Opinion Dynamics with Limited Information

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Abstract. We study opinion formation games based on the famous model proposed by Friedkin and Johsen (FJ model). In today's huge social networks the assumption that in each round agents update their opinions by taking into account the opinions of *all* their friends is unrealistic. So, we are interested in the convergence properties of simple and natural variants of the FJ model that use limited information exchange in each round and converge to the same stable point. As in the FJ model, we assume that each agent i has an intrinsic opinion $s_i \in [0,1]$ and maintains an expressed opinion $x_i(t) \in [0,1]$ in each round t. To model limited information exchange, we consider an opinion formation process where each agent i meets with one random friend j in each round t and learns only her current opinion $x_j(t)$. The amount of influence j imposes on i is reflected by the probability p_{ij} with which i meets j. Then, agent i suffers a disagreement cost that is a convex combination of $(x_i(t) - s_i)^2$ and $(x_i(t) - x_j(t))^2$. An important class of dynamics in this setting are *no regret* dynamics, i.e. dynamics that ensure vanishing regret against the experienced disagreement cost to the agents. We show an exponential gap between the convergence rate of no regret dynamics and of more general dynamics that do not ensure no regret. We prove that no regret dynamics require roughly $\Omega(1/\varepsilon)$ rounds to be within distance ε from the stable point of the FJ model. On the other hand, we provide an opinion update rule that does not ensure no regret and converges to x^* in $\tilde{O}(\log^2(1/\varepsilon))$ rounds. Finally, in our variant of the FJ model, we show that the agents can adopt a simple opinion update rule that ensures no regret to the experienced disagreement cost and results in an opinion vector that converges to the stable point x^* of the FJ model within distance ε in poly$(1/\varepsilon)$ rounds. In view of our lower bound for no regret dynamics this rate of convergence is close to best possible.

1 Introduction

The study of *Opinion Formation* has a long history (see e.g. [Jac08]). Opinion Formation is a *dynamic process* in the sense that socially connected people (e.g. family, friends, colleagues) exchange information and this leads to changes in their expressed opinions over time. Today, the advent of the internet and social media makes the study of opinion formation in large social networks even more important; realistic models of how people form their opinions by interacting with each other, are of great practical interest for prediction, advertisement etc. In an attempt to formalize the process of opinion formation, several models have been proposed over the years (see e.g., [DeG74,FJ90,HK02,DNAW00]. The common assumption underlying all these models, which dates back to DeGroot [DeG74], is that opinions evolve through a form of repeated averaging of information collected from the agents' social neighborhoods.

Our work builds on the model proposed by Friedkin and Johnsen [FJ90]. The FJ model is a variation on the DeGroot model capturing the fact that consensus on the opinions is rarely reached. According to FJ model each person i has a public opinion $x_i \in [0,1]$ and an internal opinion $s_i \in [0,1]$, which is private and invariant over time. There also exists a weighted graph $G(V,E)$ representing a social network where V stands for the persons ($|V| = n$) and E their social relations. Initially, all nodes start with their internal opinion and at each round t, update their public opinion $x_i(t)$ to a weighted average of the public opinions of their neighbors and their internal opinion,

$$x_i(t) = \frac{\sum_{j \in N_i} w_{ij} x_j(t-1) + w_{ii} s_i}{\sum_{j \in N_i} w_{ij} + w_{ii}}, \tag{1}$$

where $N_i = \{j \in V : (i, j) \in E\}$ is the set of i's neighbors, the weight w_{ij} associated with the edge $(i, j) \in E$ measures the extent of the influence that j poses on i and the weight $w_{ii} > 0$ quantifies how susceptible i is in adopting opinions that differ from her internal opinion s_i.

The FJ model is one of most influential models for opinion formation. It has a very simple update rule, making it plausible for modeling natural behavior and its basic assumptions are aligned with empirical findings on the way opinions are formed [AFH$^+$05,Kra09]. At the same time, it admits a unique stable point $x^* \in [0, 1]^n$ to which it converges with a *linear* rate [GS14]. The FJ model has also been studied under a game theoretic viewpoint. Bindel et al. considered its update rule as the minimizer of a quadratic disagreement cost function and based on it they defined the following opinion formation game [BKO11]. Each node i is a selfish agent whose strategy is the public opinion x_i that she expresses incurring her a disagreement cost

$$C_i(x_i, x_{-i}) = \sum_{j \in N_i} w_{ij}(x_i - x_j)^2 + w_{ii}(x_i - s_i)^2 \tag{2}$$

Note that the FJ model is the *simultaneous best response dynamics* and its stable point x^* is the unique Nash equilibrium of the above game. In [BKO11] they quantified its inefficiency with respect to the total disagreement cost. They proved that the *Price of Anarchy* (PoA) is 9/8 in case G is undirected and $w_{ij} = w_{ji}$. They also provided PoA bounds in the case of unweighted Eulerian directed graphs. We remark that in [BKO11] an alternative framework for studying the way opinions evolve was introduced. The opinion formation process can be described as the *dynamics* of an opinion formation game. This framework is much more comprehensive since different aspects of the opinion formation process can be easily captured by defining suitable games. Subsequent works [BGM13,BFM16,EFHS17] considered variants of the above game and studied the convergence properties of the *best response dynamics*.

1.1   Motivation and our setting

Many recent works study the Nash equilibrium x^* of the opinion formation game defined in [BKO11] under various perspectives. In [CCL16] they extended the bounds for PoA in more general classes of directed graphs, while many recently introduced influence maximization problems [GTT13,AKPT18,MMT17] are defined with respect to x^*. The reason for this scientific interest is evident: the equilibrium x^* is considered as an appropriate way to model the final opinions formed in a social network, since the *well established* FJ model converges to it.

Our work is motivated by the fact that there are notable cases in which the FJ model is not an appropriate model for the dynamic of the opinions, due to the large amount of information exchange that it implies. More precisely, at each round its update rule (1) requires that every agent learns all the opinions of her social neighbors. In today's large social networks where users usually have several hundreds of friends it is highly unlikely that, each day, they learn the opinions of all their social neighbors. In such environments it is far more reasonable to assume that individuals randomly meet a small subset of their acquaintances and these are the only opinions that they learn. Such information exchange constraints render the FJ model unsuitable for modeling the opinion formation process in such large networks and therefore, it is not clear whether x^* captures the limiting behavior of the opinions. In this work we ask:

Question 1. Is the equilibrium x^* an adequate way to model the final formed opinions in large social networks? Namely, are there simple variants of the FJ model that require limited information exchange and converge fast to x^*? Can they be justified as natural behavior for selfish agents under a game-theoretic solution concept?

To address these questions, one could define precise dynamical processes whose update rules require limited information exchange between the agents and study their convergence properties. Instead of doing so, we describe the opinion formation process in such large networks as *dynamics* of an adequate opinion formation game that captures these information exchange constraints. This way we can precisely define which *dynamics* are *natural*, and, more importantly, to study general classes of *dynamics* (e.g. no regret dynamics) without explicitly defining their update rule. The opinion formation game that we consider is a variant of the game in [BKO11] based on interpreting the weight w_{ij} as a measure of how frequently i meets j.

Definition 1. *For a given opinion vector $x \in [0,1]^n$, the disagreement cost of agent i is the random variable $C_i(x_i, x_{-i})$ defined as follows:*

- *Agent i meets one of her neighbors j with probability $p_{ij} = w_{ij}/\sum_{j \in N_i} w_{ij}$.*
- *Agent i suffers cost $C_i(x_i, x_{-i}) = (1-a_i)(x_i - x_j)^2 + a_i(x_i - s_i)^2$, where $\alpha_i = w_{ii}/(\sum_{j \in N_i} w_{ij} + w_{ii})$.*

Note that the expected disagreement cost of each agent in the above game is the same as the disagreement cost in [BKO11] (scaled by $\sum_{j \in N_i} w_{ij} + w_{ii}$). Moreover its Nash equilibrium, with respect to the expected disagreement cost, is x^*. This game provides us with a general template of all the *dynamics* examined in this paper. At round t, each agent i selects an opinion $x_i(t)$ and suffers a disagreement cost based on the opinion of the neighbor that she randomly met. At the end of the round t, she is informed only about the opinion and the index of this neighbor and may use this information to update her opinion in the next round. Obviously different update rules lead to different *dynamics*, however all of these respect the information exchange constraints: at every round each agent learns the opinion of *just one* of her neighbors. Question 1 now takes the following more concrete form.

Question 2. Can the agents update their opinions according to the limited information that they receive such that the produced opinion vector $x(t)$ converges to the equilibrium x^*? How is the convergence rate affected by the limited information exchange? Are there dynamics that ensures that the cost that the agents experience is minimal?

In what follows, we are mostly concerned about the dependence of the rate of convergence on the distance ε from the equilibrium x^*, we shall suppress the dependence on other parameters such as the size of the graph, n. We remark that the dependence of our dynamics on these constants is in fact rather good (see Section 2), and we only do this only for clarity of exposition.

Definition 2 (Informal). *We say that a dynamics converges slow resp. fast to the equilibrium x^* if it requires $\mathrm{poly}(1/\varepsilon)$ resp. $\mathrm{poly}(\log(1/\varepsilon))$ rounds to be within (expected) error ε of x^*.*

1.2   Contribution

The major contribution of the paper is proving an exponential separation on the convergence rate of *no regret dynamics* and the convergence rate of more general dynamics produced by update rules that do not ensure no regret.

