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Approximate Consensus in Highly Dynamic Networks: The Role of Averaging Algorithms

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Abstract

In this paper, we investigate the approximate consensus problem in highly dynamic networks in which topology may change continually and unpredictably. We prove that in both synchronous and partially synchronous systems, approximate consensus is solvable if and only if the communication graph in each round has a rooted spanning tree, i.e., there is a coordinator at each time. The striking point in this result is that the coordinator is not required to be unique and can change arbitrarily from round to round. Interestingly, the class of averaging algorithms, which are memoryless and require no process identifiers, entirely captures the solvability issue of approximate consensus in that the problem is solvable if and only if it can be solved using any averaging algorithm.

Concerning the time complexity of averaging algorithms, we show that approximate consensus can be achieved with precision of ε in a coordinated network model in $O(n^{n+1} \log \frac{1}{\varepsilon})$ synchronous rounds, and in $O(\Delta n^{n\Delta+1} \log \frac{1}{\varepsilon})$ rounds when the maximum round delay for a message to be delivered is Δ . While in general, an upper bound on the time complexity of averaging algorithms has to be exponential, we investigate various network models in which this exponential bound in the number of nodes reduces to a polynomial bound.

We apply our results to networked systems with a fixed topology and classical benign fault models, and deduce both known and new results for approximate consensus in these systems. In particular, we show that for solving approximate consensus, a complete network can tolerate up to $2n - 3$ arbitrarily located link faults at every round, in contrast with the impossibility result established by Santoro and Widmayer (STACS '89) showing that exact consensus is not solvable with $n - 1$ link faults per round originating from the same node.

1 Introduction

Recent years have seen considerable interest in the design of distributed algorithms for dynamic networked systems. Motivated by the emerging applications of the Internet and mobile sensor systems, the design of distributed algorithms for networks with a swarm of nodes and time-varying connectivity has been the subject of much recent work. The algorithms implemented in such dynamic networks ought to be decentralized, using local information, and resilient to mobility and link failures.

A large number of distributed applications require to reach some kind of agreement in the network in finite time. For example, processes may attempt to agree on whether to commit or abort the results of a distributed database transaction; or sensors may try to agree on estimates of a certain variable; or vehicles may attempt to align their direction of motions with their neighbors. Another example is clock synchronization where processes attempt to maintain a common time scale. In the first example, an *exact consensus* is achieved on one of the outcomes (namely, commit or abort) as opposed to the other examples where processes are required to agree on values that are sufficiently close to each other, but not necessarily equal. The latter type of agreement is referred to as *approximate consensus*.

For the exact consensus problem, one immediately faces impossibility results in truly dynamic networks in which some stabilization of the network during a sufficiently long period of time is not assumed (see e.g. [31] and [26, Chapter 5]). Because of its wide applicability, the approximate consensus problem appears as an interesting weakening of exact consensus to circumvent these impossibility results. The

objective of the paper is exactly to study computability and complexity of approximate consensus in dynamic networks in which the topology may change continually and in an unpredictable way.

1.1 Dynamic networks

We consider a fixed set of processes that operate in rounds and communicate by broadcast. In the first part of this article, rounds are supposed to be synchronous in the sense that the messages received at some round have been sent at that round. Then we extend our results to partially synchronous rounds with a maximum allowable delay bound.

At each round, the communication graph is chosen arbitrarily among a set of directed graphs that determines the network model. Hence the communication graph can change continually and unpredictably from one round to the next. Then the local algorithm at each process applies a state-transition function to its current state and the messages received from its incoming neighbors in the current communication graph to obtain a new state.

While local algorithms can be arbitrary algorithms in principle, the basic idea is to keep them simple so that coordination and agreement do not result from the local computational powers but from the flow of information across the network. In particular, we focus on *averaging algorithms* which repeatedly form convex combinations. One main feature of averaging algorithms is to be memoryless in the sense that the next value of each process is entirely determined only from the values of its incoming neighbors in the current communication graph. More importantly, they work in anonymous networks, not requiring processes to have identifiers.

The network model we consider unifies a wide variety of dynamic networks. Perhaps the most evident class of networks captured by this model is dynamic multi-agent networks in which communication links frequently go down while other links are established due to the mobility of the agents. The dynamic network model can also serve as an abstraction for static or dynamic wireless networks in which collisions and interferences make it difficult to predict which messages will be delivered in time. Finally the dynamic network model can be used to model traditional communication networks with a fixed communication graph (e.g., the complete graph) and some transient link failures.

In this model, the number of processes n is fixed, and we assume that each process knows n . This assumption can be weakened to a large extent. Indeed all our results still hold when n is not the exact number of processes but only an upper bound on this number. That allows us to extend the results to a completely dynamic network with a maximal number of processes that may join or leave. This limit even disappears for the *asymptotic consensus* problem in which processes are just required to converge to the same value.

Finally, for simplicity, we assume that all processes start the computation at the same round. In fact, it is sufficient to assume that every process eventually participates to the computation either spontaneously (in other words, it initiates the computation) or by receiving, possibly indirectly, a message from an initiator.

1.2 Contribution

We make the following contributions in this work:

(i) The main result in this paper is the exact characterization of the network models in which approximate consensus is solvable. We prove that the approximate consensus problem is solvable in a network model if and only if each communication graph in this model has a rooted spanning tree. This condition guarantees that the network has at least one coordinator in each round. The striking point is that coordinators may continually change over time without preventing nodes from converging to consensus. Accordingly the network models in which approximate consensus is solvable are called *coordinated network models*. The proof of this computability result highlights the key role played by averaging algorithms in approximate consensus: the problem is solvable if and only if it can be solved using any averaging algorithm.

(ii) With averaging algorithms, we show that agreement with precision of ε can be reached in $O(n^{n+1} \log \frac{1}{\varepsilon})$ rounds in a coordinated network model, and in only $n \log \frac{1}{\varepsilon}$ rounds in the case of a *nonsplit network model*, defined as a collection of communication graphs in which any two processes have at least one common incoming neighbor. As a matter of fact, every general upper bound for the

class of averaging algorithms has to be exponential since the *equal neighbor* averaging algorithm requires $\Omega(2^{n/3} \log \frac{1}{\varepsilon})$ rounds to reach agreement with precision of ε for the network model in [29].

(iii) As an application, we revisit the problem of approximate consensus in the context of communication faults, whether they are due to link or process failures. We first prove a new result on the solvability of approximate consensus in a complete network model in the presence of benign communication faults which shows that the number of link faults that can be tolerated increases by a factor of at least 2 when solving approximate consensus instead of consensus. Then we prove the correctness of fault-tolerant approximate consensus algorithms in a complete network by interpreting them as averaging algorithms. That allows us to extend the scope of these algorithms originally designed for the static crash failure model to a completely dynamic failure model.

(iv) Finally we extend our computability and complexity results to the case of *partially synchronous rounds* in which communication delays may be non null, but are bounded by some positive integer Δ : the messages received at some round k have not necessarily been sent at round k , but at some round ℓ with $\ell \in \{k - \Delta - 1, \dots, k\}$. We prove the same necessary and sufficient condition on network models for solvability of approximate consensus, and give an $O(n^{\Delta+1} \log \frac{1}{\varepsilon})$ upper bound on the number of rounds needed by averaging algorithms to achieve agreement with precision of ε in a coordinated network model. For nonsplit network models, this bound reduces to the polynomial bound $O(\Delta n^{2\Delta-1} \log \frac{1}{\varepsilon})$.

1.3 Related work

Agreement problems have been extensively studied in the framework of static communication graphs or with limited topology changes (e.g., [26, 4, 30, 35]). In particular, the approximate consensus problem, also called *approximate agreement*, is studied in numerous papers in the context of a complete graph and at most f faulty processes (see, e.g., [17, 18, 3]). In the case of benign failures where processes may crash or omit to send some messages, the failure model yields communication graphs with a *fixed* core of at least $n - f$ processes that have outgoing links to all processes, and so play the role of steady coordinators of the network.

There is also a large body of previous work on general dynamic networks. However, in much of them, topology changes are restricted and the sequences of communication graphs are supposed to be “well-formed” in various senses. Such well-formedness properties are actually opposite to the idea of unpredictable changes. In [2], Angluin, Fischer, and Jiang study the *stabilizing consensus problem* in which nodes are required to agree exactly on some initial value, but without necessarily knowing when agreement is reached, and they assume that any two nodes can directly communicate infinitely often. In other words, they suppose the limit graph formed by the links that occur infinitely often to be complete. To solve the consensus problem, Biely, Robinson, and Schmid [6] assume that throughout every block of $4n - 4$ consecutive communication graphs there exists a stable set of roots. Coulouma and Goddard [14] weaken the latter stability condition to obtain a characterization of the sequences of communication graphs for which consensus is solvable. Kuhn, Lynch, and Oshman [21] study variations of the *counting* problem; they assume bidirectional links and a stability property, namely the *T-interval connectivity* which stipulates that there exists a stable spanning tree over every T consecutive communication graphs. All their computability results actually hold in the case of 1-interval connectivity which reduces to a property on the *set* of possible communication graphs, and the cases $T > 1$ are investigated just to improve complexity results. Thus they fully model unpredictable topology changes, at least for computability results on counting in a dynamic network.

