

Asynchronous DeGroot Dynamics



ron.peretz@biu.ac.il

Workshop on current trends in graph and
stochastic games



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DGR

Dor Elboim

Ron P.



Galit
Ashkenzi
- Golan



Yuval
Peres



DRY



DeGroot Dynamics

- $G = (V, E)$ — undirected locally finite graph
- Agents are vertices
- $A_t \in \mathbb{R}^V$ — opinions at time t
- A_0 — initial opinions
- updating rule:
- $P: \mathbb{R}^V \rightarrow \mathbb{R}^V$
- $(PA)(v) = \frac{1}{\deg(v)} \sum_{w \in N_v} A(w)$

Timing

- Synchronous:

$$t = 0, 1, 2, \dots, A_{t+1} = PA_t$$

- Asynchronous:

iid Poisson clocks on vertices

$$A_t(v) = \begin{cases} (PA_{t-})(v) & v \text{ rings at time } t \\ A_{t-}(v) & \text{otherwise} \end{cases}$$

Known facts (synchronous timing)

- Finite graph: $\exists \lim_{t \rightarrow \infty} A_{2t}$. Furthermore,

$$G \text{ non-bipartite} \Rightarrow \lim_{t \rightarrow \infty} A_t = \sum_v \pi_v A_0(v)$$

- Infinite graph, bounded degree, bounded iid initial opinions, expectation μ

$$\forall v \quad \lim_{t \rightarrow \infty} A_t(v) = \mu, \text{ almost surely.}$$

DGR results (asynchronous timing)

- Finite graph. There exists a r.v. C s.t.

$$\forall v \quad \lim_{t \rightarrow \infty} A_t(v) = C, \text{ almost surely.}$$

- Further, iid initial opinions variance σ^2 , then

$$\text{Var}(C) = \mathcal{O}(\pi_{\max} \sigma^2).$$

- Infinite graph. Bounded degree, iid initial opinions, finite variance, then

$$\forall v \quad \lim_{t \rightarrow \infty} A_t(v) = \mu, \text{ in probability.}$$

DRY results (asynchronous timing)

- Infinite graph. Bounded degree, bounded iid initial opinions.

$$\forall v \quad \lim_{t \rightarrow \infty} A_t(v) = \mu, \text{ almost surely.}$$

- Finite graph. Consensus convergence rate.

$$\tau_\epsilon := \min\{t : \forall v, w \ A_t(v) - A_t(w) \leq \epsilon\},$$

$$\mathbb{E}[\tau_\epsilon] \leq \begin{cases} 4 \cdot \text{diam}(G) \cdot |E| \cdot \lceil \log_2(1/\epsilon) \rceil, \\ \log(2|E|/\epsilon^2) / \text{spectral-gap}(G), \\ \mathcal{O}_{\epsilon, \text{deg}(G)}(\log^{20}(|V|)). \end{cases}$$

Convergence to consensus in finite graphs

- Dirichlet energy:

$$\mathcal{E}(A) := \frac{1}{2|E|} \sum_{vw \in E} (A(v) - A(w))^2 = \langle (I - P)A, A \rangle_{\pi}$$

- $\mathcal{E}(A_t) \searrow 0, \quad \max_v(A_t(v)) \searrow C.$

- More elaborate arguments provide the rate of convergence.

Consensus variance — finite graphs

- Consider $\mu_t := \langle A_t, 1 \rangle_\pi$, martingale, $\mu_t \rightarrow C$,
 $\text{Var}(\mu_t) \rightarrow \text{Var}(C)$.

$$\begin{aligned}\mathbb{E}[(\mu_{t+h} - \mu_t)^2 \mid \mathcal{F}_t] &= h \sum_v \pi_v^2 (PA_t(v) - A_t(v))^2 + \mathcal{O}(h^2) \\ &\leq \pi_{\max} \cdot h \left\| (I - P)A_t \right\|_{L_2(\pi)}^2 + \mathcal{O}(h^2) \\ &= \pi_{\max} \cdot \mathbb{E}[\mathcal{E}(A_t) - \mathcal{E}(A_{t+h}) \mid \mathcal{F}_t] + \mathcal{O}(h^2).\end{aligned}$$

$$\text{Var}(\mu_t) = \text{Var}(\mu_0) + \pi_{\max} (E[\mathcal{E}(A_0)] - E[\mathcal{E}(A_t)]) \rightarrow \left(\sum_v \pi_v^2 + \pi_{\max} \right) \sigma^2$$

Backward looking approach — fragmentation

- Fix $o \in V$. Let X_t be RW on G originating at o .
- \mathcal{F}_t — the σ -algebra generated by clock rings.
- $m_t(v) := \mathbb{P}(X_t = v \mid \mathcal{F}_t)$.
- Observation:

$$A_t(o) \sim \sum_v m_t(v) A_0(v),$$

m, A_0 independent.