No regret dynamics are produced by update rules that ensure no regret to any agent that adopts them. Namely, the total disagreement cost of an agent that follows such a rule, is close to the total disagreement cost that she would experience by selecting the best fixed opinion in hindsight. The latter must hold regardless of the way the other agents update their opinions and of the neighbors that the agent gets to meet. This powerful property consists no regret dynamics to be *natural dynamics* for describing the behavior of agents [CBL03,EMN09,KPT11,SALS15]. We prove that if

all the agents adopt an update rule that ensures no regret, then there exists an instance of the game such that the produced opinion vector $x(t)$ requires roughly $\Omega(1/\varepsilon)$ rounds to be ε-close to x^*. No regret comes at the price of slow convergence because it provides robust guarantees. Agents who adopt no regret update rules suffer minimal total disagreement cost even if the other agents play irrationally or adversarially. In order to provide such strong guarantees, no regret rules must only depend on the opinions that the agent observes and do not take into account the weights w_{ij} of the outgoing edges (see Section 5). We call the update rules with the latter property, *graph oblivious*. In Section 5 we use a novel information theoretic argument to prove the aforementioned lower bound for this more general class.

In Section 6, we present a simple update rule whose resulting dynamics converges fast, i.e. the opinion vector $x(t)$ is ε-close to x^* in $O(\log^2(1/\varepsilon))$ rounds. The reason that the previous lower bound doesn't apply is that this rule does not ensure *no regret* to the agents that adopt it. In fact there is a very simple example with two agents, in which the first follows the rule while the second selects her opinions adversarially, where the first agent experiences regret (see Example 1 in Appendix C).

We introduce an intuitive *no regret* update rule and we show that if all agents adopt it, the resulting opinion vector $x(t)$ converges to x^*. Our rule is a *Follow the Leader algorithm*, meaning that at round t, each agent updates her opinion to the minimizer of total disagreement cost that she experienced until round $t-1$. It also has a very simple form: it is roughly the time average of the opinions that the agent observes. In Section 3, we bound its convergence rate and we show that in order to achieve ε distance from x^*, $\text{poly}(1/\varepsilon)$ rounds are sufficient. In view of our lower bound this rate is close to best possible. In Section 4, we prove its *no regret* property. This can be derived by the more general results in [HAK07]. However, we give a short and simple proof that may be of interest.

In conclusion, our results reveal that the equilibrium x^* is a robust choice for modeling the limiting behavior of the opinions of agents since, even in our limited information setting, there exist simple and natural dynamics that converge to it. The convergence rate crucially depends on whether the agents act selfishly, i.e. they are only concerned about their individual disagreement cost. We present an update rule that selfish agents can adopt (no regret update rule) and show that the resulting opinion vector converges x^* but with a slow rate, while, for non selfish agents, the update rule in Section 6 leads to a *dynamics* with fast convergence rate.

1.3   Related Work

There exists a large amount of literature concerning the FJ model. Many recent works [BGM13,CKO13], [BFM16,EFHS17] bound the inefficiency of equilibrium in variants of opinion formation game defined in [BKO11]. In [GS14] they bound the convergence time of the FJ model in special graph topologies. In [BFM16], a variant of the opinion formation game in which social relations depend on the expressed opinions is studied. They prove that the discretized version of the above game admits a potential function and thus best-response converges to the Nash equilibrium. Convergence results in other discretized variants of the FJ model can be found in [YOA+13,FGV16]. In [FPS16] they provide convergence results for limited information variants of the Heglesmann-Krause model [HK02] and the FJ model. Although they considered limited information variant of the FJ model is very similar to ours, their convergence results are much weaker, since they concern the expected value of the opinion vector.

Other works that relate to ours, concern the convergence properties of dynamics based on no regret learning algorithms. In [FV97,FS99,SA00,SALS15] it is proved that in a finite n-person game if each agent updates her mixed strategy according to a no regret algorithm the resulting *time-averaged* strategy vector converges to Coarse Correlated Equilibrium. The convergence properties

of no regret dynamics for games with infinite strategy spaces were considered in [EMN09]. They proved that for a large class of games with concave utility functions (socially concave games), the time-averaged strategy vector converges to Pure Nash Equilibrium (PNE). More recent work investigates a stronger notion of convergence of no regret dynamics. In [CHM17] they show that, in n-person finite generic games that admit unique Nash equilibrium, the strategy vector converges *locally* and fast to it. They also provide conditions for *global* convergence. Our results fit in this line of research since we show that for a game with *infinite* strategy space, the strategy vector (and not the time-averaged) converges to the Nash equilibrium x^*.

No regret dynamics in limited information settings have recently received substantial attention from the scientific community since they provide realistic models for the practical applications of game theory. Perfect payoff information is rare in practice; agents act based on random or noisy past payoff observations. Kleinberg et al. in [KPT09] treated load-balancing in distributed systems as a repeated game and analyzed the convergence properties of no regret learning algorithms under the *full information assumption* that each agent learns the load of every machine. In a subsequent work [KPT11], the same authors consider the same problem in a *limited information setting* ("bulletin board model"), in which each agent learns the load of just the machine that served him. Most relevant to ours are the works [HCM17,MS17,BM17,CHM17], where they examine the convergence properties of no regret learning algorithms when the agents observe their payoffs with some additive zero-mean random noise. In our limited information setting the agents experience random disagreement cost with expected value equal to the actual cost. The main difference is that our *noise* is not additive but due to a sampling process.

2 Our Results and Techniques

As previously mentioned, an instance of the game in [BKO11] is also an instance the game of Definition 1. Following the notation introduced earlier we have that $p_{ij} = w_{ij}/\sum_{j \in N_i} w_{ij}$ if $j \in N_i$ and 0 otherwise. Moreover, $\alpha_i = w_{ii}/(\sum_{j \in N_i} w_{ij} + w_{ii}) > 0$ since $w_{ii} > 0$ by the definition of the game in [BKO11]. If an agent i does not have outgoing edges ($N_i = \emptyset$) then $p_{ij} = 0$ for all j. Therefore $\sum_{j=1}^n p_{ij} = 0$, $\alpha_i = 1$ if $N_i = \emptyset$ and $\sum_{j=1}^n p_{ij} = 1$, $\alpha_i \in (0, 1)$ otherwise. For simplicity we adopt the following notation for an instance of the game of Definition 1.

Definition 3. *We denote an instance of the opinion formation game of Definition 1 as $I = (P, s, \alpha)$, where P is a $n \times n$ matrix with non-negative elements p_{ij}, with $p_{ii} = 0$ and $\sum_{j=1}^n p_{ij}$ is either 0 or 1, $s \in [0, 1]^n$ is the internal opinion vector, $\alpha \in (0, 1]^n$ the self confidence vector.*

An instance $I = (P, s, \alpha)$ is also an instance of the FJ model, since by the update rule (1) $x_i(t) = (1 - \alpha_i) \sum_{j \in N_i} p_{ij} x_j(t-1) + a_i s_i$. It also defines the opinion vector $x^* \in [0, 1]^n$ which is the stable point of the FJ model and the Nash equilibrium of the game in [BKO11].

Definition 4. *For a given instance $I = (P, s, \alpha)$ the equilibrium $x^* \in [0, 1]^n$ is the unique solution of the following linear system, for every $i \in V$, $x_i^* = (1 - \alpha_i) \sum_{j \in N_i} p_{ij} x_j^* + a_i s_i$.*

The fact that the above linear system always admits a solution follows by matrix norm properties. Throughout the paper we study *dynamics* of the game of Definition 1. We denote as W_i^t the neighbor that agent i met at round t, which is a random variable whose probability distribution is determined by the instance $I = (P, s, \alpha)$ of the game, $\mathbf{P}[W_i^t = j] = p_{ij}$. Another parameter of an instance I that we often use is $\rho = \min_{i \in V} \alpha_i$.

In Section 3, we examine the convergence properties of the opinion vector $x(t)$ when all agents update their opinions according to the *Follow the Leader* principle. Since each agent i must select $x_i(t)$, before knowing which of her neighbors she will meet and what opinion her neighbor will

express, this update rule says "*play the best according to what you have observed*". For a given instance (P, s, a) of the game the Follow the Leader dynamics $x(t)$ is defined in Dynamics 1 and Theorem 1 shows its convergence rate to x^*.

Dynamics 1 Follow the Leader dynamics

1: Initially $x_i(0) = s_i$ for all agents i.
2: At round $t \geq 0$ each agent i:
    3: Meets neighbor with index W_i^t, $\mathbf{P}\left[W_i^t = j\right] = p_{ij}$.
    4: Suffers cost $(1 - \alpha_i)(x_i(t) - x_{W_i^t}(t))^2 + a_i(x_i(t) - s_i)^2$ and learns the opinion $x_{W_i^t}(t)$.
    5: Updates her opinion $x_i(t + 1) = \operatorname{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t} (1 - \alpha_i)(x - x_{W_i^\tau}(\tau))^2 + \alpha_i(x - s_i)^2$ (3)

Theorem 1. *Let $I = (P, s, \alpha)$ be an instance of the opinion formation game of Definition 1 with equilibrium $x^* \in [0, 1]^n$. The opinion vector $x(t) \in [0, 1]^n$ produced by update rule (3) after t rounds satisfies*

$$\mathbf{E}\left[\|x(t) - x^*\|_\infty\right] \leq C\sqrt{\log n} \frac{(\log t)^{3/2}}{t^{\min(1/2, \rho)}},$$

where $\rho = \min_{i \in V} a_i$ and C is a universal constant.

In Section 4 we argue that, apart from its simplicity, update rule (3) ensures no regret to any agent that adopts it and therefore the FTL dynamics can be considered as *natural dynamics* for selfish agents. Since each agent i selfishly wants to minimizing the disagreement cost that she experiences, it is natural to consider that she selects $x_i(t)$ according to a *no regret algorithm* for the *online convex optimization problem* where the adversary chooses a function $f_t(x) = (1 - \alpha_i)(x - b_t)^2 + \alpha_i(x - s_i)^2$ at each round t. In Theorem 2 we prove that *Follow the Leader* is a no regret algorithm for the above OCO problem. We remark that this does not hold, if the adversary can pick functions from a different class (see e.g. chapter 5 in [Haz16]).