The network model in [21], however, assumes a static set of nodes and communication graphs that are all bidirectional and connected. The same assumptions are made to study the time complexity of several variants of consensus [22] in dynamic networks. Concerning the computability issue, such strong assumptions make exact agreement trivially solvable: since communication graphs are continually strongly connected, nodes can collect the set of initial values and then make a decision on the value of some predefined function of this set (e.g., majority, minimum, or maximum).

The most closely related pieces of work are doubtless those about asymptotic consensus and more specifically *consensus sets* studied by Blondel and Olshevsky [7]: a consensus set is a set of stochastic matrices such that every infinite product of matrices from this set converges to a rank one matrix. Computations of averaging algorithms correspond to infinite products of stochastic matrices, and the property of asymptotic consensus is captured by convergence to a rank one matrix. Hence when an upper bound on the number of nodes is known, the general notion of network models in which approximate consensus

is solvable reduces to the notion of consensus sets if we restrict ourselves to averaging algorithms. However the characterization of consensus sets in [7] is not included into our main computability result for approximate consensus, namely Corollary 8, since the fundamental assumption of a self loop at each node in communication graphs (a process can obviously communicate with itself) does not necessarily hold for the directed graphs associated to stochastic matrices in a consensus set. The characterization of compact consensus sets in [7] and our computability result of approximate consensus are thus incomparable.

In the same line, some of our positive results which make use of averaging algorithms can be shown equivalent to results about stochastic matrix products in the vast existing literature on asymptotic consensus [15, 12, 27, 1, 8, 25, 33, 24, 10, 36, 20, 28]. Notably Theorem 7 is similar to the central result in [8], but we give a different proof much simpler and direct as it requires neither star graphs (called *strongly rooted graphs* in [8]) nor Sarymsakov graphs [36]. Moreover our proof yields a significantly better upper bound on the time complexity of averaging algorithms in coordinated network models, namely $O(n^{n+1} \log \frac{1}{\varepsilon})$ instead of $O(n^{n^2} \log \frac{1}{\varepsilon})$ in [9]. The statement in Theorem 18 for the partial synchronous case with bounded delays already appears in [9, 10], but our proof strategy, which consists in a reduction to the case of synchronous nonsplit networks, yields a new and simpler proof.

2 Approximate consensus and averaging algorithms

We assume a distributed, round-based computational model in the spirit of the Heard-Of model by Charron-Bost and Schiper [11]. A system consists in a set of processes $[n] = \{1, \dots, n\}$. Computation proceeds in *rounds*: In a round, each process sends its state to its outgoing neighbors, receives values from its incoming neighbors, and finally updates its state based. The value of the updated state is determined by a deterministic algorithm, i.e., a transition function that maps the values in the incoming messages to a new state value. Rounds are communication closed in the sense that no process receives values in round k that are sent in a round different from k .

Communications that occur in a round are modeled by a directed graph $G = ([n], E(G))$ with a self-loop at each node. The latter requirement is quite natural as a process can obviously communicate with itself instantaneously. Such a directed graph is called a *communication graph*. We denote by $\text{In}_p(G)$ the set of incoming neighbors of p and by $\text{Out}_p(G)$ the set of outgoing neighbors of p in G . Similarly $\text{In}_S(G)$ and $\text{Out}_S(G)$ denote the sets of the incoming and outgoing neighbors of the nodes in a non-empty set $S \subseteq [n]$. Since there is a self-loop at each process, $S \subseteq \text{In}_S(G) \cap \text{Out}_S(G)$, and so both $\text{In}_S(G)$ and $\text{Out}_S(G)$ are non-empty. The cardinality of $\text{In}_p(G)$, i.e., the number of incoming neighbors of p , is called the *in-degree* of process p in G .

A *communication pattern* is a sequence $(G(k))_{k \geq 1}$ of communication graphs. For a given communication pattern, $E(k)$, $\text{In}_p(k)$ and $\text{Out}_p(k)$ stand for $E(G(k))$, $\text{In}_p(G(k))$ and $\text{Out}_p(G(k))$, respectively.

Each process p has a *local state* s_p the values of which at the end of round $k \geq 1$ is denoted by $s_p(k)$. Process p 's initial state, i.e., its state at the beginning of round 1, is denoted by $s_p(0)$. Let the *global state* at the end of round k be the collection $s(k) = (s_p(k))_{p \in [n]}$. The *execution* of an algorithm from global initial state $s(0)$, with communication pattern $(G(k))_{k \geq 1}$ is the unique sequence $(s(k))_{k \geq 0}$ of global states defined as follows: for each round $k \geq 1$, process p sends $s_p(k-1)$ to all the processes in $\text{Out}_p(k)$, receives $s_q(k-1)$ from each process q in $\text{In}_p(k)$, and computes $s_p(k)$ from the incoming messages, according to the algorithm's transition function.

2.1 Consensus and approximate consensus

A crucial problem in distributed systems is to achieve agreement among local process states from arbitrary initial local states. It is a well-known fact that this goal is not easily achievable in the context of dynamic network changes [19, 31], and restrictions on communication patterns are required for that. We thus define a *network model* as a non-empty set \mathcal{N} of communication graphs, those that may occur in communication patterns.

We now consider the above round-based algorithms in which the local state of process p contains two variables x_p and dec_p . Initially the range of x_p is $[0, 1]$ and $dec_p = \perp$ (which informally means that p has not decided).⁴ Process p is allowed to set dec_p to the current value of x_p , and so to a value v different from \perp , only once; in that case we say that p *decides* v . An algorithm *achieves consensus with*

⁴In the case of *binary consensus*, x_p is restricted to be initially from $\{0, 1\}$.

the communication pattern $(G(k))_{k \geq 1}$ if each execution from a global initial state as specified above and with the communication pattern $(G(k))_{k \geq 1}$ fulfills the following three conditions:

Agreement. The decision values of any two processes are equal.

Integrity. The decision value of any process is an initial value.

Termination. All processes eventually decide.

An algorithm *solves consensus* in a network model \mathcal{N} if it achieves consensus with each communication pattern formed with graphs all in \mathcal{N} . Consensus is *solvable in a network model* \mathcal{N} if there exists an algorithm that solves consensus in \mathcal{N} . Observe that consensus is solvable in \mathcal{N} in $n - 1$ rounds if each communication graph in \mathcal{N} is strongly connected. The following impossibility result due to Santoro and Widmayer [31], however, shows that network models in which consensus is solvable are highly constrained: consensus is not solvable in some “almost complete” graphs.

THEOREM 1 ([31]). *Consensus is not solvable in the network model comprising all communication graphs in which at least $n - 1$ processes have outgoing links to all other processes.*

The above theorem is originally stated by Santoro and Widmayer in the context of link faults in a complete communication graph but its scope can be trivially extended to dynamic communication networks.

To circumvent the impossibility of consensus even in such highly restricted network models, one may weaken Agreement into

ε -Agreement. The decision values of any two processes are within an *a priori* specified $\varepsilon > 0$.

and replace Integrity by:

Validity. All decided values are in the range of the initial values of processes.

An algorithm *achieves ε -consensus with the communication pattern* $(G(k))_{k \geq 1}$ if each execution from a global initial state as specified above and with the communication pattern $(G(k))_{k \geq 1}$ fulfills Termination, Validity, and ε -Agreement. An algorithm *solves approximate consensus* in a network model \mathcal{N} if for any $\varepsilon > 0$, it achieves ε -consensus with each communication pattern formed with graphs all in \mathcal{N} . Approximate consensus is *solvable in a network model* \mathcal{N} if there exists an algorithm that solves approximate consensus in \mathcal{N} .

2.2 Averaging algorithms

We now focus on *averaging algorithms* defined by the update rules for each variable x_p which are of the form:

$$x_p(k) = \sum_{q \in \text{In}_p(k)} w_{qp}(k) x_q(k-1), \quad (1)$$

where $w_{qp}(k)$ are positive real numbers with $\sum_{q \in \text{In}_p(k)} w_{qp}(k) = 1$. In other words, at each round k , process p updates x_p to some weighted average of the values $x_q(k-1)$ it has just received. For convenience, we let $w_{qp}(k) = 0$ if q is not an incoming neighbor of p in the communication graph of round k .

