

Opinion dynamics on non-sparse networks with community structure

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SEMINAR ON STOCHASTIC PROCESSES

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The opinion model

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- ▶ $\mathbf{W}_i^{(k)} \in [-d, d]^\ell$: media signals that node i receives at time k .
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- ▶ $C_{ij} \in [0, 1]$: the weight that i puts on j 's opinion.
- ▶ Update opinions according to the recursion

$$\mathbf{R}_i^{(k)} = c \sum_{j=1}^n C_{ij} \mathbf{R}_j^{(k-1)} + \mathbf{W}_i^{(k)} + (1 - c - d) \mathbf{R}_i^{(k-1)},$$

where $\{\mathbf{W}_i^{(k)} : k \geq 0\}$ are i.i.d. and $0 < c + d \leq 1$.

The mean-field limit

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- ▶ The approximating process is given by: $\mathcal{R}^{(0)} = R^{(0)}$ and

$$\begin{aligned}\mathcal{R}_i^{(k)} = & \sum_{t=0}^{k-1} (1-c-d)^t \mathbf{W}_i^{(k-t)} + 1(k \geq 2) \sum_{t=1}^{k-1} \sum_{s=1}^t a_{s,t} (M^s \bar{W})_{J_i \bullet} \\ & + \sum_{s=1}^k a_{s,k} (M^s \bar{R})_{J_i \bullet} + (1-c-d)^k \mathbf{R}_i^{(0)},\end{aligned}$$

for $k \geq 1$ and $i \in V_n$, where $a_{s,t} = \binom{t}{s} (1-c-d)^{t-s} c^s$.

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- ▶ The **media signals** are the only ones that persist in the limit, meaning they determine **polarization** in the system!

Theorem (A., Olvera-Cravioto '24)

Suppose $\theta_n \geq (6H\Lambda_n)^2 \Delta_n \log n$. Then, there exists a constant $\Gamma < \infty$ such that

$$\sup_{k \geq 0} \mathbb{E}_n \left[\left\| R^{(k)} - \mathcal{R}^{(k)} \right\|_\infty \right] \leq \Gamma \left(\sqrt{\frac{\log n}{\theta_n}} + \max_{1 \leq r, s \leq K} \left| \frac{\pi_s^{(n)} \pi_r - \pi_s \pi_r^{(n)}}{\pi_r^{(n)} \pi_s} \right| \right).$$

Moreover, for any sequence $\theta_n \rightarrow \infty$, we have

$$\sup_{k \geq 0} \max_{i \in V_n} \mathbb{E}_n \left[\left\| \mathbf{R}_i^{(k)} - \mathcal{R}_i^{(k)} \right\|_1 \right] \xrightarrow{P} 0, \quad n \rightarrow \infty.$$

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- ▶ *Intuition*: the average number of neighbors that any vertex has grows with θ_n . The larger the number of neighbors, the more their aggregate contributions behave as the average opinion.
- ▶ Since the rows in the limiting process $\{\mathcal{R}^{(k)} : k \geq 1\}$ are independent of each other, Theorem 1 yields that the trajectories of the process $\{R^{(k)} : k \geq 0\}$ are asymptotically independent, i.e., the system exhibits *propagation of chaos*.