Theorem 2. *Consider the function $f : [0, 1]^2 \mapsto [0, 1]$ with $f(x, b) = (1 - \alpha)(x - b)^2 + \alpha(x - s)^2$ for some constants $s, \alpha \in [0, 1]$. Let $(b_t)_{t=1}^{\infty}$ be an arbitrary sequence with $b_t \in [0, 1]$. If $x_t = \operatorname{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t-1} f(x, b_\tau)$ then for all t, $\sum_{\tau=0}^{t} f(x_\tau, b_\tau) \leq \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau) + O(\log t)$.*

On the positive side, the FTL dynamics converges to x^* and its update rule is simple and ensures no regret to the agents. On the negative side, its convergence rate is outperformed by the rate of FJ model. For a fixed instance $I = (P, s, \alpha)$, the FTL dynamics converges with rate $\widetilde{O}(1/t^{\min(\rho, 1/2)})$ while FJ model converges with rate $O(e^{-\rho t})$ [GS14].

Question 3. Can the agents adopt other no regret update rules such that the resulting dynamics converges fast to x^*?

The answer is no. In Section 5, we prove that fast convergence cannot be established for any *no regret dynamics*. The reason that FTL dynamics converges slowly is that rule (3) only depends on the opinions of the neighbors that agent i meets, α_i, and s_i. This is also true for any update rule that ensures no regret to the agents (see Section 5). As already mentioned, we call this larger class of update rules of update rules *graph oblivious*, and we prove slow convergence for any *graph oblivious dynamics*.

Definition 5 (graph oblivious update rule). *An graph oblivious update rule A is a sequence of functions $(A_t)_{t=0}^{\infty}$ where $A_t : [0, 1]^{t+2} \mapsto [0, 1]$.*

Definition 6 (graph oblivious dynamics). *Let a graph oblivious update rule A. For a given instance $I = (P, s, \alpha)$ the rule A produces a graph oblivious dynamics $x_A(t)$ defined as follows:*

- *Initially each agent i selects her opinion $x_i^A(0) = A_0(s_i, \alpha_i)$*
- *At round $t \geq 1$, each agent i selects her opinion $x_i^A(t) = A_t(x_{W_i^0}(0), \ldots, x_{W_i^{t-1}}(t-1), \alpha_i, s_i)$, where W_i^t is the neighbors that i meets at round t.*

Theorem 3 states that for any graph oblivious dynamics there exists an instance $I = (P, s, \alpha)$, where roughly $\Omega(1/\varepsilon)$ rounds are required to achieve convergence within error ε.

Theorem 3. *Let A be an graph oblivious update rule, which all agents use to update their opinions. For any $c > 0$ there exists an instance $I = (P, s, a)$ such that $\mathbf{E}\left[\|x_A(t) - x^*\|_\infty\right] = \Omega(1/t^{1+c})$, where $x_A(t)$ denotes the opinion vector produced by A for the instance $I = (P, s, \alpha)$.*

To prove Theorem 3, we show that graph oblivious rules whose dynamics converge fast, imply the existence of estimators for Bernoulli distributions with "small" sample complexity. The key part of the proof lies in Lemma 6, in which is proven that such estimators cannot exist. We also briefly discuss two well-known sample complexity lower bounds from the statistics literature and explain why they do not work in our case.

In Section 6, we present a simple update rule that achieves error rate $e^{-\widetilde{O}(\sqrt{t})}$. This update rule is a function of the opinions and the indices of the neighbors that i met, α_i, s_i and the i-th row the matrix P. Obviously this rule is not *graph oblivious*, due to its dependency on the i-th row and the indices, and thus does not ensure no regret to an agent that adopts it (see Example 1 in Appendix C). However it reveals that slow convergence is not a generic property of the limited information dynamics, but comes with the assumption that agents act selfishly.

3   Convergence Rate of FTL Dynamics

In this section we prove Theorem 1 which bounds the convergence time of FTL dynamics to the unique equilibrium point x^*. Notice that for an instance $I = (P, s, \alpha)$, the opinion vector $x(t) \in [0, 1]^n$ of the FTL dynamics (see Dynamics 1) can be written equivalently as follows:

- Initially all agents adopt their internal opinion, $x_i(0) = s_i$.
- At round $t \geq 1$, each agent i updates her opinion $x_i(t) = (1 - \alpha_i) \sum_{\tau=0}^{t-1} x_{W_i^\tau}(\tau)/t + \alpha_i s_i$, where W_i^τ is the neighbor that i met at round t.

Since the opinion vector $x(t)$ is a random vector, the convergence metric used in Theorem 1 is $\mathbf{E}\left[\|x(t) - x^*\|_\infty\right]$ where the expectation is taken over the random meeting of the agents. At first we present a high level idea of the proof. We remind that the unique equilibrium $x^* \in [0, 1]^n$ of the instance $I = (P, s, \alpha)$ satisfies the following equations for each agent $i \in V$,

$$x_i^* = (1 - \alpha_i) \sum_{j \in N_i} p_{ij} x_j^* + \alpha_i s_i$$

Since our metric is $\mathbf{E}\left[\|x(t) - x^*\|_\infty\right]$, we can use the above equations to bound $|x_i(t) - x_i^*|$.

$$|x_i(t) - x_i^*| = (1 - \alpha_i) \left| \frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}(\tau)}{t} - \sum_{j \in N_i} p_{ij} x_j^* \right|$$

$$= (1 - \alpha_i) \left| \sum_{j \in N_i} \frac{\sum_{\tau=0}^{t-1} \mathbf{1}[W_i^\tau = j] x_j(\tau)}{t} - \sum_{j \in N_i} p_{ij} x_j^* \right|$$

$$\leq (1 - \alpha_i) \sum_{j \in N_i} \left| \frac{\sum_{\tau=0}^{t-1} \mathbf{1}[W_i^\tau = j] x_j(\tau)}{t} - p_{ij} x_j^* \right|$$

Now assume that $|\frac{\sum_{\tau=0}^{t-1} \mathbf{1}[W_i^\tau = j]}{t} - p_{ij}| = 0$ for all $t \geq 1$, then with simple algebraic manipulations one can prove that $\|x(t) - x^*\|_\infty \leq e(t)$ where $e(t)$ satisfies the recursive equation $e(t) = (1-\rho)\frac{\sum_{\tau=0}^{t-1} e(\tau)}{t}$, where $\rho = \min a_i$. It follows that $\|x(t) - x^*\|_\infty \leq 1/t^\rho$ meaning that $x(t)$ converges to x^*. Obviously the latter assumption does not hold, however since W_i^τ are independent random variables with $\mathbf{P}[W_i^\tau = j] = p_{ij}$, $|\frac{\sum_{\tau=0}^{t-1} \mathbf{1}[W_i^\tau = j]}{t} - p_{ij}|$ tends to 0 with probability 1. In Lemma 1 we use this fact to obtain a similar recursive equation for $e(t)$ and then in Lemma 2 we upper bound its solution.

Lemma 1. *Let $e(t)$ the solution of the recursion $e(t) = \delta(t) + (1-\rho)\frac{\sum_{\tau=0}^{t-1} e(\tau)}{t}$ where $e(0) = \|x(0) - x^*\|_\infty$, $\delta(t) = \sqrt{\ln(\pi^2 n t^2/6p)/t}$ and $\rho = \min_{i \in V} \alpha_i$. Then,*

$$\mathbf{P}\left[\text{for all } t \geq 1, \ \|x(t) - x^*\|_\infty \leq e(t)\right] \geq 1 - p$$

Proof. At first we prove that with probability at least $1 - p$, for all $t \geq 1$ and all agents i:

$$\left| \frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}^*}{t} - \sum_{j \in N_i} p_{ij} x_j^* \right| \leq \sqrt{\frac{\log(\pi^2 n t^2/(6p))}{t}} := \delta(t). \tag{4}$$

Since W_i^τ are independent random variables with $\mathbf{P}[W_i^\tau = j] = p_{ij}$ and $\mathbf{E}\left[x_{W_i^\tau}^*\right] = \sum_{j \in N_i} p_{ij} x_j^*$. By the Hoeffding's inequality we get

$$\mathbf{P}\left[\left| \frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}^*}{t} - \sum_{j \in N_i} p_{ij} x_j^* \right| > \delta(t)\right] < 6p/(\pi^2 n t^2).$$

To bound the probability of error for all rounds $t \geq 1$ and all agents i, we apply the union bound

$$\sum_{t=1}^{\infty} \mathbf{P}\left[\max_i \left| \frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}^*}{t} - \sum_{j \in N_i} p_{ij} x_j^* \right| > \delta(t)\right] \leq \sum_{t=1}^{\infty} \frac{6}{\pi^2} \frac{1}{t^2} \sum_{i=1}^{n} \frac{p}{n} = p$$

As a result with probability at least $1 - p$ we have that inequality (4) holds for all $t \geq 1$ and all agents i. We now prove our claim by induction. Let $\|x(\tau) - x^*\|_\infty \leq e(\tau)$ for all $\tau \leq t - 1$. Then

$$x_i(t) = (1 - \alpha_i) \frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}(\tau)}{t} + \alpha_i s_i$$

$$\leq (1 - \alpha_i) \frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}^* + \sum_{\tau=0}^{t-1} e(\tau)}{t} + \alpha_i s_i \tag{5}$$

$$\leq (1 - \alpha_i) \left(\frac{\sum_{\tau=0}^{t-1} x_{W_i^\tau}^*}{t} + \frac{\sum_{\tau=0}^{t-1} e(\tau)}{t} \right) + \alpha_i s_i$$

$$\leq (1 - \alpha_i) \left(\sum_{j \in N_i} p_{ij} x_j^* + \delta(t) + \frac{\sum_{\tau=0}^{t-1} e(\tau)}{t} \right) + \alpha_i s_i \tag{6}$$

$$\leq x_i^* + \delta(t) + (1 - \rho) \left(\frac{\sum_{\tau=0}^{t-1} e(\tau)}{t} \right)$$

We get (5) from the induction step and (6) from inequality (4). Similarly, we can prove that $x_i(t) \geq x_i^* - \delta(t) - (1 - \rho)\frac{\sum_{\tau=0}^{t-1} e(\tau)}{t}$. As a result $\|x(t) - x^*\|_\infty \leq e(t)$ and the induction is complete. Therefore, we have that with probability at least $1 - p$, $\|x(t) - x^*\|_\infty \leq e(t)$ for all $t \geq 1$.