An *averaging algorithm with parameter* $\varrho > 0$ is an averaging algorithm with the positive weights uniformly lower bounded by ϱ :

$$\forall k \geq 1, p, q \in [n] : w_{qp}(k) \in \{0\} \cup [\varrho, 1].$$

Since we strive for distributed implementations of averaging algorithms, $w_{qp}(k)$ is required to be locally computable. Finally note that the decision rule is not specified in the above definition of averaging algorithms: the decision time immediately follows from the number of rounds that is proven to be sufficient to reach ε -Agreement.

Some averaging algorithms with locally computable weights are of particular interest, namely, the *equal neighbor averaging algorithm* and the *fixed weight averaging algorithms*.

In the equal neighbor averaging algorithm, at each round k process p chooses

$$w_{qp}(k) = 1/|\text{In}_p(k)| \quad (2)$$

for every q in $\text{In}_p(k)$. It is clearly an averaging algorithm with parameter $\varrho = 1/n$.

Given a network model \mathcal{N} , we denote by $d_p^-(\mathcal{N})$ the maximum in-degree of process p over all the graphs in \mathcal{N} . Each process p is *a priori* assigned a positive parameter $\alpha_p \geq d_p^-(\mathcal{N})$. In a fixed weight averaging algorithm, at every round k , process p chooses

$$w_{qp}(k) = \begin{cases} 1/\alpha_q & \text{if } q \neq p, \\ 1 - \sum_{q \in \text{In}_p(k) \setminus \{p\}} 1/\alpha_q & \text{if } q = p. \end{cases} \quad (3)$$

for each q in $\text{In}_p(k)$. We verify that $\varrho = \min\{1/\alpha_p \mid p \in [n]\}$ is a positive lower bound on positive weights.

3 Solvability of approximate consensus

In this section, we characterize the network models in which approximate consensus is solvable. For that we first prove that if any two processes have a common incoming neighbor in each communication graph of a network model \mathcal{N} , then every averaging algorithm solves approximate consensus in \mathcal{N} . Then we extend this result to *coordinated network models* where each communication graph has a spanning tree with a root that plays the role of a *coordinator*. The latter result which is quite intuitive in the case of a fixed coordinator, actually holds when coordinators vary over time. Conversely we show that if approximate consensus is solvable in \mathcal{N} , then \mathcal{N} is necessarily a coordinated network model.

3.1 Nonsplit network model

We say a directed graph G is *nonsplit* if for all pairs of processes $(p, q) \in [n]^2$, it holds that

$$\text{In}_p(G) \cap \text{In}_q(G) \neq \emptyset. \quad (4)$$

Accordingly we define a *nonsplit network model* as a network model in which each communication graph is nonsplit. Note that a special case of a nonsplit communication graph is one in which all processes have one common incoming neighbor, i.e., hear of at least one common process r .

Intuitively, the occurrence of a nonsplit communication graph makes the variables x_p in an averaging algorithm to come closer together: by definition of nonsplit communication graphs, any two processes p and q have at least one common incoming neighbor r , leading to a common term in both p 's and q 's average. The following theorem formalizes this intuition, showing that approximate consensus is achieved in nonsplit network models.

THEOREM 2. *In a nonsplit network model of n processes, every averaging algorithm with parameter ϱ achieves ε -consensus in $\frac{1}{\varrho} \log \frac{1}{\varepsilon}$ rounds. In particular, the equal neighbor averaging algorithm achieves ε -consensus in $n \log \frac{1}{\varepsilon}$ rounds.*

Proof. Validity is trivially satisfied by definition of an averaging algorithm.

For ε -Agreement, we first observe that the set of update rules (1) can be concisely rewritten as

$$x(k) = W(k)x(k-1) \quad (5)$$

where $x(k)$ is the vector in \mathbb{R}^n whose p -th entry is the value held by process p at time k and $W(k)$ denotes the $n \times n$ matrix whose entry at the p -th row and q -th column is equal to

$$W_{pq}(k) = w_{qp}(k).$$

By definition of an averaging algorithm, each matrix $W(k)$ is stochastic and the positive entries are lower bounded by $\varrho \in]0, 1]$.

For any positive integers k and ℓ , $\ell \geq k$, we let

$$W(\ell : k) = W(\ell) \dots W(k).$$

In particular $W(k : k) = W(k)$. From the recurrence relation (5) we derive

$$x(k) = W(k : 1)x(0). \quad (6)$$

Since each $G(k)$ is a nonsplit communication graph, we obtain that for any two processes p, q there is a process r with

$$\min(W_{pr}(k), W_{qr}(k)) \geq \varrho.$$

The coefficient of ergodicity of a stochastic matrix P introduced by Dobrushin [16] and defined by

$$\delta(P) = 1 - \min_{p,q} \sum_{r=1}^n \min(P_{pr}, P_{qr})$$

thus satisfies the inequality

$$\delta(W(k)) \leq 1 - \varrho. \quad (7)$$

Besides a result by Seneta [32] combined with a straightforward argument of convex duality shows that for any stochastic matrix P , the coefficient $\delta(P)$ coincides with the matrix seminorm

$$\sup_{x \notin \mathbb{R}\mathbb{1}} \frac{\delta(Px)}{\delta(x)}$$

associated to the seminorm on \mathbb{R}^n defined by $\delta(x) = \max_p(x_p) - \min_p(x_p)$, where $\mathbb{R}\mathbb{1}$ is the line of vectors with equal components. Consequently δ is a matrix seminorm, and so is sub-multiplicative.

Since $\delta(P) \leq 1$ for any stochastic matrix P , we conclude that

$$\delta(W(k : 1)) \leq (1 - \varrho)^k.$$

Because of the inequality

$$1 - a \leq e^{-a}$$

when $a \geq 0$ and because $\delta(x(0)) \leq 1$, it follows that if $k \geq \frac{1}{\varrho} \log \frac{1}{\varepsilon}$, then $\delta(x(k)) \leq \varepsilon$. This completes the proof of Theorem 2. \square

For technical purposes, we now extend Theorem 2 in two directions. We first observe that the above proof does not make use of the assumption of a self-loop at each node of communication graphs. Therefore Theorem 2 still holds for *generalized network models* in which each process does not necessarily communicate with itself. The second extension concerns the granularity at which the assumption of nonsplit communication graphs holds. Let the *product* of two directed graphs G and H with the same set of nodes V be the directed graph $G \circ H$ with set of nodes V and a link from p to q if there exists a node r such that $(p, r) \in E(G)$ and $(r, q) \in E(H)$. For any positive integer K , we say a network model \mathcal{N} is *K -nonsplit* if any product of K graphs from \mathcal{N} is nonsplit.

COROLLARY 3. *In a generalized K -nonsplit network model of n processes, every averaging algorithm with parameter ϱ achieves ε -consensus in $K \left(\frac{1}{\varrho}\right)^K \log \frac{1}{\varepsilon} + K - 1$ rounds.*

Proof. We repeat the beginning of the proof of Theorem 2 and we form the matrix product $W(k : 1)$. When grouping matrices K by K , $W(k : 1)$ turns out to be a product of $\lfloor \frac{k}{K} \rfloor$ blocks of the form $W(\ell + K - 1 : \ell)$ and at most $K - 1$ remaining stochastic matrices. Each block matrix is nonsplit and its positive entries are lower bounded by ϱ^K . Hence for any two processes p, q there is a process r with

$$\min(W_{pr}(\ell + K - 1 : \ell), W_{qr}(\ell + K - 1 : \ell)) \geq \varrho^K.$$

It follows that the coefficient of ergodicity δ of each block satisfies

$$\delta(W(\ell + K - 1 : \ell)) \leq 1 - \varrho^K.$$

By the sub-multiplicativity of δ and since $\delta(P) \leq 1$ when P is a stochastic matrix, we obtain that

$$\delta(W(k : 1)) \leq (1 - \varrho^K)^{\lfloor k/K \rfloor}.$$

Since $\delta(x(0)) \leq 1$, it follows that if $k \geq K \left(\frac{1}{\varrho}\right)^K \log \frac{1}{\varepsilon} + K - 1$, then $\delta(x(k)) \leq \varepsilon$. We conclude as in the proof of Theorem 2. \square

3.2 Coordinated network model

We begin by recalling some basic notions on directed graphs. A directed graph G is said to be p -rooted, for some node p , if for every node there exists a directed path terminating at this node and originating at p . Such a node p is called a *root* of G , and R_G denotes the set of roots in G . If R_G is non-empty, then G is said to be *rooted*.

