

Polar Opinion Dynamics in Social Networks

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► Introduction

Models for polar opinion dynamics

Asymptotic behavior of the models

Brief introduction into non-smooth convergence analysis

Convergence analysis of the models for polar opinion dynamics

Summary

Motivation

- Social network consisting of *agents*
- Each agent holds an opinion
- Agents' opinions change due to the agents' interaction
- Opinions are *polar* (*iOS vs. Android, Republicans vs. Democrats*)
- Goal: model opinion formation and learn from the model

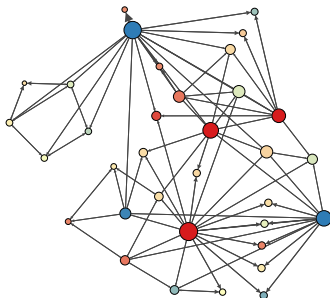


Figure: Zachary's Karate Club network [Zac77]

Problem statement

- Directed, strongly connected social network of n agents
- Row-stochastic adjacency matrix $\mathbf{W} \in [0, 1]^{n \times n}$
- $(\mathbf{W})_{ij} = w_{ij}$ – how much agent i relatively “trusts” agent j
- $\mathbf{x}(t) \in [-1, 1]^n$ – agents’ opinions at time t
- Goals:
 - ◊ Design a sociologically plausible model governing evolution of $\mathbf{x}(t)$
$$\dot{\mathbf{x}}(t) = M(\mathbf{x}(t), t)$$
 - ◊ The model *must* capture the competing nature of opinions.
 - ◊ Analyze the dynamical behavior of the model to understand the dependency of $\mathbf{x}(\infty)$ upon $\mathbf{x}(0)$ and $\mathbf{W}$.

Existing opinion dynamics models

DeGroot [DeG74]

$$\mathbf{x}(t+1) = \mathbf{W}\mathbf{x}(t) \quad (\dot{\mathbf{x}} = -\mathbf{L}\mathbf{x}, \dot{\mathbf{x}} = \Delta\mathbf{x})$$

Time-varying DeGroot [Mor05]

$$\mathbf{x}(t+1) = \mathbf{W}(t)\mathbf{x}(t)$$

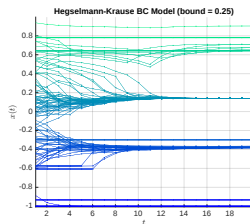
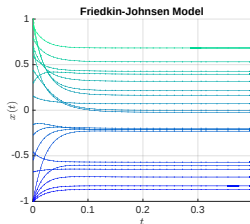
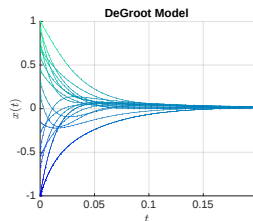
Friedkin-Johnsen [FJ99]

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{W}\mathbf{x}(t) + (\mathbf{I} - \mathbf{A})\mathbf{x}(0)$$

$\mathbf{A}$ – diagonal matrix of susceptibilities

Bounded Confidence [HK02, Lor07]

$$\mathbf{x}(t+1) = \mathbf{W}(\mathbf{x}(t))\mathbf{x}(t)$$
$$w_{ij}(\mathbf{x}) > 0 \Leftrightarrow |x_i - x_j| \leq bound$$



Other models: SI/SIS/SIR-like, Independent Cascade, Linear Threshold, Voter, Bayesian, ...

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General model for polar opinion dynamics

- *Key idea* – agents' opinion formation behavior must change based on the agents' current beliefs

$$\mathbf{x}(t+1) = \mathbf{A}(\mathbf{x}(t))\mathbf{W}\mathbf{x}(t) + (\mathbf{I} - \mathbf{A}(\mathbf{x}(t)))\mathbf{x}(t)$$