Lemma 2. *Let $e(t)$ be a function satisfying the recursion $e(t) = \delta(t) + (1-\rho)\sum_{\tau=0}^{t-1} e(\tau)/t$ and $e(0) = \|x(0) - x^*\|_\infty$, where $\delta(t) = \sqrt{\ln(Dt^{2.5})/t}$, $\delta(0) = 0$, and $D > e^{2.5}$ is a positive constant. Then $e(t) \leq \sqrt{2\ln(D)}\frac{(\ln t)^{3/2}}{t^{\min(\rho, 1/2)}}$.*

Theorem 1 follows by direct application of Lemma 2 and both proofs can be found in the Appendix A.

4   Follow the Leader ensures no regret

In this section we provide rigorous definitions of *no regret* algorithms and explain why update rule (3) ensures no regret to any agent that repeatedly play the game of Definition 1. Based on the cost that the agents experience, we consider an appropriate *Online Convex Optimization* problem. This problem can be viewed as a "game" played between an adversary and a player. *At round $t \geq 0$,*

1. *the player selects a value $x_t \in [0, 1]$.*
2. *the adversary observes the x_t and selects a $b_t \in [0, 1]$*
3. *the player receives cost $f(x_t, b_t) = (1 - \alpha)(x_t - b_t)^2 + \alpha(x_t - s)^2$.*

where α, s are constants in $[0, 1]$. The goal of the player is to pick x_t based on the history $(b_0, \ldots, b_{t-1})$ in a way that minimizes her total cost. Generally, different OCO problems can be defined by a set of functions $\mathcal{F}$ that the adversary chooses from and a feasibility set $\mathcal{K}$ from which the player picks her value (see [Haz16] for an introduction to the OCO framework). In our case the feasibility set is $\mathcal{K} = [0, 1]$ and the set of functions is $\mathcal{F}_{\alpha,s} = \{x \mapsto (1-\alpha)(x-b)^2 + \alpha(x-s)^2 : b \in [0, 1]\}$. As a result, each selection of the constants s, α lead to a different OCO problem.

Definition 7. *An algorithm A for the OCO problem with $\mathcal{F}_{a,s}$ and $\mathcal{K} = [0, 1]$ is a sequence of functions $(A_t)_{t=1}^\infty$ where $A_t : [0, 1]^t \mapsto [0, 1]$.*

Definition 8. *An algorithm A is no regret for the OCO problem with $\mathcal{F}_{a,s}$ and $\mathcal{K} = [0, 1]$ if and only if for all sequences $(b_t)_{t=0}^\infty$ that the adversary may choose, if $x_t = A_t(b_0, \ldots, b_{t-1})$ then for all t $\sum_{\tau=0}^t f(x_\tau, b_\tau) \leq \min_{x \in [0,1]} \sum_{\tau=0}^t f(x, b_\tau) + o(t)$.*

Informally speaking if the player selects the value x_t according to a *no regret algorithm* then she does not regret for not playing any fixed value no matter what the choices of the adversary are. Theorem 2 states that *Follow the Leader* i.e. $x_t = \mathrm{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t-1} f(x, b_\tau)$ is a no regret algorithm for all the OCO problems with $\mathcal{F}_{\alpha,s}$.

Returning to the dynamics of the game in Definition 1, it is reasonable to consider that each agent i selects $x_i(t)$ according to no regret algorithm A_i for the OCO problem with $\mathcal{F}_{s_i,\alpha_i}$, since by Definition 8,

$$\frac{1}{t}\sum_{\tau=0}^t f_i(x_i(\tau), x_{W_i^\tau}(\tau)) \leq \frac{1}{t}\min_{x \in [0,1]}\sum_{\tau=0}^t f_i(x, x_{W_i^\tau}(\tau)) + \frac{o(t)}{t}$$

The latter means that the time averaged total disagreement cost that she suffers is close to the time averaged cost by expressing the best fixed opinion and this holds no matter the opinions of the neighbors that i meets. Meaning that even if the other agents selected their opinions maliciously, her total experienced cost would still be in a sense minimal. Under this perspective update rule (3) is a rational choice for selfish agents and as a result FTL dynamics is a *natural* limited information variant of the FJ model.

We now present the key steps for proving Theorem 2. We first prove that a similar strategy that also takes into account the value b_t admits no regret (Lemma 3). Obviously knowing the value b_t before selecting x_t is in direct contrast with the OCO framework, however proving the no regret property for this algorithm easily extends to establishing the no regret property of *Follow the Leader*. The proofs of the subsequent lemmas and Theorem 2 can be found in the Appendix B.

Lemma 3. *Let $\{b_t\}_{t=0}^{\infty}$ be an arbitrary sequence with $b_t \in [0,1]$. Let $y_t = \mathrm{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau)$ then for all t, $\sum_{\tau=0}^{t} f(y_\tau, b_\tau) \le \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau)$.*

Now we can understand reason why *Follow the Leader* admits no regret. Since the cost incurred by the sequence y_t is at most that of the best fixed value, we can compare the cost incurred by x_t with that of y_t. Since the functions in $\mathcal{F}_{\alpha,s}$ are quadratic, the extra term $f(x, b_t)$ that y_t takes into account doesn't change dramatically the minimum of the total sum. Namely, x_t, y_t are relatively close.

Lemma 4. *For all $t \ge 0$, $f(x_t, b_t) \le f(y_t, b_t) + 2\frac{1-\alpha}{t+1} + \frac{(1-\alpha)^2}{(t+1)^2}$.*

5   Lower Bound for Graph Oblivious Dynamics

In this section we prove that any no regret dynamics cannot converge much faster than FTL dynamics (Dynamics 1). The main result of the section is Theorem 3 that establishes slow convergence for the more general class of *graph oblivious dynamics*

To illustrate why Theorem 3 serves our purpose, consider the following no regret dynamics. For every instance $I = (P, s, \alpha)$, each agent i uses the Online Gradient Descent[3] to update her opinion, i.e. $x_i(t+1) = x_i(t) - 1/\sqrt{t}(x_i(t) - (1 - \alpha_i)x_{W_i^t}(t) - \alpha_i s_i)$ and $x(t)$ is the produced opinion vector. It is easy to see that the opinion of an agent i at round t only depends on the observed opinion, α_i and s_i. As a result, Theorem 3 applies and establishes the existence of an instance I such that $x(t)$ converges slowly to x^*.

Using the above reasoning we can use Theorem 3 to prove that any no regret dynamics converges slowly. Let us select for each $(s, \alpha) \in [0,1]^2$ a no regret algorithm $A_{s,\alpha}$[4] for the OCO problem with $\mathcal{F}_{s,\alpha}$. This selection defines the following no regret dynamics: for every instance $I = (P, s, \alpha)$ each agent i updates her opinion according to A_{s_i, α_i}, resulting in an opinion vector $x(t)$. Note that such a selection can be encoded as a graph oblivious update rule. Specifically, the function $A_t : \{0,1\}^{t+2} \mapsto [0,1]$ is defined as $A_t(b_0, \dots, b_{t-1}, a, s) = A_{a,s}^t(b_0, \dots, b_{t-1})$. As a result, Theorem 3 applies again.

In Lemma 5 we show that any graph oblivious update rule A, can be used as an estimator of the parameter $p \in [0,1]$ of Bernoulli random variable. Since we prove Theorem 3 using a reduction to an estimation problem we shall first briefly introduce some definitions and notation. For simplicity we will restrict the following definitions of estimators and risk to the case of estimating the parameter p of Bernoulli random variables. Given t independent samples from a Bernoulli random variable $B(p)$ an estimator is an algorithm that takes these samples as input and outputs an answer in $[0,1]$.

Definition 9. *An estimator $\theta = (\theta_t)_{t=1}^{\infty}$ is a sequence of functions, $\theta_t : \{0,1\}^t \mapsto [0,1]$.*

Perhaps the first estimator that comes to one's mind is the *sample mean*, that is $\theta_t = \sum_{i=1}^{t} X_i/t$. To measure the efficiency of an estimator we define the *risk*, which corresponds to the expected error of an estimator.

Definition 10. *Let P be a Bernoulli distribution with mean p and P^t be the corresponding t-fold product distribution. The risk of an estimator $\theta = (\theta_t)_{t=1}^{\infty}$ is $\mathbf{E}_{(X_1,\dots,X_t) \sim P^t} [|\theta_t(X_1, \dots, X_t) - p|]$, which we will denote by $\mathbf{E}_p [|\theta_t(X_1, \dots, X_t) - p|]$ or $\mathbf{E}_p [|\theta_t - p|]$ for brevity.*

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[3]   Online Gradient Descent is an influential no regret algorithm proposed by Zinkevic in [Zin03] for the general OCO problem, where the adversary can select any convex function with bounded gradient. The latter directly implies that it also ensures no regret in our simpler OCO problem with $\mathcal{F}_{s_i, \alpha_i}$ and $\mathcal{K} = [0,1]$.

[4]   These s, α are scalars in $[0,1]$ and should not be confused with the internal opinion vector s and the self confidence vector α of an instance $I = (P, s, \alpha)$.