PROPOSITION 4. *Let S be a non-empty set of nodes of a directed graph G . If S has no incoming link, then S contains all the roots of G , i.e.,*

$$\text{In}_S(G) \subseteq S \Rightarrow R_G \subseteq S.$$

The *condensation* of a directed graph G , denoted by G^* , is the directed graph of the strongly connected components of G . Clearly a directed graph G is rooted if and only if its condensation G^* is. Using that G^* is acyclic, we can show the following characterization of rooted graphs.

PROPOSITION 5. *A directed graph G is rooted if and only if its condensation G^* has a sole node without incoming neighbors.*

As a consequence of the above proposition, a nonsplit directed graph is rooted.

Intuitively, while communication graphs remain p -rooted, process p gathers the values in its strongly connected component, computes some weighted average value, and attempts to impose this value to the rest of the processes. In other words, its particular position in the network makes p to play the role of *network coordinator* in any averaging algorithm. Accordingly, we define a *coordinated network model* as a network model in which each communication graph is rooted.

From the above discussion, it is easy to grasp why in the particular case of a steady coordinator, all processes converge to a common value and so achieve approximate consensus when running an averaging algorithm. We now show that approximate consensus is actually achieved even when coordinators change over time. For that, we begin with the following elementary lemma.

LEMMA 6. *For each system with n processes, any coordinated network model is $(n - 1)$ -nonsplit.*

Proof. Let H_1, \dots, H_{n-1} be a sequence of $n - 1$ communication graphs, each of which is rooted. For each process $p \in [n]$ and each index $k \in \{0, \dots, n - 1\}$, we define the sets $S_p(k)$ by

$$S_p(0) = \{p\} \quad \text{and} \quad S_p(k) = \text{In}_{S_p(k-1)}(H_k) \quad \text{for } k \in \{1, \dots, n - 1\}. \quad (8)$$

We easily check that for any $k \in \{1, \dots, n - 1\}$,

$$S_p(k) = \text{In}_p(H_k \circ \dots \circ H_1). \quad (9)$$

Because of the self-loops at all nodes in communication graphs, $S_p(k) \subseteq S_p(k + 1)$. Hence none of the sets $S_p(k)$ is empty.

We now show that for any processes $p, q \in [n]$,

$$S_p(n - 1) \cap S_q(n - 1) \neq \emptyset. \quad (10)$$

If $p = q$, then (10) trivially holds. Otherwise, assume by contradiction that (10) does not hold; it follows that for any index $k \in \{0, \dots, n - 1\}$, the sets $S_p(k)$ and $S_q(k)$ are disjoint.

Let us consider the sequences $S_p(0) \subseteq \dots \subseteq S_p(n - 1)$, $S_q(0) \subseteq \dots \subseteq S_q(n - 1)$, and

$$S_p(0) \cup S_q(0) \subseteq \dots \subseteq S_p(n - 1) \cup S_q(n - 1).$$

Because $|S_p(0) \cup S_q(0)| \geq 2$ if $p \neq q$ and $|S_p(n - 1) \cup S_q(n - 1)| \leq n$, the latter sequence cannot be strictly increasing. Therefore there exists some index $\ell \in \{0, \dots, n - 2\}$ such that

$$S_p(\ell) \cup S_q(\ell) = S_p(\ell + 1) \cup S_q(\ell + 1).$$

By assumption, we have $S_p(\ell) \cap S_q(\ell) = \emptyset$ and $S_p(\ell + 1) \cap S_q(\ell + 1) = \emptyset$. Hence

$$S_p(\ell) = S_p(\ell + 1) \quad \text{and} \quad S_q(\ell) = S_q(\ell + 1).$$

By (8) and Proposition 4, both $S_p(\ell)$ and $S_q(\ell)$ contain the nonempty set of roots of $H_{\ell+1}$, a contradiction to the disjointness assumption. Thus (10) follows.

Because of (9), this proves that the directed graph $H_{n-1} \circ \dots \circ H_1$ is nonsplit. \square

We now apply Corollary 3 to obtain the following result.

THEOREM 7. *In a coordinated network model of n processes, every averaging algorithm with parameter ρ achieves ε -consensus in $\left(\frac{1}{\rho}\right)^n n \log \frac{1}{\varepsilon} + n - 1$ rounds. In particular, the equal neighbor averaging algorithm achieves ε -consensus in $O\left(n^{n+1} \log \frac{1}{\varepsilon}\right)$ rounds.*

COROLLARY 8. *The approximate consensus problem is solvable in any coordinated network model.*

Interestingly Lemma 6 corresponds to a *uniform translation* in the Heard-Of model [11] that transforms each block of $n - 1$ consecutive rounds with rooted communication graphs into one macro-round with a nonsplit communication graph. If each process applies an equal neighbor averaging procedure only at the end of each macro-round instead of applying it round by round, the resulting distributed algorithm, which is no more an averaging algorithm, achieves ε -consensus in only $O\left(n^2 \log \frac{1}{\varepsilon}\right)$ rounds.

3.3 Necessity for the coordinated model to solve approximate consensus

As we now show, there exists an algorithm, whether or not it is an averaging algorithm, achieving approximate consensus in a network model \mathcal{N} only if \mathcal{N} is coordinated.

THEOREM 9. *In any non-coordinated network model, the approximate consensus problem is not solvable.*

Proof. We proceed by contradiction and we assume that there exists an algorithm that solves approximate consensus in a non-coordinated network model \mathcal{N} .

Let G be a communication graph in \mathcal{N} that is not rooted. Then by Proposition 5, the condensation G^* has at least two nodes without incoming neighbors. Let P and Q denote the set of processes corresponding to two such nodes in G^* , i.e., to two strongly connected components of G without incoming links.

Then we consider three executions of the algorithm which share the same communication pattern, namely the sequence with the fixed graph G , and which differ only in the initial state: in the first execution all processes start with 0, in the second one they all start with 1, and in the third every process in P starts with 0 while all the others — including processes in Q — start with 1. By Validity, all processes finally decide 0 and 1 in the first and the second execution, respectively. Moreover the first and the third executions are indistinguishable from the viewpoint of each process in P ; in particular each process in P makes the same decision, namely 0, in both of these executions. Similarly each process in Q makes the same decision, namely 1, in the second and the third execution. Therefore the third execution violates ε -agreement as soon as $\varepsilon < 1$, a contradiction with the assumption that the algorithm solves approximate consensus. \square

COROLLARY 10. *The approximate consensus problem is solvable in a network model \mathcal{N} if and only if \mathcal{N} is a coordinated model.*

At the risk of oversimplifying, one might say that understanding averaging algorithms is understanding backward products of stochastic matrices,

$$W(k : 1) = W(k)W(k - 1) \dots W(1)$$

as k grows to infinity. The graph associated to a stochastic matrix W of size $n \times n$ is the directed graph $G(W)$ with the set of vertices equal to $[n]$ and a set of directed edges E defined by

$$(p, q) \in E \Leftrightarrow W_{pq} > 0.$$

The communication graph at round k thus coincides with the graph associated to $W(k)$. Following the terminology in [7], a set \mathcal{P} of stochastic matrices is a *consensus set* if every infinite backward product of matrices from \mathcal{P} converges to a rank one matrix. When limiting ourselves to averaging algorithms, Corollary 10 then reduces to a necessary and sufficient condition on a compact set of stochastic matrices with positive diagonals to form a consensus set. In particular, we obtain a graph-based characterization of stochastic matrices with positive diagonals whose powers converge to a rank one matrix.

COROLLARY 11. *A compact set \mathcal{P} of stochastic matrices with positive diagonals is a consensus set if and only if the directed graph associated to each matrix in \mathcal{P} is rooted.*

4 Time complexity of averaging algorithms

As opposed to the approximate consensus algorithm sketched in Section 3.2, based on the translation of coordinated rounds into a nonsplit macro-round, one main advantage of averaging algorithms is that they do not require processes to have identifiers. Unfortunately the upper bound on the decision times of averaging algorithms in Theorem 7 is quite large, namely exponential in the number of processes, while the decision times of the approximate consensus algorithm in Section 3.2 are at most quadratic. Our goal in this section is precisely to study the time complexity of averaging algorithms for a coordinated network model of anonymous processes.

As shown in Theorem 2, the assumption of dynamic nonsplit networks drastically reduces the decision time of averaging algorithms: for instance, the decision time of the equal neighbor algorithm is actually linear. Another class of network models with polynomial decision times for some averaging algorithms are the bidirectional connected network models, i.e., those whose network model is a set of bidirectional and connected networks: from a result by Chazelle [10], we derive a fixed weight averaging algorithm that achieves ε -consensus in $O(n^3 \log \frac{1}{\varepsilon})$ rounds in these dynamic networks. However in the non-bidirectional case, we show that the same algorithm may exhibit an $\Omega(2^{n/3} \log \frac{1}{\varepsilon})$ decision time, demonstrating that a general upper bound on decision times in averaging algorithms has to be exponential.