General model for polar opinion dynamics

- *Key idea* – agents' opinion formation behavior must change based on the agents' current beliefs

$$\begin{aligned} \mathbf{x}(t+1) &= \mathbf{A}(\mathbf{x}(t))\mathbf{W}\mathbf{x}(t) + (\mathbf{I} - \mathbf{A}(\mathbf{x}(t)))\mathbf{x}(t) \\ \mathbf{x}(t+1) &= \mathbf{A} \quad \quad \mathbf{W}\mathbf{x}(t) + (\mathbf{I} - \mathbf{A} \quad \quad)\mathbf{x}(0) \end{aligned} \quad (\text{FJ})$$

General model for polar opinion dynamics

- *Key idea* – agents' opinion formation behavior must change based on the agents' current beliefs

$$\mathbf{x}(t+1) = \mathbf{A}(\mathbf{x}(t))\mathbf{W}\mathbf{x}(t) + (\mathbf{I} - \mathbf{A}(\mathbf{x}(t)))\mathbf{x}(t)$$

- **General model for polar opinion dynamics [ABS17]:**

$$\dot{\mathbf{x}} = -\mathbf{A}(\mathbf{x})\mathbf{L}\mathbf{x}$$

where

$$\mathbf{x} = \mathbf{x}(t) \in [-1, 1]^n,$$

$$\mathbf{A}(\mathbf{x}) : [-1, 1]^n \rightarrow \mathbf{diag}([0, 1]^n),$$

$$\mathbf{L} = (\mathbf{D}^{out} - \mathbf{W}) - \text{out-degree Laplacian of the network.}$$

[ABS17] Amelkin V., Bullo F., Singh A.K. “Polar Opinion Dynamics in Social Networks”, IEEE Transactions on Automatic Control (2017)

Three instances of the general model

- Model with stubborn positives:

$$A(x) = 1/2 (I - \text{diag}(x)), \quad \dot{x} = -1/2 (I - \text{diag}(x)) Lx$$

- Model with stubborn neutrals:

$$A(x) = \text{diag}(x)^2, \quad \dot{x} = -\text{diag}(x)^2 Lx$$

- Model with stubborn extremists:

$$A(x) = (I - \text{diag}(x))^2, \quad \dot{x} = -(I - \text{diag}(x))^2 Lx$$

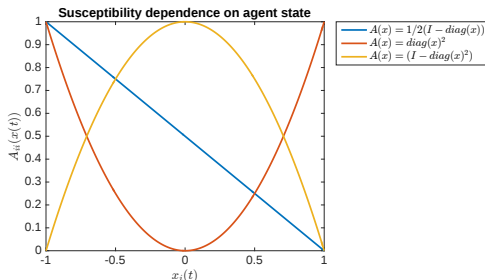


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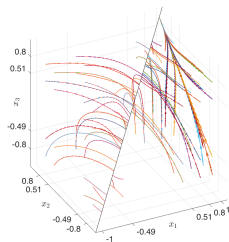
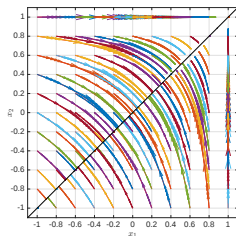
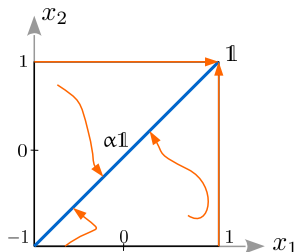
Brief introduction into non-smooth convergence analysis

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Convergence: model with stubborn positives $\dot{x} = -1/2(I - \text{diag}(x))Lx$

- If $x(0) < \mathbf{1}$, then $\lim_{t \rightarrow \infty} x(t) = \alpha \mathbf{1}$ for some $\alpha \in [0, 1)$.
- If $\exists i \in \{1, \dots, n\} : x_i = 1$, then $\lim_{t \rightarrow \infty} x(t) = \mathbf{1}$.