The risk $\mathbf{E}_p\left[|\theta_t - p|\right]$ quantifies the error rate of the estimated value $\hat{p} = \theta_t(Y_1, \ldots, Y_t)$ to the real parameter p as the number of samples t grows. Since p is unknown, any meaningful estimator $\theta = (\theta_t)_{t=1}^{\infty}$ must guarantee that $\lim_{t \to \infty} \mathbf{E}_p\left[|\theta_t - p|\right] = 0$ for all p. For example, *sample mean* has error rate $\mathbf{E}_p\left[|\theta_t - p|\right] \leq \frac{1}{2\sqrt{t}}$.

Lemma 5. *Let A a graph oblivious update rule such that for all instances $I = (P, s, a)$,*

$$\lim_{t \to \infty} t^{1+c}\mathbf{E}\left[\|x_A(t) - x^*\|_\infty\right] = 0.$$

Then there exists an estimator $\theta_A = (\theta_t^A)_{t=1}^{\infty}$ such that for all $p \in [0, 1]$, $\lim_{t \to \infty} t^{1+c}\mathbf{E}_p\left[|\theta_t^A - p|\right] = 0$.

Proof. We construct an estimator $\theta_A = (\theta_t^A)_{t=1}^{\infty}$ using the update rule A. Consider the instance I_p described in Figure 1. By straightforward computation, we get that the equilibrium point of the graph is $x_c^* = p/3, x_1^* = p/6 + 1/2, x_0^* = p/6$. Now consider the opinion vector $x_A(t)$ produced by the update rule A for the instance I_p. Note that for $t \geq 1$,

- $x_1^A(t) = A_t(x_c(0), \ldots, x_c(t-1), 1/2, 1)$
- $x_0^A(t) = A_t(x_c(0), \ldots, x_c(t-1), 1/2, 0)$
- $x_c^A(t) = A_t(x_{W_c^0}(0), \ldots, x_{W_c^{t-1}}(t-1), 1/2, 1)$

The key observation is that the opinion vector $x_A(t)$ is a deterministic function of the index sequence $W_c^0, \ldots, W_c^{t-1}$ and does not depend on p. Thus, we can construct the estimator θ_A with $\theta_t^A(W_c^0, \ldots, W_c^{t-1}) = 3x_c^A(t)$. For a given instance I_p the choice of neighbor W_c^t is given by the value of the Bernoulli random variable with parameter p ($\mathbf{P}\left[W_c^t = 1\right] = p$). As a result, $\mathbf{E}_p\left[|\theta_t^A - p|\right] = 3\mathbf{E}\left[|x_c^A(t) - p/3|\right] \leq 3\mathbf{E}\left[\|x_A(t) - x^*\|_\infty\right]$. Since for any instance I_p, we have that $\lim_{t \to \infty} t^{1+c}\mathbf{E}\left[\|x_A(t) - x^*\|_\infty\right] = 0$. It follows that $\lim_{t \to \infty} t^{1+c}\mathbf{E}_p\left[|\theta_t^A - p|\right] = 0$ for all $p \in [0, 1]$.

$$a_1 = 1/2, s_1 = 1 \qquad\qquad a_c = 1/2, s_c = 0 \qquad\qquad a_0 = 1/2, s_0 = 0$$
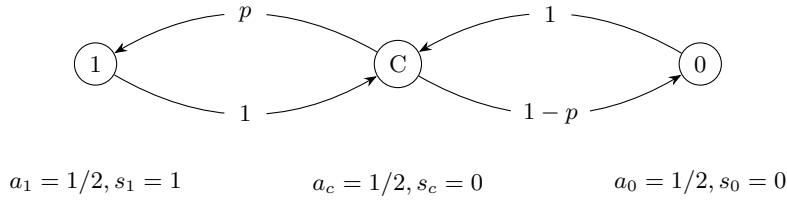
Fig. 1

In order to prove Theorem 3 we just need to prove the following claim.

Claim. For any estimator $\theta = (\theta_t)_{t=1}^{\infty}$ there exists a $p \in [0, 1]$ such that $\lim_{t \to \infty} t^{1+c}\mathbf{E}_p\left[|\theta_t - p|\right] > 0$.

The above claim states that for any estimator $\theta = (\theta_t)_{t=1}^{\infty}$, we can inspect the functions $\theta_t : \{0, 1\}^t \mapsto [0, 1]$ and then choose a $p \in [0, 1]$ such that the function $\mathbf{E}_p\left[|\theta_t - p|\right] = \Omega(1/t^{1+c})$. As a result, we have reduced the construction of a lower bound concerning the round complexity of a dynamical process to a lower bound concerning the sample complexity of estimating the parameter p of a Bernoulli distribution. The claim follows by Lemma 6, which we present at the end of the section.

At this point we should mention that it is known that $\Omega(1/\varepsilon^2)$ samples are needed to estimate the parameter p of a Bernoulli random variable within additive error ε. Another well-known result is that taking the average of the samples is the *best* way to estimate the mean of a Bernoulli random variable. These results would indicate that the best possible rate of convergence for an *graph oblivious dynamics* would be $O(1/\sqrt{t})$. However, there is some fine print in these results which does not allow us to use them. In order to explain the various limitations of these methods and results

we will briefly discuss some of them. We remark that this discussion is not needed to understand the proof of Lemma 6.

The oldest sample complexity lower bound for estimation problems is the well-known Cramer-Rao inequality. Let the function $\theta_t : \{0, 1\}^t \mapsto [0, 1]$ such that $\mathbf{E}_p[\theta_t] = p$ for all $p \in [0, 1]$, then

$$\mathbf{E}_p\left[(\theta_t - p)^2\right] \geq \frac{p(1-p)}{t}. \tag{7}$$

Since $\mathbf{E}_p[|\theta_t - p|]$ can be lower bounded by $\mathbf{E}_p[(\theta_t - p)^2]$ we can apply the Cramer-Rao inequality and prove our claim in the case of *unbiased* estimators, $\mathbf{E}_p[\theta_t] = p$ for all t. Obviously, we need to prove it for any estimator θ, however this is a first indication that our claim holds.

Sample complexity lower bounds without assumptions about the estimator are usually given as lower bounds for the *minimax risk*, which was defined [5] by Wald in [Wal39] as

$$\min_{\theta_t} \max_{p \in [0,1]} \mathbf{E}_p\left[|\theta_t - p|\right].$$

Minimax risk captures the idea that after we pick the best possible algorithm, an adversary inspects it and picks the worst possible $p \in [0, 1]$ to generate the samples that our algorithm will get as input. The methods of Le'Cam, Fano, and Assouad are well-known information-theoretic methods to establish lower bounds for the minimax risk. For more on these methods see [Yu97,Tsy08]. As we stated before, it is well known that the minimax risk for the case of estimating the mean of a Bernoulli is lower bounded by $\Omega(1/\sqrt{t})$ and this lower bound can be established by Le Cam's method. In order to show why such results do no work for our purposes we shall sketch how one would apply Le Cam's method to get this lower bound. To apply Le Cam's method, one typically chooses two Bernoulli distributions whose means are far but their total variation distance is small. Le Cam showed that when two distributions are close in total variation then given a sequence of samples $X_1, \ldots, X_t$ it is hard to tell whether these samples were produced by P_1 or P_2. The hardness of this *testing* problem implies the hardness of *estimating* the parameters of a family of distribution. For our problem the two distributions would be $B(1/2 - 1/\sqrt{t})$ and $B(1/2 + 1/\sqrt{t})$. It is not hard to see that their total variation distance is at most $O(1/t)$, which implies a lower bound $\Omega(1/\sqrt{t})$ for the minimax risk. The problem here is that the parameters of the two distributions depend on the number of samples t. The more samples the algorithm gets to see, the closer the adversary takes the 2 distributions to be. For our problem we would like to *fix* an instance and then argue about the rate of convergence of any algorithm on this instance. Namely, having an instance that depends on t does not work for us.

Trying to get a lower bound without assumptions about the estimators while respecting our need for a fixed (independent of t) p we prove Lemma 6. In fact, we show something stronger: for *almost all* $p \in [0, 1]$, any estimator θ cannot achieve rate $o(1/t^{1+c})$.

Lemma 6. *Let* $\theta = (\theta_t)_{t=1}^\infty$ *be a Bernoulli estimator with error rate* $\mathbf{E}_p[|\theta_t - p|]$. *For any* $c > 0$, *if we select* p *uniformly at random in* $[0, 1]$ *then* $\lim_{t \to \infty} t^{1+c}\mathbf{E}_p[|\theta_t - p|] > 0$ *with probability* 1.

Proof. Since θ_t is a function from $\{0, 1\}^t$ to $[0, 1]$, θ_t can have at most 2^t different values. Without loss of generality we assume that θ_t takes the same value $\theta_t(x)$ for all $x \in \{0, 1\}^t$ with the same number of 1's. For example, $\theta_3(\{1, 0, 0\}) = \theta_3(\{0, 1, 0\}) = \theta_3(\{0, 0, 1\})$. This is due to the fact that for any $p \in [0, 1]$,

$$\sum_{0 \leq i \leq t} \sum_{\|x\|_1 = i} |\theta_t(x) - p| \, p^i (1-p)^{t-i} \geq \sum_{0 \leq i \leq t} \binom{t}{i} \left| \frac{\sum_{\|x\|_1=i} \theta_t(x)}{\binom{t}{i}} - p \right| p^i (1-p)^{t-i}.$$

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[5] Although the minimax risk is defined for any estimation problem and loss function, for simplicity, we write the minimax risk for estimating the mean of a Bernoulli random variable.