4.1 Bidirectional connected network models

The consensus algorithm in [6] with a linear decision time can be used in the context of bidirectional connected networks since any process is then a root, and the set of roots is the set of all processes. However contrary to any averaging algorithm, it does not tolerate deviations from bidirectional connected network models: for instance, it does not tolerate any link removal in the case of a bidirectional tree. In other words, even if linear, the algorithm in [6] is not relevant for approximate consensus in the setting of dynamic networks that are bidirectional only most of the time.

Interestingly in any bidirectional connected network model with n processes, a fixed weight algorithm with parameter ϱ achieves ε -consensus in $O(\frac{1}{\varrho} n^2 \log \frac{1}{\varepsilon})$ rounds for any $0 < \varepsilon < \varrho/n$ (see e.g., Theorem 1.6 in [10]). Hence in such network models, there exist fixed weight averaging algorithms that solve approximate consensus with polynomial decision times.

The proof in [10] is based on some classical spectral gap arguments. Let W be any stochastic matrix; its spectral radius is then equal to 1. By the Perron-Frobenius theorem, the eigenvalue 1 is actually a simple eigenvalue with positive eigenvectors if the matrix W is *primitive*, i.e., the directed graph defined by its positive entries is strongly connected and aperiodic. If W is a primitive matrix, then its transpose W^T is also primitive with the same spectral radius, namely 1. It follows that 1 is a simple eigenvalue of W^T with some positive eigenvectors. Hence there exists a unique positive vector π , called the *Perron vector of W* , such that $W^T \pi = \pi$ and $\sum_p \pi_p = 1$. Chazelle observes that the Perron vectors of the stochastic matrices $W(k)$ associated to the execution of a fixed weight averaging algorithm with a communication pattern composed of bidirectional graphs are constant, even though the network topology may change over time. Using the inner product on \mathbb{R}^n defined by

$$\langle x, y \rangle_\pi = \sum_{p=1}^n \pi_p x_p y_p$$

where π is the common Perron vector of the stochastic matrices $W(k)$ and the fact that each matrix $W(k)$ is self-adjoint with respect to this inner product, Chazelle establishes some bounds on the spectral gap of every matrix $W(k)$ when the communication graph at round k is additionally connected, which allows him to conclude.

4.2 Exponential decision time in unidirectional networks

We develop the example given by Olshevsky and Tsitsiklis [29], inspired by [13], of a strongly connected uni-directional network model and a fixed weight averaging algorithm that, in contrast to the bidirectional case, exhibits a necessarily exponentially large decision time.⁵ More specifically, we show that the

⁵We would like to thank Alex Olshevsky for pointing us to this example.

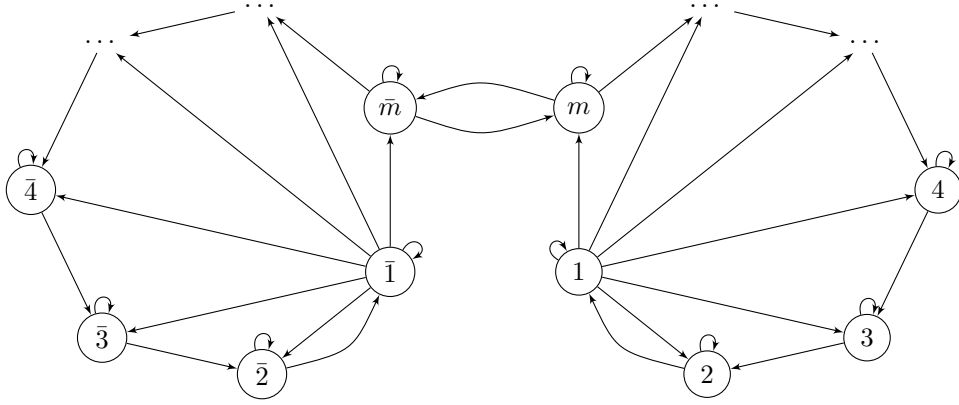


Figure 1: Example of a network with exponential decision time of the equal neighbor algorithm

algorithm achieves ε -consensus in $\Omega(2^{n/3} \log \frac{1}{\varepsilon})$ rounds. The example does not even require the network to be dynamic, using a time-constant network only. The fixed weight averaging algorithm used in the example corresponds to the equal neighbor algorithm for the considered static network.

The communication graph, that we call the m -butterfly graph, is depicted in Figure 1. It has $n = 2m$ processes and consists of two isomorphic parts that are connected by a bidirectional link. We list the links between the processes $1, 2, \dots, m$, which also determine the links between the processes $m+1, m+2, \dots, 2m$ via the isomorphism $\bar{p} = 2m - p + 1$. The links between the processes $1, 2, \dots, m$ are: (a) the links $(p+1, p)$ for all $p \in [m-1]$ and (b) the links $(1, p)$ for all $p \in [m]$. In addition, it contains a self-loop at each process and the two links (m, \bar{m}) and (\bar{m}, m) . Hence the m -butterfly graph is strongly connected.

THEOREM 12 ([29]). *In the coordinated model consisting of the m -butterfly graph, for any $\varepsilon > 0$, the equal neighbor averaging algorithm does not achieve ε -consensus by round K if $K = O(4^{m/3} \log \frac{1}{\varepsilon})$.*

The complete proof we give here is based on spectral gap arguments, and therein differs from the proof in [29]. Let W be any stochastic matrix, and let π denote its Perron vector. For any subset $S \subseteq [n]$, we let

$$\Phi_S(W) = \pi(S)^{-1} \sum_{p \in S} \sum_{q \notin S} \pi_q W_{pq}$$

where $\pi(S) = \sum_{r \in S} \pi_r$. Then the Cheeger constant of the matrix W is defined as the minimal $\Phi_S(W)$ of all nonempty S with $\pi(S) \leq 1/2$, i.e.,

$$\Phi(W) = \min_{\substack{S \subseteq [n] \\ 0 < \pi(S) \leq 1/2}} \Phi_S(W).$$

Combining Theorem 7.3 and Theorem 12.3 in [23], we obtain the following Cheeger inequality: if λ denotes an eigenvalue of W other than 1 with the greatest absolute value and $\pi_{\min} = \min_p(\pi_p)$, then

$$|\lambda| \geq 1 - C \cdot \Phi(W) \cdot \log \frac{1}{\pi_{\min}} \quad (11)$$

where C is some universal constant.

We are now in position to prove Theorem 12.

Proof. Let W be the stochastic matrix of size $n = 2m$ associated with the equal-neighbor averaging algorithm when the communication graph is the m -butterfly graph. We verify that W is a primitive matrix and its Perron vector is given by

$$\pi_1 = \frac{1}{5}, \quad \pi_p = \frac{3}{5 \cdot 2^p} \text{ for } p \in \{2, \dots, m-1\} \quad \text{and} \quad \pi_m = \frac{3}{5 \cdot 2^{m-1}}.$$

By symmetry, this also defines the Perron vector for the remaining indices between $m + 1$ and $2m$ since $\pi_p = \pi_{2m-p+1}$. Hence the smallest entry of W 's Perron vector is

$$\pi_{\min} = \pi_m = \frac{3}{5 \cdot 2^{m-1}}.$$

Choosing $S = \{1, 2, \dots, m\}$, we have $\pi(S) = 1/2$, and

$$\Phi_S(W) = 2\pi_m W_{m\bar{m}} = \frac{1}{5 \cdot 2^{m-2}}.$$

Hence $\Phi(W) \leq \frac{1}{5 \cdot 2^{m-2}}$. The above Cheeger inequality (11) gives the existence of an eigenvalue $\lambda \neq 1$ of W with

$$1 - |\lambda| = O\left(\frac{m}{2^m}\right) \quad (12)$$

We extend the definition of the vector semi-norm δ to complex vectors by setting

$$\delta(z) = 2 \inf_{c \in \mathbb{C}} \|z - c \cdot \mathbf{1}\|_\infty.$$

For all real vectors x and y , we have

$$\max\{\delta(x), \delta(y)\} \leq \delta(x + iy) \leq 2 \max\{\delta(x), \delta(y)\}. \quad (13)$$

Let w be a δ -normalized (possibly complex) eigenvector associated to λ ; thus $\delta(W^k w) = |\lambda|^k$. Writing $w = u + iv$, we deduce from (13) that

$$2 \max\{\delta(W^k u), \delta(W^k v)\} \geq \delta(W^k w) = |\lambda|^k \delta(w) \geq |\lambda|^k \max\{\delta(u), \delta(v)\},$$

which shows that either $\delta(W^k u)/\delta(u) \geq |\lambda|^k/2$ or $\delta(W^k v)/\delta(v) \geq |\lambda|^k/2$. This means $\delta(W^k) \geq |\lambda|^k/2$. We use the inequality $1 - a \geq e^{-2a}$, which holds for all $0 \leq a \leq 0.7968$. Together with (12), it shows

$$\delta(W^k) = \exp(-O(km/2^m)) = \exp\left(-O(k/2^{n/3})\right).$$

This means that for every $\varepsilon > 0$ and every $K = O(2^{n/3} \log \frac{1}{\varepsilon})$, there exist initial values between 0 and 1 such that $\delta(x(K)) > \varepsilon$, i.e., in the equal neighbor algorithm, processes should not decide at time K in order not to violate ε -Agreement when the communication graph is the time-constant m -butterfly graph. \square

5 Approximate consensus with dynamic faults

Time varying communication graph may result from benign communication faults in the case of message losses. With such an interpretation of missing links in communication graphs, Theorem 1 coincides with the impossibility result of consensus established by Santoro and Widmayer [31] for synchronous systems with n processes connected by a complete communication graph and $n - 1$ communication faults per round.

