

Stochastic modeling and analysis of adaptive voter models

Presentation by Vineeth S. Varma

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Section 1

Research context & motivation

A classical Interacting Particles System: the Voter Model (VM)

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Only one social interaction is modeled: mimetism.

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Definition 1.1 (Homophily)

Homophily is the natural trend one has to connect with alike people.

Definition 1.2 (selective exposure)

dismiss dissonant information and gainsayers.

Section 2

The model



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The Adaptive Voter Model (AVM)

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- two additional edge-dynamics that are **Node-centric**:
 - ① a **link-breaking** procedure; agent l picks u.r an $m \in N_l$ and breaks his directed link *only if* $x_l(t^-) \neq x_m(t^-)$:
selective exposure
 - ② a **link-creation** procedure; agent l explores his social environment by picking a m according to some linking rules.

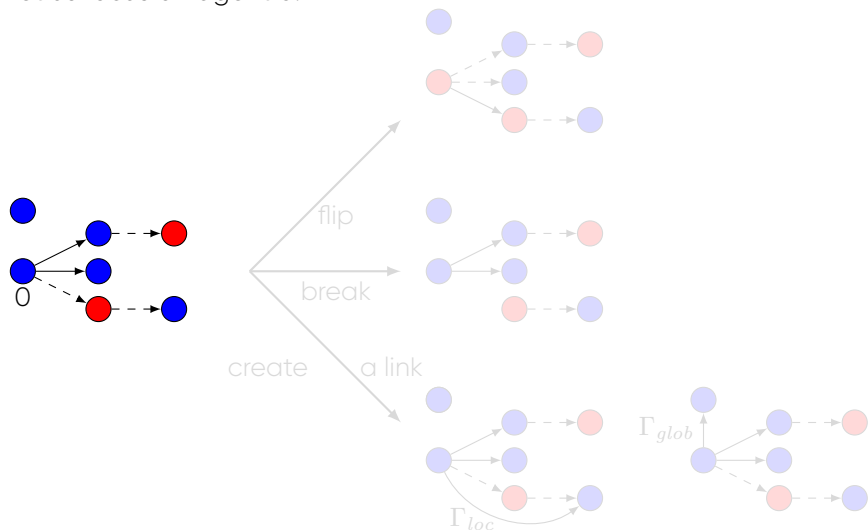
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Or **Edge-centric** rules: i.e., each edge has an independent link breaking/creation rate.

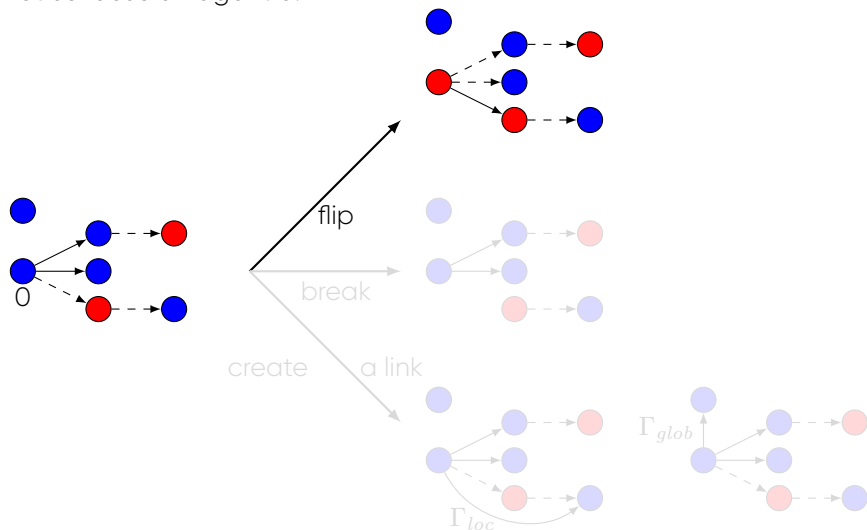
An example in picture

Let us focus on agent 0:



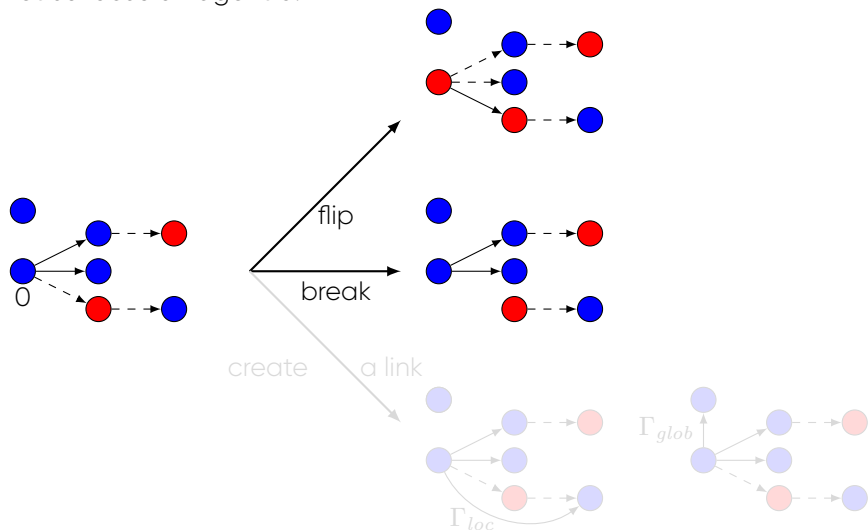
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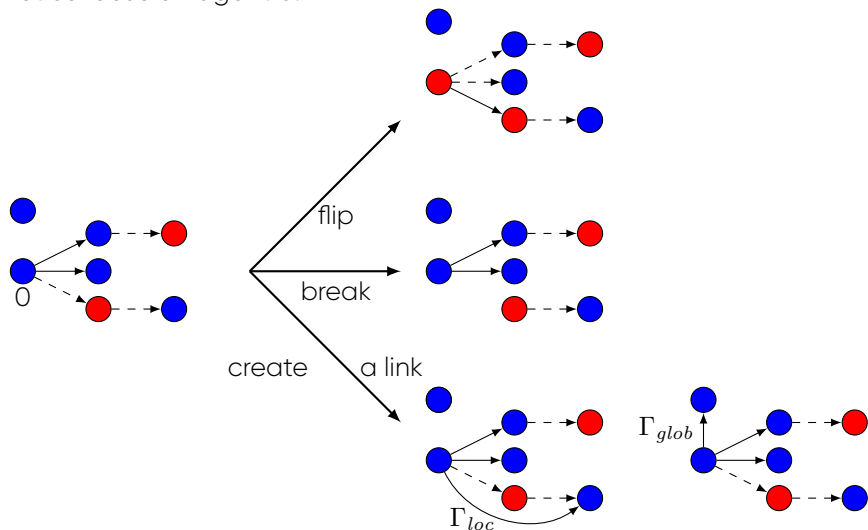
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Related literature

The classical VM has been extensively analyzed with various refinements:

- Originally analyzed on the infinite lattice \mathbb{Z}^d in [Lig12], and on a tree-like interaction network [Lig+99];
- based on a group-pressure mechanism¹ [CMP09; Mob15];
- under heterogeneous networks [SAR08];
- using the majority rule [Yil+10].

The AVM (Adaptive VM) also attracts a growing attention:

- most of the work focuses on global linkage [Dur+12; GB08];
- the 2-hop linkage² is also studied but in a lesser extent [Mal+16; RMS18];

Mostly, there always are only two parameters: the flip intensity ϕ and the ratio $\frac{\gamma}{\beta}$: nodes break and rewire instantaneously.

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Node-centric systems

Normalizing with the degree, we get a more agent-based system:

- Local linkage:

$$\bar{\Gamma}_{glob}(lm; x, A) = \gamma(1 - a_{lm}) \sum_j \frac{a_{lj}}{\deg(l; A)} \frac{a_{jm}}{\deg(j; A)} \underbrace{\mathbb{1}_{(x_l = x_m)}}_{\text{Homophily}}$$

agent l picks a neighbour j U.R among N_l and then picks an agent UR among N_j , and gets eventually connected if they have same spin.

- flip: $\bar{\Phi}(k; x, A) = \phi \sum_j \frac{a_{kj}}{\deg(k; A)}$: agent k picks UR one of its neighbour and copies its spin.
- Break: $\bar{B}(lm; x, A) = \beta \frac{a_{lm}}{\deg(l; A)} \underbrace{\mathbb{1}_{(x_l \neq x_m)}}_{\text{Sel. Exp.}}$

Limit points of a Markov Process

Definition 3.1 (absorbing points)

An absorbing point ∂ of a Markov process $(Z_t)_t$ is a state such that

$$Z_{t_0} = \partial \implies Z_t = \partial \forall t \geq t_0. \quad (1)$$

Remark 3.2

*There can be several absorbing points, but it is still stronger than an absorbing set: when Z reaches a ∂ , then it stays **constant** forever.*

For the AVMs under consideration, the absorbing points are attractive in the following sense:

$$T_{abs} := \inf \{ t > 0 : (X^K, A^K)(t) \text{ reaches an absorbing point} \}.$$

In addition, T_{abs} is of finite mean: $\mathbb{E}T_{abs} < \infty$ (and then a.s finite).