For any estimator θ with error rate $\mathbf{E}_p\left[|\theta_t - p|\right]$ there exists another estimator θ' that satisfies the above property and $\mathbf{E}_p\left[|\theta'_t - p|\right] \leq \mathbf{E}_p\left[|\theta_t - p|\right]$ for all $p \in [0, 1]$. Thus, we can assume that θ_t takes at most $t + 1$ different values. Let A denote the set of p for which the estimator has error rate $o(1/t^{1+c})$, that is

$$A = \{p \in [0, 1] : \lim_{t \to \infty} t^{1+c} \mathbf{E}_p\left[|\theta_t - p|\right] = 0\}.$$

We show that if we select p uniformly at random in $[0, 1]$ then $\mathbf{P}\left[p \in A\right] = 0$. We also define the set

$$A_k = \{p \in [0, 1] : \text{for all } t \geq k, \ t^{1+c} \mathbf{E}_p\left[|\theta_t - p|\right] \leq 1\}.$$

Observe that if $p \in A$ then there exists t_p such that $p \in A_{t_p}$, meaning that $A \subseteq \bigcup_{k=1}^{\infty} A_k$. As a result,

$$\mathbf{P}\left[p \in A\right] \leq \mathbf{P}\left[p \in \bigcup_{k=1}^{\infty} A_k\right] \leq \sum_{k=1}^{\infty} \mathbf{P}\left[p \in A_k\right].$$

To complete the proof we show that $\mathbf{P}\left[p \in A_k\right] = 0$ for all k. Notice that $p \in A_k$ implies that for $t \geq k$, the estimator θ must always have a value $\theta_t(i)$ close to p. Using this intuition we define the set

$$B_k = \{p \in [0, 1] : \text{for all } t \geq k, \ t^{1+c} \min_{0 \leq i \leq t} |\theta_t(i) - p| \leq 1\}.$$

We now show that $A_k \subseteq B_k$. Since $p \in A_k$ we have that for all $t \geq k$

$$t^{1+c} \min_{0 \leq i \leq t} |\theta_t(i) - p| \sum_{i=0}^{t} \binom{t}{i} p^i (1-p)^{t-i} \leq t^{1+c} \sum_{i=0}^{t} \binom{t}{i} |\theta_t(i) - p| \, p^i (1-p)^{t-i} = t^{1+c} \mathbf{E}_p\left[|\theta_t - p|\right] \leq 1.$$

Thus, $\mathbf{P}\left[p \in A_k\right] \leq \mathbf{P}\left[p \in B_k\right]$. We write the set B_k as

$$B_k = \bigcap_{t=k}^{\infty} \{p \in [0, 1] : \ \min_{0 \leq i \leq t} |\theta_t(i) - p| \leq 1/t^{1+c}\}.$$

As a result, $\mathbf{P}\left[p \in B_k\right] \leq \mathbf{P}\left[\min_{0 \leq i \leq t} |\theta_t(i) - p| \leq 1/t^{1+c}\right]$, for all $t \geq k$. Each value $\theta_t(i)$ "covers"
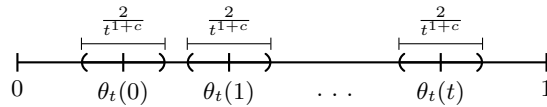

Fig. 2: Estimator output at time t

length $1/t^{1+c}$ from its left and right, as shown in Figure 2, and since there are at most $t + 1$ such values, by the union bound we get $\mathbf{P}\left[p \in B_k\right] \leq 2(t+1)/t^{1+c}$, for all $t \geq k$. We conclude that $\mathbf{P}\left[p \in B_k\right] = 0$.

6   Limited Information Dynamics with Fast Convergence

We already discussed that the reason that graph oblivious dynamics suffer slow convergence is that the update rule depends only on the expressed opinions. Based on works for asynchronous distributed minimization algorithms [BT97,CC16], we provide an update rule showing that information about the graph G combined with agents that do not act selfishly can restore the fast convergence rate.

Our update rule, depends not only on the expressed opinions of the neighbors that an agent i meets but also on the i-th row of matrix P. We have already mentioned that while this update rule guaranties fast convergence it does not guarantee no regret to the agents. To make this concrete we include a simple example in Appendix C. Agents that choose to update their opinions according to Dynamics 2 will experience regret if the other agents play irrationally.

In update rule (8), each agent stores the *most recent* opinions of the random neighbors that she meets in an array and then updates her opinion according to their weighted sum (each agent knows row i of P). For a given instance $I = (P, s, \alpha)$ we call the produced dynamics *Row Dependent dynamics* (Dynamics 2).

The problem with this approach is that the opinions of the neighbors that she keeps in her array are *outdated*, i.e. the opinion of a neighbor of agent i has changed since their last meeting. The good news are that as long as this outdatedness is bounded we can still achieve fast convergence to the equilibrium. By bounded outdatedness we mean that there exists a number of rounds B such that all agents have met all their neighbors at least once from $t - B$ to t. The latter is formally stated in Lemma 7 and its proof can be found in Appendix C.

Remark 1. Update rule (8), apart from the opinions and the indices of the neighbors that an agent meets, also depends on the the exact values of the weights p_{ij} and that is why *Row Dependent dynamics* converge fast. We mention that the lower bound of Section 5 still holds even if the agents also use the indices of the neighbors that they meet to update their opinion, since Lemma 5 can be easily modified to cover this case. The latter implies that any update rule that ensures fast convergence would require from each agent i to be *aware* of the i-th row of matrix P.

Dynamics 2 Row Dependent dynamics

1: Initially $x_i(0) = s_i$ for all agent i.
2: Each agent i keeps an array M_i of length $|N_i|$, randomly initialized.
3: At round $t \geq 0$ each agent i:
    4: Meets neighbor with index W_i^t, $\mathbf{P}\left[W_i^t = j\right] = p_{ij}$.
    5: Suffers cost $(1 - \alpha_i)(x_i(t) - x_{W_i^t}(t))^2 + a_i(x_i(t) - s_i)^2$ and learns $(x_{W_i^t}(t), W_i^t)$.
    6: Updates her array M_i and opinion: $M_i[W_i^t] \leftarrow x_{W_i^t}(t), \quad x_i(t+1) = (1 - \alpha_i) \sum_{j \in N_i} p_{ij} M_i[j] + \alpha_i s_i$ (8)

Lemma 7. *Let $\rho = \min_i a_i$, and $\pi_{ij}(t)$ be the most recent round before round t, that agent i met her neighbor j. If for all $t \geq B$, $t - B \leq \pi_{ij}(t)$ then, for all $t \geq kB$, $\|x(t) - x^*\|_\infty \leq (1 - \rho)^k$.*

In Row Dependent dynamics there does not exist a fixed length window B that satisfies the requirements of Lemma 7. However we can select a length value such that the requirements hold with high probability. To do this observe that agent i simply needs to wait to meet the neighbor j with the smallest weight p_{ij}. Therefore, after $\log(1/\delta)/\min_j p_{ij}$ rounds we have that with probability at least $1 - \delta$ agent i met all her neighbors at least once. Since we want this to be true for all agents we shall roughly take $B = 1/\min_{p_{ij} > 0} p_{ij}$. In Appendix C we give the detailed argument that leads to Theorem 4, showing that the convergence rate of update rule (8) is fast.

Theorem 4. *Let $I = (P, s, \alpha)$ be an instance of the opinion formation game of Definition 1 with equilibrium $x^* \in [0, 1]^n$ and let $\rho = \min_{i \in V} a_i$. The opinion vector $x(t) \in [0, 1]^n$ produced by update rule (8) after t rounds satisfies $\mathbf{E}\left[\|x(t) - x^*\|_\infty\right] \leq 2 \exp(-\rho \min_{ij} p_{ij} \sqrt{t}/(4 \ln(nt)))$.*

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A   Convergence Rate of FTL Dynamics

We present the proofs of Lemma 2 and Theorem 1 of Section 3

Lemma 2. *Let $e(t)$ be a function satisfying the recursion $e(t) = \delta(t) + (1-\rho)\sum_{\tau=0}^{t-1} e(\tau)/t$ and $e(0) = \|x(0) - x^*\|_\infty$, where $\delta(t) = \sqrt{\ln(Dt^{2.5})/t}$, $\delta(0) = 0$, and $D > e^{2.5}$ is a positive constant. Then $e(t) \leq \sqrt{2\ln(D)}\frac{(\ln t)^{3/2}}{t^{\min(\rho,\,1/2)}}$.*

Proof. Observe that for all $t \geq 0$ the function $e(t)$ the following recursive relation

$$e(t+1) = e(t)\left(1 - \frac{\rho}{t+1}\right) + \delta(t+1) - \delta(t) + \frac{\delta(t)}{t+1} \tag{9}$$

For $t = 0$ we have that

$$e(1) = (1-\rho)e(0) + \delta(1) = (1-\rho)e(0) + \sqrt{\ln D} \tag{10}$$

Observe that for $D > e^{2.5}$, $\delta(t)$ is decreasing for all $t \geq 1$. Therefore, $\delta(t+1) - \delta(t) + \frac{\delta(t)}{t+1} \leq \frac{\delta(t)}{t+1}$ and from equations (9) and (10) we get that for all $t \geq 0$

$$e(t+1) \leq e(t)\left(1 - \frac{\rho}{t+1}\right) + \frac{\sqrt{\ln(D(t+1)^2)}}{(t+1)^{3/2}} \leq e(t)\left(1 - \frac{\rho}{t+1}\right) + \frac{\sqrt{2\ln(D(t+1))}}{(t+1)^{3/2}}$$

