0]}{\sum_{v_\ell \in \mathcal{V}} \pi_\ell^{\max}[0]} = \frac{\rho_d}{\chi^{\max}}, \quad \forall v_j \in \mathcal{V}$$

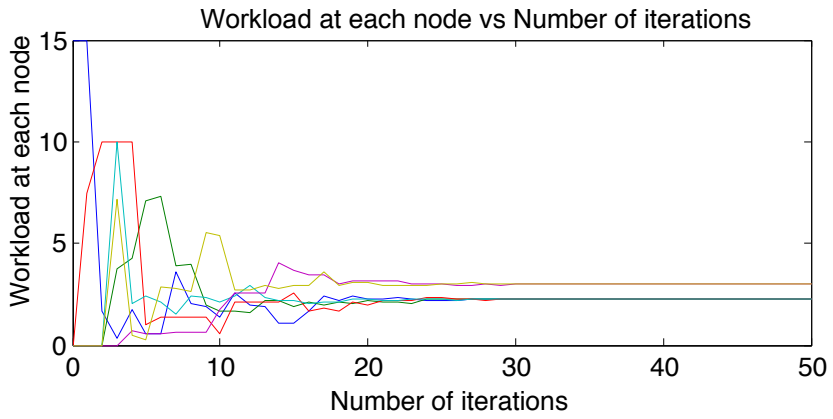
- Node v_j can obtain the amount of its load as

$$\lim_{k\to\infty} \mu_j[k]\pi_j^{\max} = \frac{\rho_d}{\chi^{\max}}\pi_j^{\max}$$

- The capacity of the mappers in this network is given by $\pi^{\max}[0] = (3 \;\; 3 \;\; 3 \;\; 3 \;\; 4 \;\; 4)^T$



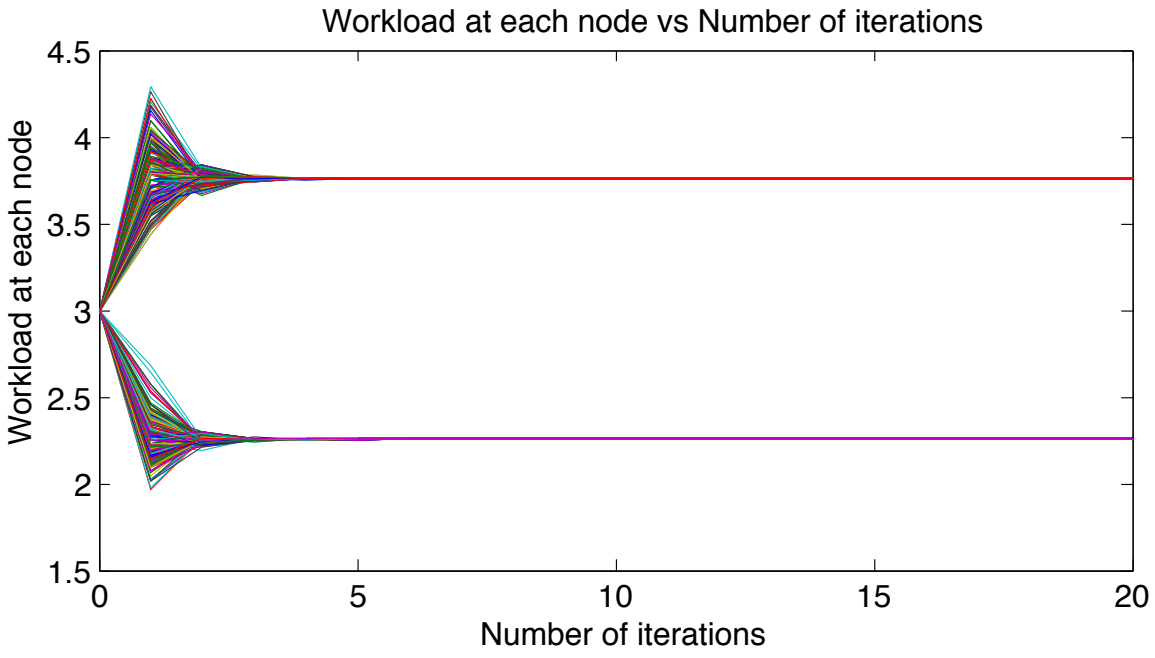




- the demanded workload amount injected into the network of mappers is given by $\pi[0] = (15 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0)^T$

- The amount of workload offered in the network by each node in the presence of asymmetric time-varying delays

- We consider a set of 500 mappers each with initial workload $\pi_j[0] = 3$
- Half of them have capacity $\pi_j^{max} = 3$ and the other half $\pi_i^{max} = 5$, $i \neq j$



Concluding Remarks and Future Directions

Conclusions:

- Proposed a distributed algorithm for workload distribution in MapReduce networks of clusters
  - allows mappers on heterogeneous nodes to operate asynchronously
  - operates in directed networks
  - nodes converge to proportional workload balancing
  - has limited local information exchanges

Future work:

- Preliminary results: assumed the load can be a continuous number, whereas in reality the workload has to be quantized
- Resources needed to serve each of the map jobs may not be known *a priori* $\rightarrow$ not possible to allocate a precise fraction of the total job to each server
- Fault-tolerance capabilities for mappers to re-adapt their workload distribution in the face of machine failures within a large data center

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Thank You!

Questions?

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