In the light of Theorem 7, we now revisit the problem of approximate consensus in the context of communication faults, whether they are due to link or process failures. We begin with a corollary of Theorem 7 that gives a new result on the solvability of approximate consensus in a complete synchronous network. Then we explain how Theorem 7 provides a new understanding of some classical procedures in approximate consensus algorithms to tolerate benign process failures, and how it extends the correctness of these procedures to *dynamic* failure models. We also derive the known result that approximate consensus is solvable in an asynchronous system with a complete communication graph and process failures if and only if there is a strict majority of non faulty processes.

5.1 Link faults

We begin with a simple sufficient condition for a directed graph to be rooted.

LEMMA 13. *Any directed graph with n nodes and at least $n^2 - 3n + 3$ links is rooted.*

Proof. Let G be a directed graph with n nodes that is not a rooted graph. Then the condensation of G has two nodes without incoming link. We denote the corresponding two strongly connected components in G by S_1 and S_2 , and their cardinalities by n_1 and n_2 , respectively. Therefore the number of links in G that are not self-loops is at most equal to $n^2 - n - n_1(n - n_1) - n_2(n - n_2)$. Since for every pair of integers n_1, n_2 in $[n - 1]$, we have

$$n^2 - n - n_1(n - n_1) - n_2(n - n_2) \leq n^2 - 3n + 2,$$

it follows that G has at most $n^2 - 3n + 2$ links. \square

From the equality $n^2 - 3n + 3 = (n^2 - n) - (2n - 3)$, we immediately derive the following theorem.

THEOREM 14. *Approximate consensus is solvable in a complete network with n processes if there are at most $2n - 3$ link faults per round.*

Interestingly, compared with the impossibility result for consensus in Theorem 1, the above theorem shows that the number of link faults that can be tolerated increases by a factor of at least 2 when solving approximate consensus instead of consensus. Besides it is easy to construct a non-rooted communication graph with $n^2 - 2n + 2$ links which, combined with Theorem 9, shows that the bound in the above theorem is tight.

5.2 Dynamic sender faulty omission model

Of particular interest are the failure models for complete networks in which process senders are blamed for message losses: in this way, one limits the number of nodes which are origins of missing links in communication graphs to some integer $f \in [n - 1]$. Parameter f is not a global upper bound over the whole executions, but bounds the number of faulty senders *round by round*. The resulting failure model, referred to as the *dynamic sender faulty model*, thus handles dynamic failures.

Theorem 2 directly applies since the corresponding communication graphs are nonsplit, even in the case $f = n - 1$. Moreover following the proof of Theorem 2, at least $n - f$ columns of the stochastic matrix $W(k)$ associated to round k of an equal neighbor averaging algorithm are positive; hence $W(k)$ satisfies

$$\delta(W(k)) \leq \frac{f}{n},$$

which shows that decisions can be made at round $\log_2 \frac{1}{\varepsilon}$ when only a minority of processes may be faulty. Using the inequalities

$$\log \frac{n}{f} \leq \log \left(1 + \frac{1}{n-1} \right) \leq \frac{1}{n},$$

we derive a linear time complexity in the number of processes in the wait-free case, i.e., $f = n - 1$.

COROLLARY 15. *In a complete synchronous network with n processes and the dynamic sender faulty model, the equal neighbor averaging algorithm achieves ε -consensus in $n \log \frac{1}{\varepsilon}$ rounds. If in each round, only a minority of processes may be faulty, then processes can decide from round $\log_2 \frac{1}{\varepsilon}$ onwards.*

In the context of omission models with static faulty senders, different algorithmic procedures have been introduced for solving approximate consensus with averaging algorithms (for instance, see [17, 18]). We briefly recall two of them, namely the *Reduce* and the *Center* procedures, and explain how both correctness and time complexity of the resulting approximate consensus algorithms immediately follow from Theorem 2 in the sender faulty omission model.

The first procedure is designed for the case $n > 2f$. For each process, it consists in replacing each missing value by some arbitrary value smaller than 0, and then in computing the mean of the values that remain after removing the f smallest values. This procedure, called *Reduce*, corresponds to a *logical* communication graph that is also rooted: among the $n - f$ values selected by a process, at least $n - 2f$ are

actually selected by all the other processes. Theorem 2 ensures that the averaging algorithms resulting from the Reduce procedure achieve approximate consensus. For an equal neighbor averaging algorithm, the stochastic matrix $W(k)$ associated to round k has at least $n - 2f$ positive columns and satisfies

$$\delta(W(k)) \leq 1 - \frac{n - 2f}{n - f} = \frac{f}{n - f}.$$

From $f/n \leq f/(n - f)$, we conclude that the Reduce procedure slows down equal neighbor averaging algorithms, even though time complexity remains linear: the Reduce procedure is useless in the context of omissions and has been actually introduced to tolerate Byzantine failures.

For tolerating f crash failures, Fekete [18] introduced another procedure, called *Center*, which is actually a refinement of the Reduce procedure: at every round, each process selects the $n - f$ or $n - f + 1$ central values it has just received. More precisely, if process p receives $n - t$ values at round k , then either $f - t$ is even and p removes the $(f - t)/2$ smallest values and the $(f - t)/2$ greatest values, or $f - t$ is odd and p only removes the $(f - t - 1)/2$ smallest values and the $(f - t - 1)/2$ greatest values. In the case $f - t$ is even, p applies the equal neighbor averaging rule to update its local variable: all the selected values have the same weight, namely $1/(n - f)$. Otherwise $f - t$ is odd and p computes the weighted average of the selected values with the same weight $1/(n - f)$ for all values except the smallest and the greatest one whose weight is half, namely $1/2(n - f)$. As a corollary of Theorem 7, we can prove the correctness of the Center procedure to solve approximate consensus in the dynamic sender faulty model. Moreover we can check that the stochastic matrix $W(k)$ associated to round k satisfies

$$\delta(W(k)) \leq \frac{f}{2(n - f)}.$$

Therefore the Center procedure improves the simple equal neighbor averaging algorithms if $2f < n$. The results in [18] concerning crash failures can thus be directly derived from Theorem 7 and from the translation of the Center procedure in terms of averaging algorithms, and thus are noticeably extended to the dynamic sender faulty model.

5.3 Asynchronous systems with crash failures

We now consider asynchronous complete networks with n processes among which at most f may crash. As observed in [11], in such networks we can easily implement communication graphs G such that for each process p ,

$$|\text{In}_p(G)| = n - f.$$

If only a minority of processes may crash, i.e., $n > 2f$, we thus obtain a nonsplit network model, and Theorem 2 applies. In particular, approximate consensus can be solved with an equal neighbor averaging algorithm that terminates in a linear number of rounds. Observe that time complexity drastically reduces in synchronous networks to the constant $\log_2 \frac{1}{\varepsilon}$ in Corollary 15.

COROLLARY 16. *In an asynchronous complete network of n processes among which a minority may crash, nonsplit rounds can be implemented and the equal neighbor averaging algorithm in which all non-crashed processes decide at round $n \log \frac{1}{\varepsilon}$ achieves ε -consensus.*

The equal neighbor averaging algorithm coincides with the *AsynchApproxAgreement* algorithm proposed in [26] to solve the approximate consensus problem in the case $n > 3f$: Lynch claimed that “a more complicated algorithm is needed for $n > 2f$.” Corollary 16 shows that this algorithm actually works while $n > 2f$.

Finally a simple partitioning argument shows that approximate consensus is not solvable if $n \leq 2f$.