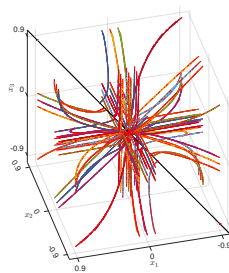
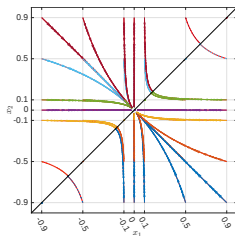
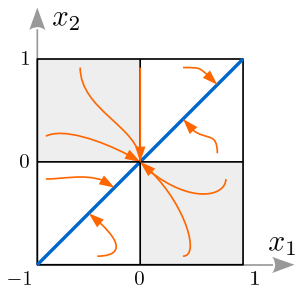


Convergence: model with stubborn neutrals $\dot{x} = -\text{diag}(x)^2 Lx$

- If
 - ◊ $x < 0$ (negative semi-open orthant) or
 - ◊ $x > 0$ (positive semi-open orthant),

then $\lim_{t \rightarrow \infty} x(t) = \alpha \mathbb{1}$ for some

- ◊ $\alpha \in [-1, 0)$ or
 - ◊ $\alpha \in (0, 1]$, respectively.
- Otherwise, $\lim_{t \rightarrow \infty} x(t) = 0$.



Convergence: model with stubborn extremists $\dot{x} = -(I - \text{diag}(x)^2)Lx$

- If $|x(0)| < \mathbb{1}$, then $x(\infty) = \alpha \mathbb{1}$ for some $\alpha \in (-1, 1)$.
- If all closed agents in $x(0)$ have the same state, -1 or 1 , then $x(\infty)$ is either $-\mathbb{1}$ or $\mathbb{1}$, respectively.
- If there are some closed agents having different opinions $x_1(0)$, and there may be some open agents $x_2(0)$, then

$$x(\infty) = P^T [x_1(0)^T, (I - W_{22})^{-1} W_{21} x_1(0)^T]^T$$

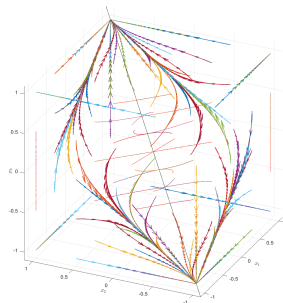
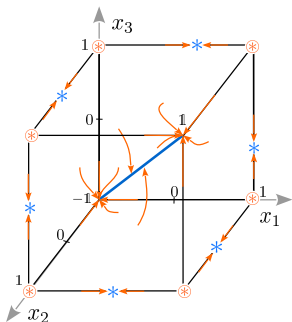


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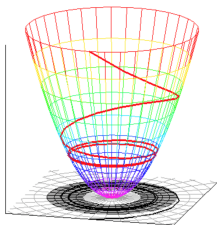
General idea behind convergence analysis

Lyapunov Direct Method [Lya92]

Find $V(\mathbf{x}) : D \rightarrow \mathbb{R} \in C^1(D)$ with a unique minimum at $\mathbf{x}^*$, whose directional derivative $\mathcal{L}_f(V(\mathbf{x})) = \langle \nabla V(\mathbf{x}), f(\mathbf{x}) \rangle$ along the trajectories of the system $\dot{\mathbf{x}} = f(\mathbf{x})$ is non-positive and zero at $\mathbf{x}^*$. Then, $\mathbf{x}^*$ is asymptotically stable.

LaSalle Invariance Principle [LL61]

Given a compact $S \subseteq D$ forward-invariant w.r.t. system $\dot{\mathbf{x}} = f(\mathbf{x})$, find $V(\mathbf{x}) : D \rightarrow \mathbb{R} \in C^1(D)$ with $\mathcal{L}_f(V(\mathbf{x})) \leq 0$. Then, trajectories starting in S converge to the largest invariant subset of the 0-level set of $\mathcal{L}_f(V(\mathbf{x}))$.

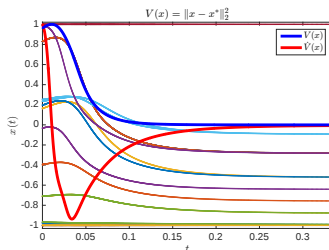


Quadratic Lyapunov function

(The image is due to Matt Kawski @ ASU)

When smooth analysis does not work

- Quadratic Lyapunov functions generally¹ do not work well for directed networks.
 - ◊ Formally, for a negative Laplacian flow $\dot{\mathbf{x}} = -\mathbf{L}\mathbf{x} = f(\mathbf{x})$, if $V(\mathbf{x}) = \|\mathbf{x} - \mathbf{x}^*\|_2^2$, then $\mathcal{L}_f V(\mathbf{x}) \leq 0 \Leftrightarrow G(L)$ is weight-balanced.
 - ◊ Informally, while such $V(\mathbf{x})$ are often non-negative and 0 only at $\mathbf{x}^*$, their Lie derivative occasionally happens to be positive.