The absorbing configurations for Γ_{glob}

If we take global linking Γ_{glob} , the **absorbing points** are:

$$\mathcal{A}_{glob} = \left\{ (x, a) \in \mathcal{S}_K : \forall (l, m) \in [K]^2, (x_l = x_m \text{ and } a_{lm} = 1) \right. \\ \left. \text{or } (x_l \neq x_m \text{ and } a_{lm} = 0) \right\}$$

An absorbing state is then a clustered configuration where

- $C^+ \cup C^- = [K]$, $C^+ \cap C^- = \emptyset$,
- with $x_k = +1 \forall l \in C^+$ and $x_k = -1 \forall k \in C^-$,
- and with no links between the two blocks: $a_{C^+C^-} = a_{C^-C^+} = 0$.

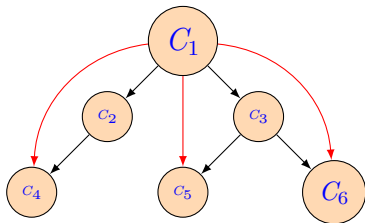
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If we take local linkage Γ_{loc} , the **absorbing points** are:

$$\mathcal{A}_{loc} = \left\{ (x, a) \in \mathcal{S}_K : k \xrightarrow{\text{path}} j \implies a_{kj} = 1 \text{ and } x_k = x_j \right\}.$$

Remark 3.3

In the case of $\Gamma = \Gamma_{loc}$, there can be much more than two clusters because when two sets $U, V \subset [K]$ get disconnected: $a_{lm} = 0$ $\forall (l, m) \in U \times V$, then they stay disconnected **forever**.



1-path-length completion:

$$\forall k \in C_1, j \in C_6, a_{kj} = 1.$$

C_p are all complete graphs:
 $\forall i, j \in C_p, a_{ij} = 1.$

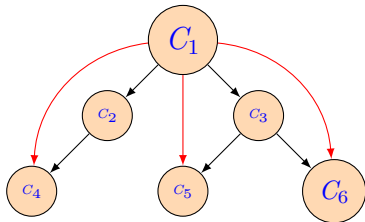
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How does discordance survive ?

Definition 3.4 (Discordance)

We say an edge lm is discordant if $a_{lm} \mathbb{1}_{(x_l \neq x_m)} > 0$. We can define total discordance of any configuration $(x, a) \in \mathcal{S}_K$ as

$$\mathcal{D}(x, a) := \sum_{lm} a_{lm} \mathbb{1}_{(x_l \neq x_m)} \quad (2)$$

Definition 3.5

slow extinction Define $T_K := \inf \{t > 0 : \mathcal{D}(X(t), A(t)) = 0\}$. We say that discordance *slowly extincts* if

$$\exists c > 0, \mathbb{P} (T_K < e^{cK}) < e^{-cK}. \quad (3)$$

For which values of ϕ, β, γ does the discordance slowly extinct ?

Section 4

A discrete time free global-linkage AVM

Model

We have a discrete time Markov process described by $(X(t), A(t))$, described as follows. For all $i \in \mathcal{V}$ and $t \in \{1, 2, \dots\}$, we have

$$\Pr(X_i(t+1) = -X_i(t)) = \frac{\phi}{N} \frac{N_i^-(t)}{\max\{1, N_i(t)\}}. \quad (4)$$

Additionally, for any $j \in \mathcal{V}$,

$$\Pr(A_{i,j}(t+1) = 0 | A_{i,j}(t) = 1) = \beta \frac{1}{\max\{1, N_i^-(t)\}} \quad (5)$$

and

$$\Pr(A_{i,j}(t+1) = 1 | A_{i,j}(t) = 0) = \gamma \frac{1}{\max\{1, N - N_i(t)\}} \quad (6)$$

where $N_i(t) = \sum_{j=1}^N A_{i,j}(t)$ and $N_i^-(t) = \sum_{j=1}^N A_{i,j}(t) 0.5 |X_i(t) - X_j(t)|$.