Now let $g(t) = \frac{\sqrt{2\ln(Dt)}}{t^{3/2}}$ to obtain for all $t \geq 1$

$$
\begin{aligned}
e(t) &\leq (1 - \frac{\rho}{t})e(t-1) + g(t)\\
&\leq (1 - \frac{\rho}{t})(1 - \frac{\rho}{t-1})e(t-2) + (1 - \frac{\rho}{t})g(t-1) + g(t)\\
&\leq (1 - \frac{\rho}{t})\cdots(1-\rho)e(0) + \sum_{\tau=1}^{t} g(\tau)\prod_{i=\tau+1}^{t}\left(1 - \frac{\rho}{i}\right)\\
&\leq \frac{e(0)}{t^\rho} + \sum_{\tau=1}^{t} g(\tau)e^{-\rho\sum_{i=\tau+1}^{t}\frac{1}{i}}\\
&\leq \frac{e(0)}{t^\rho} + \sum_{\tau=1}^{t} g(\tau)e^{-\rho(H_t - H_\tau)}\\
&\leq \frac{e(0)}{t^\rho} + e^{-\rho H_t}\sum_{\tau=1}^{t} g(\tau)e^{\rho H_\tau}\\
&\leq \frac{e(0)}{t^\rho} + \frac{\sqrt{2}}{t^\rho}\sum_{\tau=1}^{t}\tau^\rho\frac{\sqrt{\ln(D\tau)}}{\tau^{3/2}}\\
&\leq \frac{e(0)}{t^\rho} + \frac{\sqrt{2\ln D}}{t^\rho}\sum_{\tau=1}^{t}\frac{\sqrt{\ln \tau}}{\tau^{3/2-\rho}}
\end{aligned}
$$

We observe that

$$\sum_{\tau=1}^{t}\frac{\sqrt{\ln \tau}}{\tau^{3/2-\rho}} \leq \int_{\tau=1}^{t}\frac{\sqrt{\ln \tau}}{\tau^{3/2-\rho}}\mathrm{d}\tau \tag{11}$$

since, $\tau \mapsto \frac{\sqrt{\ln \tau}}{\tau^{3/2-\rho}}$ is a decreasing function of τ for all $\rho \in [0,1]$.

– If $\rho \leq 1/2$ then

$$\int_{\tau=1}^{t} \tau^{\rho} \frac{\sqrt{\ln \tau}}{\tau^{3/2}} \mathrm{d}\tau \leq \sqrt{\ln t} \int_{\tau=1}^{t} \frac{1}{\tau} \mathrm{d}\tau = (\ln t)^{3/2}$$

– If $\rho > 1/2$ then

$$\begin{aligned}
\int_{\tau=1}^{t} \tau^{\rho} \frac{\sqrt{\ln \tau}}{\tau^{3/2}} \mathrm{d}\tau &= \int_{\tau=1}^{t} \tau^{\rho-1/2} \frac{\sqrt{\ln \tau}}{\tau} d\tau \\
&= \frac{2}{3} \int_{\tau=1}^{t} \tau^{\rho-1/2} ((\ln \tau)^{3/2})' \mathrm{d}\tau \\
&= \frac{2}{3} t^{\rho-1/2} (\ln t)^{3/2} - (\rho - 1/2) \frac{2}{3} \int_{\tau=1}^{t} \tau^{\rho-3/2} (\ln \tau)^{3/2} \mathrm{d}\tau \\
&\leq \frac{2}{3} t^{\rho-1/2} (\ln t)^{3/2}
\end{aligned}$$

Theorem 1. *Let $I = (P, s, \alpha)$ be an instance of the opinion formation game of Definition 1 with equilibrium $x^* \in [0,1]^n$. The opinion vector $x(t) \in [0,1]^n$ produced by update rule (3) after t rounds satisfies*

$$\mathbf{E}\left[\|x(t) - x^*\|_\infty\right] \leq C\sqrt{\log n} \frac{(\log t)^{3/2}}{t^{\min(1/2,\rho)}},$$

where $\rho = \min_{i \in V} a_i$ and C is a universal constant.

Proof. By Lemma 1 we have that for all $t \geq 1$ and $p \in [0,1]$,

$$\mathbf{P}\left[\|x(t) - x^*\|_\infty \leq e_p(t)\right] \geq 1 - p$$

where $e_p(t)$ is the solution of the recursion, $e_p(t) = \delta(t) + (1-\rho)\frac{\sum_{\tau=0}^{t-1} e_p(\tau)}{t}$ with $\delta(t) = \sqrt{\frac{\log(\pi^2 n t^2/(6p))}{t}}$. Setting $p = \frac{1}{12\sqrt{t}}$ we have that

$$\mathbf{P}\left[\|x(t) - x^*\|_\infty \leq e(t)\right] \geq 1 - \frac{1}{12\sqrt{t}}$$

where $e(t)$ is the solution of the recursion $e(t) = \delta(t) + (1-\rho)\frac{\sum_{\tau=0}^{t-1} e_p(\tau)}{t}$ with $\delta(t) = \sqrt{\frac{\log(2\pi^2 n t^{2.5})}{t}}$. Since $2\pi^2 \geq e^{2.5}$, Lemma 2 applies and $e(t) \leq C\sqrt{\log n}\frac{\log t^{3/2}}{t^{\min(\rho,1/2)}}$ for some universal constant C. Finally,

$$\mathbf{E}\left[\|x(t) - x^*\|_\infty\right] \leq \frac{1}{12\sqrt{t}} + (1 - \frac{1}{12\sqrt{t}})C\sqrt{\log n}\frac{(\log t)^{3/2}}{t^{\min(\rho,1/2)}} \leq (C + \frac{1}{12})\sqrt{\log n}\frac{(\log t)^{3/2}}{t^{\min(\rho,1/2)}}$$

B   Follow the leader ensures no regret

We present the detailed proofs of Lemma 3, Lemma 4 and Theorem 2 of Section 4.

Lemma 3. *Let $\{b_t\}_{t=0}^{\infty}$ be an arbitrary sequence with $b_t \in [0,1]$. Let $y_t = \operatorname{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau)$ then for all t, $\sum_{\tau=0}^{t} f(y_\tau, b_\tau) \leq \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau)$.*

Proof. By definition of y_t, $\sum_{\tau=0}^{t} f(y_t, b_\tau) = \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau)$, so

$$
\begin{aligned}
\sum_{\tau=0}^{t} f(y_\tau, b_\tau) - \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau) &= \sum_{\tau=0}^{t} f(y_\tau, b_\tau) - \sum_{\tau=0}^{t} f(y_t, b_\tau) \\
&= \sum_{\tau=0}^{t-1} f(y_\tau, b_\tau) - \sum_{\tau=0}^{t-1} f(y_t, b_\tau) \\
&\leq \sum_{\tau=0}^{t-1} f(y_\tau, b_\tau) - \sum_{\tau=0}^{t-1} f(y_{t-1}, b_\tau)
\end{aligned}
$$

The last inequality follows by the fact that $y_{t-1} = \operatorname{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t-1} f(x, b_\tau)$ Inductively, we prove that $\sum_{\tau=0}^{t} f(y_\tau, b_\tau) \leq \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau)$.

Lemma 4. *For all $t \geq 0$, $f(x_t, b_t) \leq f(y_t, b_t) + 2\frac{1-\alpha}{t+1} + \frac{(1-\alpha)^2}{(t+1)^2}$.*

Proof. We first prove that for all t,

$$
|x_t - y_t| \leq \frac{1 - \alpha}{t + 1}. \tag{12}
$$

By definition $x_t = \alpha s + (1 - \alpha)\frac{\sum_{\tau=0}^{t-1} b_\tau}{t}$ and $y_t = \alpha s + (1 - \alpha)\frac{\sum_{\tau=0}^{t} b_\tau}{t+1}$.

$$
\begin{aligned}
|x_t - y_t| &= (1 - \alpha)\left| \frac{\sum_{\tau=0}^{t-1} b_\tau}{t} - \frac{\sum_{\tau=0}^{t} b_\tau}{t+1} \right| \\
&= (1 - \alpha)\left| \frac{\sum_{\tau=0}^{t-1} b_\tau - t b_t}{t(t+1)} \right| \\
&\leq \frac{1 - \alpha}{t + 1}
\end{aligned}
$$

The last inequality follows from the fact that $b_\tau \in [0, 1]$. We now use inequality (12) to bound the difference $f(x_t, b_t) - f(y_t, b_t)$.

$$
\begin{aligned}
f(x_t, b_t) &= \alpha(x_t - s)^2 + (1 - \alpha)(x_t - y_t)^2 \\
&\leq \alpha(y_t - s)^2 + 2\alpha |y_t - s| |x_t - y_t| + \alpha |x_t - y_t|^2 \\
&\quad + (1 - \alpha)(y_t - y_t)^2 + 2(1 - \alpha)|y_t - y_t| |x_t - y_t| + (1 - \alpha)|x_t - y_t|^2 \\
&\leq f(y_t, b_t) + 2 |x_t - y_t| + |y_t - x_t|^2 \\
&\leq f(y_t, b_t) + 2\frac{1 - \alpha}{t + 1} + \frac{(1 - \alpha)^2}{(t + 1)^2}
\end{aligned}
$$

Theorem 2. *Consider the function $f : [0,1]^2 \mapsto [0,1]$ with $f(x,b) = (1 - \alpha)(x - b)^2 + \alpha(x - s)^2$ for some constants $s, \alpha \in [0,1]$. Let $(b_t)_{t=1}^{\infty}$ be an arbitrary sequence with $b_t \in [0,1]$. If $x_t = \operatorname{argmin}_{x \in [0,1]} \sum_{\tau=0}^{t-1} f(x, b_\tau)$ then for all t, $\sum_{\tau=0}^{t} f(x_\tau, b_\tau) \leq \min_{x \in [0,1]} \sum_{\tau=0}^{t} f(x, b_\tau) + O(\log t)$.*

Proof. Theorem 2 easily follows by Lemma 3

$$\sum_{\tau=0}^{t} f(x_\tau, b_\tau) \leq \sum_{\tau=0}^{t} f(y_\tau, b_\tau) + \sum_{\tau=0}^{T} 2\frac{1-\alpha}{\tau+1} + \sum_{\tau=0}^{t} \frac{(1-\alpha)^2}{(\tau+1)^2}$$

$$\leq \min_{x\in[0,1]} \sum_{\tau=0}^{t} f(x, y_\tau) + 2(1-\alpha)(\log t + 1) + (1-\alpha)\frac{\pi^2}{6}$$

$$\leq \min_{x\in[0,1]} \sum_{\tau=0}^{t} f(x, y_\tau) + O(\log t)$$

C   Limited Information Dynamics with Fast Convergence

We are now going to state and prove a series of lemmas that culminate in the proof of Theorem 4.