- Thus, it may worth time to look for a non-smooth Lyapunov function, even for a system $\dot{\mathbf{x}} = f(\mathbf{x})$ with a continuous vector field f .

¹Quadratic Lyapunov functions *may* work for directed networks; for example, paper [KBG14] shows an ad hoc design of one such function for a specific non-linear system – individual-level network SIS.

Tools from non-smooth stability analysis – Generalized Gradient

Let $V : \mathbb{R}^d \rightarrow \mathbb{R}$ be locally Lipschitz², and $\Omega_V \subset \mathbb{R}^d$ be the set of points where V fails to be differentiable.

Generalized Gradient [Cla90]:

$$\begin{aligned}\partial V(\mathbf{x}) &= \text{co} \left\{ \lim_{i \rightarrow \infty} \nabla V(\mathbf{x}_i) \mid \mathbf{x}_i \rightarrow \mathbf{x}, \mathbf{x}_i \notin N_0 \cup \Omega_V \right\}, \\ \text{co} \{ \} &- \text{convex hull}, \\ N_0 &- \text{any set of Lebesgue measure zero.}\end{aligned}$$

In English:

- compute $\nabla V(\mathbf{x})$ *around* each point where V is non-differentiable,
- and take the convex hull of all discovered ∇V (“around $\mathbf{x}$ ”) as $\partial V(\mathbf{x})$.

² $\forall x \in \mathbb{R}^d \exists R, C(x) \in \mathbb{R}_+ \forall y \in \mathfrak{B}(x, R) : |V(x) - V(y)| \leq C(x) \|x - y\|$

Set-valued Lie Derivative [Cor08, BC99]: For a locally Lipschitz $V : \mathbb{R}^d \rightarrow \mathbb{R}$ and system $\dot{x} = f(x)$, the **set-valued Lie derivative** $\tilde{\mathcal{L}}_f V(x)$ of V w.r.t. system $\langle \mathbb{R}^d, f \rangle$ is defined as

$$\tilde{\mathcal{L}}_f V(x) = \{a \in \mathbb{R} \mid \forall \xi \in \partial V(x) : \langle \xi, f(x) \rangle = a\}$$

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$$\mathcal{L}_f V(x) = \langle \xi, f(x) \rangle, \quad \xi = \nabla V(x) \quad - \text{compare}$$

Generalized Invariance Principle $\sim$ [Cor08, BC99]

If the following holds

- (i) $V : \mathbb{R}^d \rightarrow \mathbb{R}$ is locally Lipschitz and regular, (was $V \in C^1(D)$)
- (ii) $S \subset \mathbb{R}^d$ is compact and invariant for system $\dot{x} = f(x)$, and
- (iii) $\max \tilde{\mathcal{L}}_f V(x) \leq 0$ for each $x \in S$, (was $\mathcal{L}_f V(x) \leq 0$)

then all solutions $x : [0, \infty) \rightarrow \mathbb{R}^d$ starting in S converge to the largest invariant subset M of

$$S \cap \text{cl}\{x \in \mathbb{R}^d \mid 0 \in \tilde{\mathcal{L}}_f V(x)\} \quad (\text{was } S \cap \{x \in \mathbb{R}^d \mid \mathcal{L}_f V(x) = 0\})$$

If M is finite, then the limit of each solution $x(0) \in S$ exists and is an element of M .