6 Averaging algorithms in partially synchronous systems

The round-based computational model considered so far assumes that rounds are communication closed layers: messages from one process to another are delivered in the rounds in which they are sent. To guarantee the latter condition, processes just need to timestamp the messages they send with the current

round number, and to discard old messages, i.e., messages sent in previous rounds. In a perfect synchronous network with transmission delays upper bounded by D , rounds are implemented in an optimal way when using timeouts that are equal to D ; in this way, no messages are discarded. If the network is not perfectly synchronous, an aggressive politics for timeouts may result in discarding many messages while large timeouts drastically slow down the system. To manage the trade-off between timeliness and connectivity, one may relax the condition of communication closed layers by allowing processes to receive *outdated* messages. However the number of rounds between the sending and the receipt of messages should be bounded to keep the system efficient. This notion of *partially synchronous rounds* coincides with the model of distributed asynchronous computation developed by Tsitsiklis in [34, 5].

In the case of averaging algorithms with a bound on message delays equal to Δ , the local variable x_p is updated according to the following rule:

$$x_p(k) = \sum_{q \in \text{In}_p(k)} w_{qp}(k) x_q(\kappa_q^p(k)), \quad (14)$$

where $\kappa_q^p(k) \in \{k - \Delta, \dots, k - 1\}$. Since each process p has immediate access to its own local variable x_p , we further assume that for every partially synchronous round k ,

$$\kappa_p^p(k) = k - 1.$$

We call such an execution a Δ -*bounded execution*. The case of zero communication delays is captured by $\Delta = 1$, and equation (14) corresponds in this case to an execution of the averaging algorithm with synchronous rounds. We do not require the functions κ_q^p to be either non-decreasing, surjective, or injective. In other words, communications between processes may be non-FIFO and unreliable (duplication and loss).

Note that the communication graph $G(k)$ in round k is understood to be the graph defined by the incoming values at round k , i.e., (p, q) is a link in $G(k)$ if and only if $w_{qp}(k) > 0$.

We now extend Theorems 2 and 7 to partially synchronous rounds. Our proof strategy is based on a reduction to the synchronous case: each process corresponds to a set of Δ virtual processes, and every Δ -bounded execution of an averaging algorithm with n processes coincides with a synchronous execution of an averaging algorithm with $n\Delta$ processes.

6.1 Reduction to synchronous rounds

We mimic the reduction of a Δ -th order ordinary differential equation to a system of Δ ordinary differential equations of first order. We define the vectors $\tilde{x}(k) \in \mathbb{R}^{n\Delta}$ by setting

$$\tilde{x}_{p\Delta-d}(k) = x_p(k-d) \quad (15)$$

for $p \in [n]$, $0 \leq d \leq \Delta - 1$, and with the auxiliary definition $x(-k) = x(0)$ for all the positive integers k . We also define the the $\Delta n \times \Delta n$ matrix $\tilde{W}(k)$ by

$$\tilde{W}_{p\Delta-d, q\Delta-d'}(k) = \begin{cases} w_{qp}(k) & \text{if } d = 0 \text{ and } d' = k - \kappa_q^p(k) - 1 \\ 1 & \text{if } p = q \text{ and } d' = d - 1 \\ 0 & \text{else} \end{cases} \quad (16)$$

The key point is that the vector $\tilde{x}(k)$ is updated according to the linear recursion with “zero delay”

$$\tilde{x}(k) = \tilde{W}(k)\tilde{x}(k-1), \quad (17)$$

which we prove now. For $d \neq 0$, we have

$$\begin{aligned} (\tilde{W}(k)\tilde{x}(k-1))_{p\Delta-d} &= \sum_b \tilde{W}_{p\Delta-d, b}(k) \cdot \tilde{x}_b(k-1) = \tilde{x}_{p\Delta-(d-1)}(k-1) \\ &= x_p(k-1-(d-1)) = x_p(k-d) = \tilde{x}_{p\Delta-d}(k), \end{aligned}$$

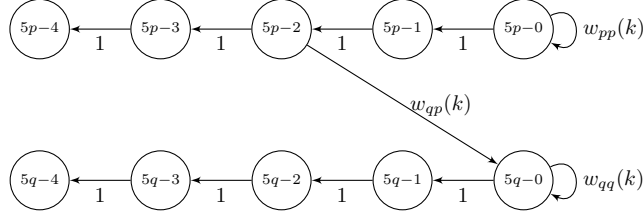


Figure 2: Part of the graph $\tilde{G}(k)$ corresponding to link (p, q) in $G(k)$, $\Delta = 5$, and $\kappa_q^p(k) = 2$

while for $d = 0$, we have

$$\begin{aligned} (\tilde{W}(k)\tilde{x}(k-1))_{p\Delta} &= \sum_b \tilde{W}_{p\Delta, b}(k) \cdot \tilde{x}_b(k-1) = \sum_q w_{qp}(k) \cdot \tilde{x}_{q\Delta - (k - \kappa_q^p(k) - 1)}(k-1) \\ &= \sum_q w_{qp}(k) \cdot x_q(\kappa_q^p(k)) = x_p(k) = \tilde{x}_{p\Delta}(k). \end{aligned}$$

In any case, we have $(\tilde{W}(k)\tilde{x}(k-1))_b = \tilde{x}_b(k)$, which shows (17).

We easily check that each matrix $\tilde{W}(k)$ is stochastic with positive entries at most equal to ϱ . Because of (16), we have

$$\tilde{W}_{p\Delta, p\Delta}(k) = w_{pp}(k), \quad (18)$$

which is positive since there is a self-loop at p in the communication graph $G(k)$.

Let $\tilde{G}(k) = ([n\Delta], \tilde{E}(k))$ be the directed graph associated to the stochastic matrix $\tilde{W}(k)$, i.e., there is a link (a, b) in $\tilde{G}(k)$ if and only if $\tilde{W}_{b,a}(k) > 0$. The graph $\tilde{G}(k)$ can be seen as the communication graph of a network of $n\Delta$ processes with the restriction that some nodes have no self-loop. By (18), there is however a self-loop at each node $p\Delta$ with $p \in [n]$. Figure 2 shows part of $\tilde{G}(k)$ corresponding to one link (p, q) in $G(k)$.

6.2 Nonsplit network model

Even if the communication graph $G(k)$ is nonsplit, the graph $\tilde{G}(k)$ contains two nodes without a common incoming neighbor when $\Delta > 1$. However we will show that in a nonsplit network model, each cumulative graph over $2\Delta - 1$ rounds is nonsplit, which allows us to extend Theorem 2 to the partially synchronous case.

THEOREM 17. *In a nonsplit network model of n processes, every averaging algorithm with parameter ϱ achieves ε -consensus in $(2\Delta - 1)\left(\frac{1}{\varrho}\right)^{2\Delta-1} \log \frac{1}{\varepsilon} + 2\Delta - 2$ rounds of a Δ -bounded execution.*

Proof. Validity is clear because of the fact that every value in $\tilde{x}(k)$, and hence in $x(k)$ is a convex combination of values in $x(0)$.

For ε -Agreement, we first show that each matrix $\tilde{W}(k + 2\Delta - 2 : k)$ is nonsplit. We consider its associated graph

$$\tilde{G}(k + 2\Delta - 2 : k) = \tilde{G}(k) \circ \dots \circ \tilde{G}(k + 2\Delta - 2)$$

and two arbitrary nodes $a = p\Delta - d$ and $b = q\Delta - d'$. Since the original communication graph $G(k\Delta - 1)$ is nonsplit, p and q have a common incoming neighbor r in this graph, i.e., for some $r_1 = r\Delta - d_1$ and $r_2 = r\Delta - d_2$, there is a link from r_1 to $p\Delta$ and a link from r_2 to $q\Delta$ in the directed graph $\tilde{G}(k + \Delta - 1)$. Following the links of the graphs $\tilde{G}(k), \dots, \tilde{G}(k + 2\Delta - 2)$ depicted in Figure 3, we obtain a path from $r\Delta$ to a with $\Delta - d_1 - 1$ self-loops at node $r\Delta$, and $\Delta - d - 1$ self-loops at node $p\Delta$. This directed path corresponds to a link from $r\Delta$ to a in $\tilde{G}(k + 2\Delta - 2 : k)$. In the same way, we have a link from $r\Delta$ to b in $\tilde{G}(k + 2\Delta - 2 : k)$, which proves that the latter graph is nonsplit.

Since each positive entry of $\tilde{W}(k + 2\Delta - 2 : k)$ is at most equal to $\varrho^{2\Delta-1}$, the recurrence relation (14) thus corresponds to the synchronous execution of an averaging algorithm with parameter $\varrho^{2\Delta-1}$ in a generalized $2\Delta - 1$ -nonsplit network model of $n\Delta$ processes.