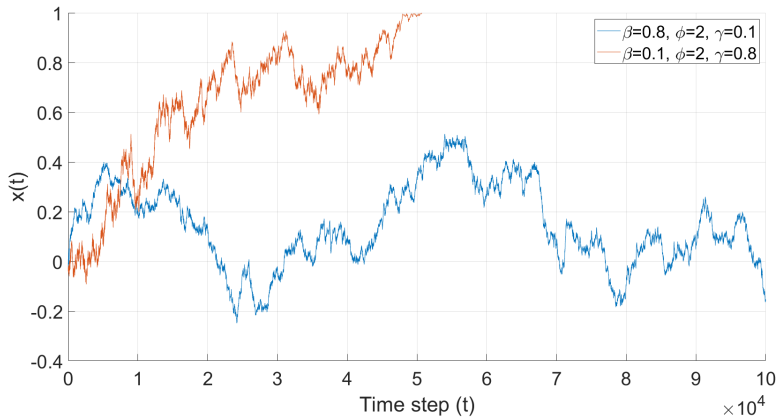
Metastability criteria (conjecture)

$$\begin{aligned}\text{Define: } x(t) &:= \frac{\sum_{i=1}^N X_i(t)}{N}, \\ N_S(t) &= \sum_{i=1}^N \max\{0, SX_i(t)\}, \\ a_{S_1 S_2} &= \frac{\sum_{i,j} a_{i,j} 1(X_i=S_1)(X_j=S_2)}{\max\{1, N_{S_1}(t)\} \max\{1, N_{S_2}(t)\}}.\end{aligned}$$

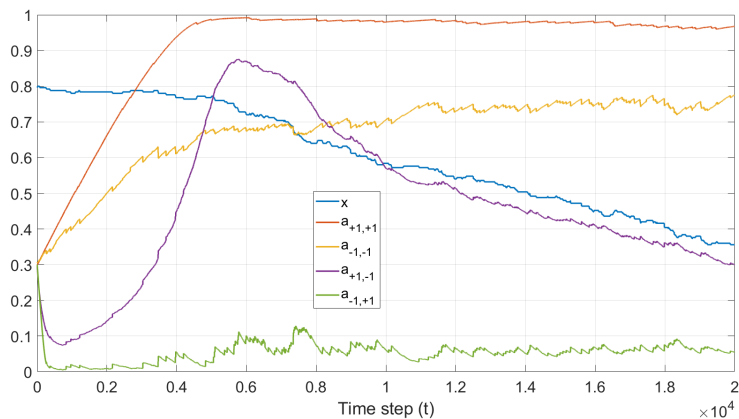
Approximation and metastability

Fr $\beta \gg \gamma$, $a_{+1,-1} > a_{-1,+1}$ (eventually) when $x < 0$
This leads to $x = 0$ being an attractive.

Simulations



Simulations



Illustrative simulation with $\phi = 0.1$

Section 5

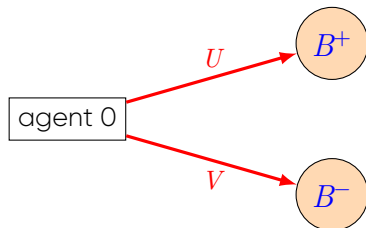
Local linkage: study of an interesting particular case



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Description of the initial configuration

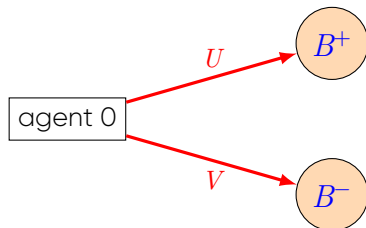
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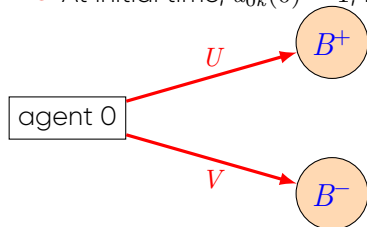
- $x_j = \sigma 1$ for $j \in B^\sigma$;
- the two blocks are of **same size**: $|B^+| = |B^-| = K \gg 1$
- the two blocks are **static complete graphs**:
 $\forall t \geq 0, a_{lm}(t) = 1$ for all $(l, m) \in (B^+)^2 \cup (B^-)^2$.
- Furthermore, the two blocks stay **totally disconnected one with the other**: $a_{ml} = a_{lm} = 0 \forall (l, m) \in B^+ \times B^-$.



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- Furthermore, the two blocks stay **totally disconnected one with the other**: $a_{ml} = a_{lm} = 0 \forall (l, m) \in B^+ \times B^-$.
- At initial time, $a_{0k}(0) = 1$, for all $k \in B^+ \cup B^-$.



$$U(t) := \sum_{k \in B^+} a_{0k}(t) \text{ and } \bar{U}(t) := \frac{1}{K} U(Kt)$$

$$V(t) := \sum_{k \in B^-} a_{0k}(t) \text{ and } \bar{V}(t) := \frac{1}{K} V(Kt).$$

the ODE approximation

Proposition 5.1 (long-term behaviour)