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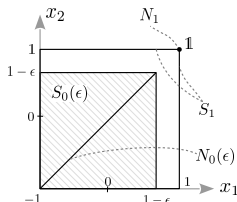
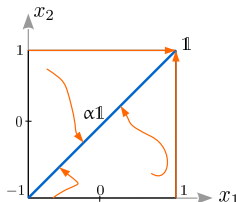
- Model

$$\dot{\mathbf{x}} = -\mathbf{A}(\mathbf{x})\mathbf{L}\mathbf{x}, \text{ - general model,}$$

$$\mathbf{A}(\mathbf{x}) = (\mathbf{I} - \mathbf{diag}(\mathbf{x}))/2,$$

$$\dot{\mathbf{x}} = -1/2(\mathbf{I} - \mathbf{diag}(\mathbf{x}))\mathbf{L}\mathbf{x} \text{ - model with stubborn positives.}$$

- State space partition:



$$[-1, 1]^n = \lim_{\epsilon \rightarrow +0} S_0(\epsilon) \cup S_1,$$

$$S_0(\epsilon) = [-1, 1 - \epsilon]^n, \quad N_0(\epsilon) = \{\alpha \mathbf{1} \mid \alpha \in [-1, 1 - \epsilon]\},$$

$$S_1 = \{\mathbf{P}^\top \mathbf{x} \mid \mathbf{x} \in \cup_{k=1}^n \{1\}^k \times [-1, 1)^{n-k}\}, \quad N_1 = \mathbf{1}.$$

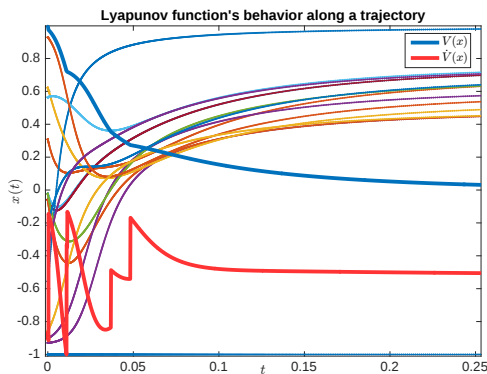
Convergence analysis of the model with stubborn positives: $S_0(\epsilon) \rightsquigarrow N_0(\epsilon)$

- Convergence from $S_0(\epsilon) = [-1, 1 - \epsilon]^n$ to $N_0(\epsilon) = \{\alpha \mathbf{1} \mid \alpha \in [-1, 1 - \epsilon]\}$.

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- Lyapunov function candidate** [Mor04, Hen08, Bul16]

$$V_{\max-\min}(\mathbf{x}) = \max(\mathbf{x}) - \min(\mathbf{x}).$$



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- Computing $\partial V(\mathbf{x})$:

$$\partial(c_1 g_1(\mathbf{x}) + c_2 g_2(\mathbf{x})) = c_1 \partial g_1(\mathbf{x}) + c_2 \partial g_2(\mathbf{x}) \quad (*)$$

$$\partial \max \{g_1(\mathbf{x}), \dots, g_k(\mathbf{x})\} = \mathbf{co} \cup \{\partial g_i \mid g_i \text{ attains max at } \mathbf{x}\} \quad (**)$$

$$g_i(\mathbf{x}) = \mathbf{x}_i, i \in \{1, \dots, n\} - \text{locally Lipschitz, regular}$$

$$\partial V_{\max}(\mathbf{x}) = \partial(\max(\mathbf{x})) = \mathbf{P}^\top [\boldsymbol{\alpha}^\top, \mathbf{0}^\top]^\top, \quad \alpha - \text{"convex"}$$

$$\partial V_{-\min}(\mathbf{x}) = \partial(-\min(\mathbf{x})) = \mathbf{P}^\top [-\boldsymbol{\beta}^\top, \mathbf{0}^\top]^\top, \quad \beta - \text{"convex"}$$

$$\partial V_{\max-\min}(\mathbf{x}) = \mathbf{P}^\top [\boldsymbol{\alpha}^\top, -\boldsymbol{\beta}^\top, \mathbf{0}^\top]^\top$$

Convergence analysis of the model with stubborn positives: $S_0(\epsilon) \rightsquigarrow N_0(\epsilon)$