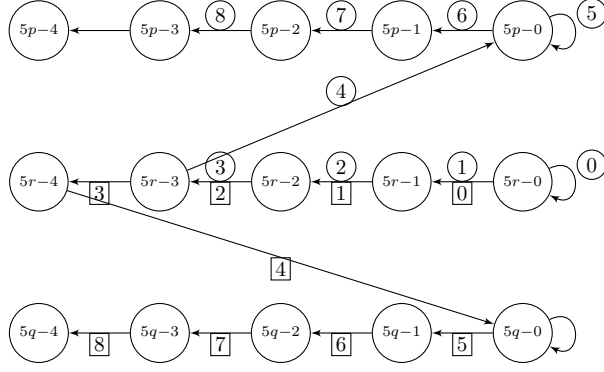


Figure 3: Paths from $r\Delta$ to $a = p\Delta - 3$ and $b = q\Delta - 4$ in the cumulative graph $\tilde{G}(k + 2\Delta - 2 : k)$ with $\Delta = 5$. The link labels ℓ (circled for the path to a , boxed for the path to b) denote the use of that link in round $k + \ell$.

Since $\delta(\tilde{x}(0)) = \delta(x(0)) \leq 1$, we deduce from Corollary 3 that if $k \geq (2\Delta - 1) \left(\frac{1}{\varepsilon}\right)^{2\Delta - 1} \log \frac{1}{\varepsilon} + 2\Delta - 2$, then $\delta(\tilde{x}(k)) \leq \varepsilon$. Observing $\delta(x(k)) \leq \delta(\tilde{x}(k))$ for each positive integer k shows ε -Agreement, which completes the proof. \square

6.3 Coordinated network model

Contrary to the nonsplit property, $\tilde{G}(k)$ is rooted whenever $G(k)$ is. However some nodes in $\tilde{G}(k)$ have no self-loops, and so we cannot apply Theorem 7 to the averaging algorithm and the virtual network model corresponding to (17). Then we will use another strategy which consists in proving that each cumulative graph over $n\Delta$ rounds is nonsplit.

THEOREM 18. *In a coordinated network model, every averaging algorithm with parameter ϱ achieves ε -consensus in $n\Delta \left(\frac{1}{\varrho}\right)^{n\Delta} \log \frac{1}{\varepsilon} + n\Delta - 1$ rounds of a Δ -bounded execution.*

Proof. Validity is clear because of the fact that every value in $\tilde{x}(k)$, and hence in $x(k)$ is a convex combination of values in $x(0)$.

For ε -Agreement, we first show that each matrix $\tilde{W}(k + n\Delta - 1 : k)$ is nonsplit. We consider its associated graph

$$\tilde{G}(k + n\Delta - 1 : k) = \tilde{G}(k) \circ \dots \circ \tilde{G}(k + n\Delta - 1)$$

and two arbitrary nodes $a = p\Delta - d$ and $b = q\Delta - d'$. This then proves the theorem by Corollary 3.

Let k and ℓ be two positive integers such that $\ell \geq K$. For every $b \in [n\Delta]$, we define the sets

$$\tilde{S}_b(\ell) = \{a \in [n\Delta] \mid (a, b) \text{ is a link of } \tilde{G}(\ell : k)\}$$

and for every $c \in [n\Delta]$,

$$T_c(\ell) = \{p \in [n] \mid (p\Delta, c) \text{ is a link of } \tilde{G}(\ell : k)\}.$$

Because each $(p\Delta - \delta, p\Delta - \delta + 1)$ with $0 \leq \delta \leq \Delta - 1$ is a link of all graphs $\tilde{G}(k)$, we have $p \in T_a(k + d)$ and $q \in T_b(k + d')$. The existence of the self-loops at the nodes $r\Delta$ for all $r \in [n]$ implies the monotonicity property $T_c(\ell) \subseteq T_c(\ell + 1)$, which in particular gives

$$p \in T_a(k + \Delta - 1) \quad \text{and} \quad q \in T_b(k + \Delta - 1). \quad (19)$$

Mimicking the proof of Theorem 7, we show that

$$T_a(k + n\Delta - 1) \cap T_b(k + n\Delta - 1) \neq \emptyset, \quad (20)$$

which then concludes the proof.

If $p = q$, then (20) clearly holds by (19). Otherwise, consider the nondecreasing sequences

$$\begin{aligned} T_a(k + \Delta - 1) &\subseteq T_a(k + 2\Delta - 1) \subseteq \dots \subseteq T_a(k + n\Delta - 1), \\ T_b(k + \Delta - 1) &\subseteq T_b(k + 2\Delta - 1) \subseteq \dots \subseteq T_b(k + n\Delta - 1), \end{aligned}$$

and

$$\begin{aligned} T_a(k + \Delta - 1) \cup T_b(k + \Delta - 1) &\subseteq T_a(k + 2\Delta - 1) \cup T_b(k + 2\Delta - 1) \\ &\subseteq \dots \subseteq T_a(k + n\Delta - 1) \cup T_b(k + n\Delta - 1). \end{aligned}$$

Because $|T_a(k + \Delta - 1) \cup T_a(k + \Delta - 1)| \geq 2$ if $p \neq q$ and $|T_a(k + n\Delta - 1) \cup T_b(k + n\Delta - 1)| \leq n$, the latter sequence cannot be strictly increasing. There hence exists some $\ell \in \{1, \dots, n - 1\}$ such that

$$T_a(k + \ell\Delta - 1) \cup T_b(k + \ell\Delta - 1) = T_a(k + (\ell + 1)\Delta - 1) \cup T_b(k + (\ell + 1)\Delta - 1) .$$

Because of the disjointness assumption, this means

$$T_a(k + \ell\Delta - 1) = T_a(k + (\ell + 1)\Delta - 1) \quad \text{and} \quad T_b(k + \ell\Delta - 1) = T_b(k + (\ell + 1)\Delta - 1) .$$

We now show that both $T_a(k + \ell\Delta - 1)$ and $T_b(k + \ell\Delta - 1)$ contain the roots of $G(k + \ell\Delta)$, showing (20).

Suppose not, i.e., without loss of generality $T_a(k + \ell\Delta - 1)$ does not contain all roots of $G(k + \ell\Delta)$. By Proposition 4, there is an edge (p, q) in $G(k + \ell\Delta)$ such that

$$q \in T_a(k + \ell\Delta - 1) \quad \text{and} \quad p \notin T_a(k + \ell\Delta - 1) . \quad (21)$$

There hence exists some $\delta \in \{0, \dots, \Delta - 1\}$ such that $(p\Delta - \delta, q\Delta)$ is a link of $\tilde{G}(k + \ell\Delta)$, which means that

$$p\Delta - \delta \in \tilde{S}_a(k + \ell\Delta) .$$

It follows that $p\Delta \in \tilde{S}_a(k + \ell\Delta + \Delta - 1)$, which means

$$p \in T_a(k + (\ell + 1)\Delta - 1) = T_a(k + \ell\Delta - 1) .$$

This is a contradiction to (21) and concludes the proof. \square

Theorem 18 shows that, even in the class of Δ -bounded executions, approximate consensus is solvable in a network model \mathcal{N} if \mathcal{N} is a coordinated model. By Theorem 9, the latter condition is also necessary for the subset of 1-bounded executions, and so *a fortiori* for Δ -bounded executions. The characterization of the network models in which approximate consensus is solvable in Corollary 10 then holds for computations with partially synchronous rounds as well as with synchronous rounds.

7 Conclusion and Future Work

The main goal of this paper has been to characterize the dynamic network models in which approximate consensus is solvable. Interestingly anonymity of processes does not affect solvability in such networks. We have further established some upper bounds on the time complexity of averaging algorithms, all of which solve approximate consensus in dynamic networks. We have proved each of our computability and complexity results first for synchronous rounds and in a second step for partially synchronous rounds which allow for bounded message delays.

As for exact consensus, approximate consensus does not require strong connectivity and it can be solved under the sole assumption of rooted communication graphs. However contrary to the condition of a stable set of roots and identifiers supposed in [6] for achieving consensus, approximate consensus can be solved even though roots arbitrarily change over time and processes are anonymous. In these respects, approximate consensus seems to be more suitable than consensus for handling real network dynamicity.

A number of questions are suggested by this work. For example, it would be of high interest to design approximate consensus algorithms that tolerate Byzantine process failure, i.e., arbitrary process behaviors. Certain interesting questions also remain to be studied in the benign case. In particular general lower bounds on the time complexity of approximate consensus, be it for general algorithms or averaging algorithms would vastly improve the comprehension of the approximate consensus problem.

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