Convergence in probability — infinite graphs

- $\text{Var}(A_t(o)) = \sum_v \mathbb{E}[(m_t(v))^2] \sigma^2$

- **Proposition.**

$$\sum_v \mathbb{E}[(m_t(v))^2] = \mathcal{O}\left(\frac{\text{deg}(G)}{\sqrt{t}}\right).$$

Proof of the proposition

- X_t^1, X_t^2 two RWs originating at o , same Poisson cloaks, independent trajectories.
- Observation. $\mathbb{E}[m_t(v)^2] = \mathbb{P}(X_t^1 = X_t^2 = v)$.
- $\sum_v \mathbb{E}[(m_t(v))^2] = \mathbb{P}(X_t^1 = X_t^2) = ?$

Proof of the proposition

- \hat{X}_n^1, \hat{X}_n^2 — resp. (independent) trajectories
- $N_1(t), N_2(t)$ — resp. Poisson jumps
- i.e., $X^i(t) = \hat{X}_{N_i(t)}^i$.

Proof of the proposition

$$\mathbb{P}(X_t^1 = X_t^2) = \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \mathbb{P}(p_{n_1} < \hat{X}^1, p_{n_2}^{-1} < \hat{X}^2, N_1(t) = n_1, N_2(t) = n_2)$$

$$= \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \mathbb{P}(p_{n_1} < \hat{X}^1) \mathbb{P}(p_{n_2}^{-1} < \hat{X}^2)$$

$$\mathbb{P}(N_1(t) = n_1, N_2(t) = n_2 | p_{n_1} < \hat{X}^1, p_{n_2}^{-1} < \hat{X}^2)$$

$$= \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \mathbb{P}(p_{n_1} < \hat{X}^1) \mathbb{P}(p_{n_2}^{-1} < \hat{X}^2)$$

$$\mathbb{P}(N_1(t) = n_1, N_2(t) = n_2 | p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

Proof of the proposition

$$\dots = \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \mathbb{P}(p_{n_1} < \hat{X}^1) \mathbb{P}(p_{n_2}^{-1} < \hat{X}^2)$$

$$\mathbb{P}(N_1(t) = n_1, N_2(t) = n_2 \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

$$\leq \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \frac{\deg(G)}{\deg(o)} \mathbb{P}(p < \hat{X}^1)$$

$$\mathbb{P}(N_1(t) = n_1, N_2(t) = n_2 \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

$$= \frac{\deg(G)}{\deg(o)} \sum_n \sum_{p \in C_n} \mathbb{P}(p < \hat{X}^1)$$

$$\mathbb{P}(N_1(t) + N_2(t) = n \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

Proof of the proposition

$$\dots = \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \mathbb{P}(p_{n_1} < \hat{X}^1) \mathbb{P}(p_{n_2}^{-1} < \hat{X}^2)$$

$$\mathbb{P}(N_1(t) = n_1, N_2(t) = n_2 \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

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$$\mathbb{P}(N_1(t) + N_2(t) = n \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

Proof of the proposition

$$\dots = \sum_n \sum_{p \in C_n} \sum_{n_1+n_2=n} \mathbb{P}(p_{n_1} < \hat{X}^1) \mathbb{P}(p_{n_2}^{-1} < \hat{X}^2)$$

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$$\mathbb{P}(N_1(t) = n_1, N_2(t) = n_2 \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$

$O(\mathbb{P}(N_2(t)=4))$

$$= \frac{\deg(G)}{\deg(o)} \sum_n \sum_{p \in C_n} \mathbb{P}(p < \hat{X}^1) = O\left(\frac{\deg(o)}{n^2}\right)$$

$$\mathbb{P}(N_1(t) + N_2(t) = n \mid p < \hat{X}^1, p^{-1} < \hat{X}^2)$$