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- Computing $\tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x})$:

$$\tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x}) = \{a \in \mathbb{R} \mid \forall \boldsymbol{\xi} \in \partial V(\mathbf{x}) : \langle \boldsymbol{\xi}, f(\mathbf{x}) \rangle = a\}$$

$$\begin{aligned} \boldsymbol{\xi}^\top f(\mathbf{x}) &= - \begin{bmatrix} \boldsymbol{\alpha} \\ -\boldsymbol{\beta} \\ \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{A}_{\max}(\mathbf{x}) & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{\min}(\mathbf{x}) & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_{\text{mid}}(\mathbf{x}) \end{bmatrix} \times \\ &\times \begin{bmatrix} (\mathbf{I} - \mathbf{W}_{11}) & -\mathbf{W}_{12} & -\mathbf{W}_{13} \\ -\mathbf{W}_{21} & (\mathbf{I} - \mathbf{W}_{22}) & -\mathbf{W}_{23} \\ -\mathbf{W}_{31} & -\mathbf{W}_{32} & (\mathbf{I} - \mathbf{W}_{33}) \end{bmatrix} \begin{bmatrix} \mathbf{x}_{\max} \\ \mathbf{x}_{\min} \\ \mathbf{x}_{\text{mid}} \end{bmatrix} = \\ &= -(\boldsymbol{\alpha}^\top \mathbf{A}_{\max}(\mathbf{x})(\mathbf{x}_{\max} - [\mathbf{W}_{11} \mathbf{W}_{12} \mathbf{W}_{13}]\mathbf{x}) + \\ &\quad \boldsymbol{\beta}^\top \mathbf{A}_{\min}(\mathbf{x})([\mathbf{W}_{21} \mathbf{W}_{22} \mathbf{W}_{23}]\mathbf{x} - \mathbf{x}_{\min})) \leq 0. \end{aligned}$$

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- Computing $\tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x})$:

$$\max \tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x}) \leq 0,$$

$$N_0(\epsilon) - 0\text{-level set of } \tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x}).$$

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$$\max \tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x}) \leq 0,$$

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- Invariance of compact $S_0(\epsilon)$: comes at no cost from $\max \tilde{\mathcal{L}}_f V_{\max}(\mathbf{x}) \leq 0$.

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$$N_0(\epsilon) - 0\text{-level set of } \tilde{\mathcal{L}}_f V_{\max-\min}(\mathbf{x}).$$

- Invariance of compact $S_0(\epsilon)$: comes at no cost from $\max \tilde{\mathcal{L}}_f V_{\max}(\mathbf{x}) \leq 0$.
- From Invariance Principle, all solutions starting in $S_0(\epsilon)$ converge asymptotically to $N_0(\epsilon)$.

Convergence analysis for other models

- For other part(s) of the state space and other models, use same techniques.
- Lyapunov functions based on a combination of V_{max} , V_{min} usually work.

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► Summary

- Polar opinion dynamics can be modeled with non-linear dynamical system whose behavior can be formally analyzed.
- Generally, non-smooth Lyapunov functions can be applied to the stability analysis of continuous non-linear systems over directed networks.
- Our convergence proofs did not rely on a particular shape of $A(x)$ (only when its diagonal elements are zero / non-zero) and, thus, can be carried over to other models of similar form.
- Similar techniques can be used to design Lyapunov functions out of convex components.

- ▶ Victor Amelkin, Francesco Bullo, and Ambuj K. Singh, *Polar opinion dynamics in social networks*, IEEE Transactions on Automatic Control (2017).
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~ Thanks ~

Questions?

Let $S \subseteq [-1, 1]^n$ be a non-empty compact forward-invariant set, and

$$N = S \cap \{\alpha \mathbf{1} \mid \alpha \in [-1, 1]\}$$

be its non-empty subset of consensus states. Further, assume that in S , the agents' susceptibility functions $A_{ii}(x)$ agree upon their zeros in that

$$\forall x \in S \ \forall i, j \in \{1, \dots, n\} : A_{ii}(x) = A_{jj}(x) = 0 \rightarrow x_i = x_j.$$

Then, all trajectories $x(t)$ of $\dot{x} = -A(x)Lx$ starting in S converge to N as $t \rightarrow \infty$.