Lemma 7. *Let $\rho = \min_i a_i$, and $\pi_{ij}(t)$ be the most recent round before round t, that agent i met her neighbor j. If for all $t \geq B$, $t - B \leq \pi_{ij}(t)$ then, for all $t \geq kB$, $\|x(t) - x^*\|_\infty \leq (1-\rho)^k$.*

Proof. To prove our claim we use induction on k. For the induction base $k = 1$,

$$|x_i(t) - x_i^*| = |(1-\alpha_i) \sum_{j\in N_i} p_{ij}(x_j(\pi_{ij}(t)) - x_j^*)| \leq (1-\alpha_i) \sum_{j\in N_i} p_{ij}|x_j(\pi_{ij}(t)) - x_j^*| \leq (1-\rho)$$

Assume that for all $t \geq (k-1)B$ we have that $\|x(t) - x^*\|_\infty \leq (1-\rho)^{k-1}$. For $k \geq 2$, we again have that

$$|x_i(t) - x_i^*| \leq (1-\rho) \sum_{j\in N_i} p_{ij}|x_j(\pi_{ij}(t)) - x_j^*|$$

Since $t - B \leq \pi_{ij}(t)$ and $t \geq kB$ we obtain that $\pi_{ij}(t) \geq (k-1)B$. As a result, the inductive hypothesis applies, $|x_j(\pi_{ij}(t)) - x_j^*| \leq (1-\rho)^{k-1}$ and $|x_i(t) - x_i^*| \leq (1-\rho)^k$.

We now turn our attention to the problem of calculating the size of window B, such that with high probability all agents have outdatedness at most B. We first state a useful fact concerning the coupons collector problem.

Lemma 12. *Suppose that the collector picks coupons with different probabilities, where n is the number of distinct coupons. Let w be the minimum of these probabilities. If he selects $\ln n/w + c/w$ coupons, then:*

$$\mathbf{P}\left[\text{collector hasn't seen all coupons}\right] \leq \frac{1}{e^c}$$

Lemma 13. *Let $\pi_{ij}(t)$ be the most recent round before round t that agent i met agent j and $B = 2\ln(\frac{nt}{\delta})/\min_{ij} p_{ij}$. Then with probability at least $1-\delta$, for all $\tau \geq B$ and for all $i, j \in N_i$*

$$\tau - B \leq \pi_{ij}(\tau) \leq \tau - 1.$$

Proof. For simplicity we denote $w = \min_{ij} p_{ij}$. Consider an agent i at round $\tau \geq B$ where $B = 2\ln(\frac{nt}{\delta})/w$ and assume that there exists an agent $j \in N_i$ such that $\pi_{ij}(\tau) < \tau - B$. Agent i can be viewed as a coupon collector that has buyed B coupons but has not found the coupon corresponding to agent j. Since $N_i < n$ and $\min_{j\in N_i} p_{ij} \geq w$ by Lemma 12 we have that

$$\mathbf{P}\left[\text{there exists } j \in N_i \text{ s.t. } \pi_{ij}(\tau) < \tau - B\right] \leq \frac{\delta}{nt}$$

The proof follows by a union bound for all agent i and all round $B \leq \tau \leq t$.

By direct application of Lemma 7 and Lemma 13, we obtain the following corollary that will be useful in proving Theorem 4.

Corollary 1. *Let $x(t)$ the opinion vector produced by update rule (8) for the instance $I = (P, s, \alpha)$, then with probability at least $1 - \delta$*

$$\|x(t) - x^*\|_\infty \leq \exp\left(-\frac{\rho t \min_{ij} p_{ij}}{2 \ln(\frac{nt}{\delta})}\right)$$

where $\rho = \min_{i \in V} \alpha_i$.

Proof. Let $B = 2 \ln(\frac{nt}{\delta}) / \min_{ij} p_{ij}$. By Lemma 13 we have that with probability at least $1 - \delta$, for all $i, j \in N_i$ and for all $\tau \geq B$,

$$\tau - B \leq \pi_{ij}(\tau)$$

As a result, with probability at least $1 - \delta$ the requirements of Lemma 7 are satisfied, meaning that

$$\|x(t) - x^*\|_\infty \leq (1 - \rho)^{\frac{t}{B}} \leq \exp\left(-\frac{\rho t \min_{ij} p_{ij}}{2 \ln(\frac{nt}{\delta})}\right)$$

We can now prove Theorem 4 using the previous results.

Theorem 4. *Let $I = (P, s, \alpha)$ be an instance of the opinion formation game of Definition 1 with equilibrium $x^* \in [0, 1]^n$ and let $\rho = \min_{i \in V} a_i$. The opinion vector $x(t) \in [0, 1]^n$ produced by update rule (8) after t rounds satisfies $\mathbf{E}[\|x(t) - x^*\|_\infty] \leq 2 \exp(-\rho \min_{ij} p_{ij} \sqrt{t}/(4 \ln(nt)))$.*

Proof. Let $u(t) = \|x(t) - x^*\|_\infty$ and $w = \min_{ij} p_{ij}$. From Corollary 1 we obtain:

$$\mathbf{P}\left[u(t) > \exp\left(-\frac{\rho w t}{2 \ln(\frac{nt}{\delta})}\right)\right] \leq \delta$$

for every probability $\delta \in [0, 1]$. Also, since all the parameters of the problem lie in $[0, 1]$, we have

$$\mathbf{E}[u(t)|u(t) > r] \leq 1$$

Now, by the conditional expectations identity, we get:

$$\mathbf{E}[u(t)] = \mathbf{E}[u(t)|u(t) > r]\mathbf{P}[u(t) > r] + \mathbf{E}[u(t)|u(t) \leq r]\mathbf{P}[u(t) \leq r]$$
$$\leq \delta + r$$

where $r = \exp\left(-\frac{\rho w t}{2 \ln(\frac{nt}{\delta})}\right)$. If we set $\delta = \exp\left(-\frac{\rho w \sqrt{t}}{2 \ln nt}\right)$, then:

$$\mathbf{E}[u(t)] \leq \exp\left(-\frac{\rho w \sqrt{t}}{2 \ln nt}\right) + \exp\left(-\frac{\rho w t}{2 \ln(\frac{nt}{\delta})}\right)$$

We now evaluate r for our choice of probability δ:

$$r = \exp\left(-\frac{\rho w t}{2\ln\left(\frac{nt}{p}\right)}\right)$$

$$= \exp\left(-\frac{\rho w t}{2\ln\left(\frac{nt}{\exp\left(-\frac{\rho w \sqrt{t}}{2\ln nt}\right)}\right)}\right)$$

$$= \exp\left(-\frac{\rho w t}{2\ln nt + 2\frac{\rho w \sqrt{t}}{2\ln nt}}\right)$$

$$\leq \exp\left(-\frac{\rho w t}{4\ln(nt)\sqrt{t}}\right)$$

$$= \exp\left(-\frac{\rho w \sqrt{t}}{4\ln(nt)}\right)$$

Using the previous calculation, we obtain:

$$\mathbf{E}\left[u(t)\right] \leq \exp\left(-\frac{\rho w \sqrt{t}}{2\ln(nt)}\right) + \exp\left(-\frac{\rho w \sqrt{t}}{4\ln(nt)}\right)$$

$$\leq 2\exp\left(-\frac{\rho w \sqrt{t}}{4\ln(nt)}\right)$$

$$= 2\exp\left(-\rho \min_{ij} p_{ij}\frac{\sqrt{t}}{4\ln(nt)}\right)$$

Example 1. The purpose of this example is to illustrate that the update rule (8) does not ensure the no regret property. If some agents for various reasons exhibit irrational or adversarial behavior, agents that adopt update rule (8) may experience regret. That is the reason that *Row Dependent dynamics* converge exponetially faster that any *no regret dynamics* incluing the *FTL dynamics*.

Consider the instance of the game of Definition 1 consisting of two agents. Agent 1 adopts update rule (8) and has $s_1 = 0, \alpha_1 = 1/2, p_{12} = 1$ and agent 2 plays adversarially. Thus, s_2, α_2, p_{21} don't need to be specified. By update rule (8), $x_1(t) = x_2(t-1)/2$ and thus total disagreement cost that agent 1 experiences until round t is

$$\sum_{\tau=0}^{t}\frac{1}{2}x_1(t)^2 + \frac{1}{2}(x_1(t) - x_2(t))^2 = \sum_{\tau=0}^{t}\frac{1}{8}x_2(t-1)^2 + \frac{1}{2}(\frac{1}{2}x_2(t-1) - x_2(t))^2.$$

Since agent 2 plays adversarially, she selects $x_2(t) = 0$ if t is even and 1 otherwise. As a result, the total cost that agent 1 experiences is $\sum_{\tau=0}^{t}\frac{1}{2}x_1(t)^2 + \frac{1}{2}(x_1(t) - x_2(t))^2 \simeq 3t/8$. Now agent 1 regrets for no adopting the fixed opinion $1/3$ during the whole game play. Selecting $x_1(t) = 1/3$ for all t, would incur him total disagreement cost $\sum_{\tau=0}^{t}\frac{1}{2}(1/3)^2 + \frac{1}{2}(1/3 - x_2(t))^2 \simeq 7t/36$ which is less than $3t/8$.