Let T be a finite horizon time. the system (\bar{U}, \bar{V}) can be approximated as follows:

$$d\bar{U}(t) = F_1(\bar{U}, \bar{V})dt + d\epsilon_u(t), \quad (7)$$

$$d\bar{V}(t) = F_2(\bar{U}, \bar{V})dt + d\epsilon_v(t), \quad (8)$$

with $F = (F_1, F_2) : [0, 1]^2 \rightarrow [0, 1]^2$ being the following vector field:

$$F_1(u, v) = \frac{u}{(u+v)^2} (\gamma(1-u)u\mathbb{1}_{(u<1)} - \beta v\mathbb{1}_{(u>0)}), \quad (9)$$

$$F_2(u, v) = \frac{v}{(u+v)^2} (\gamma(1-v)v\mathbb{1}_{(v<1)} - \beta u\mathbb{1}_{(v>0)}), \quad (10)$$

and where $(\epsilon_u, \epsilon_v) \rightarrow 0$ as $K \rightarrow \infty$ for an appropriate norm.

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two regimes

Proposition 5.2

For $\gamma > \beta$, a first equilibrium $p = (w^*, w^*)$ appears on the diagonal, with $w^* = 1 - \frac{\beta}{\gamma}$. Moreover, for $\gamma > 3\beta$, two extra (unstable) equilibria q_1, q_2 appear and p becomes stable.

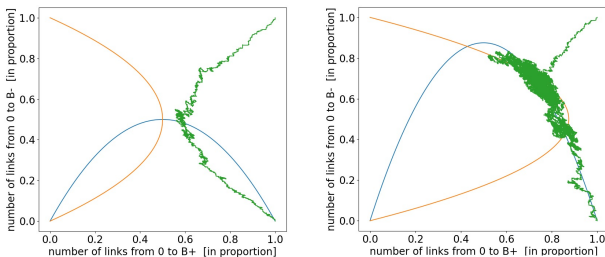


Figure 1: The green curve corresponds to the trajectory of $(\bar{U}, \bar{V}) \in [0, 1]^2$. For $\frac{\gamma}{\beta} = 3.1$, persistent hesitation occurs (right). On the contrary, agent 0 is quickly convinced when $\frac{\gamma}{\beta} = 2.9$ (left).

Open questions

- What kind of additional results can be obtained for the general local linkage $\Gamma = \Gamma_{loc}$?
- Does a limiting (deterministic) system exist ?

Section 6

Ongoing work



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Stochastic rates: edge-centric

- Free-global linkage: $\Gamma_{fglo}(lm; x, A) = \gamma(1 - a_{lm})$,
OR
- Global linkage: $\Gamma_{glob}(lm; x, A) = \gamma(1 - a_{lm}) \underbrace{\mathbb{1}_{(x_l=x_m)}}_{\text{Homophily}}$,
OR
- Local linkage: $\Gamma_{loc}(lm; x, A) := \gamma(1 - a_{lm}) \sum_j a_{lj} a_{jm} \underbrace{\mathbb{1}_{(x_l=x_m)}}_{\text{Homophily}}$
- Break: $B(lm; x, A) = \beta a_{lm} \underbrace{\mathbb{1}_{(x_l \neq x_m)}}_{\text{Sel. Exp.}}$
- flip: $\Phi(k; x, A) = \phi \sum_j a_{kj} \mathbb{1}_{(x_l \neq x_m)}$ (standard voter model scheme)

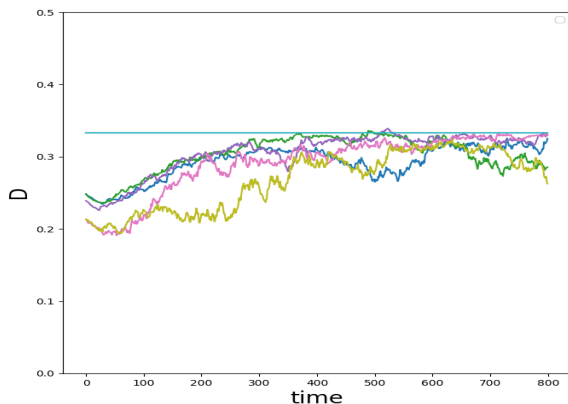
Definition 6.1 (discordance)

The total discordance $\mathcal{D}(x, a)$ of any configuration $(x, a) \in \mathcal{S}_K$ is defined as:

$$\mathcal{D}(x, a) := \frac{1}{K^2} \sum_{lm} a_{lm} \mathbb{1}_{(x_l \neq x_m)} = \frac{1}{K^2} (a_{C^+ C^-} + a_{C^- C^+}). \quad (11)$$

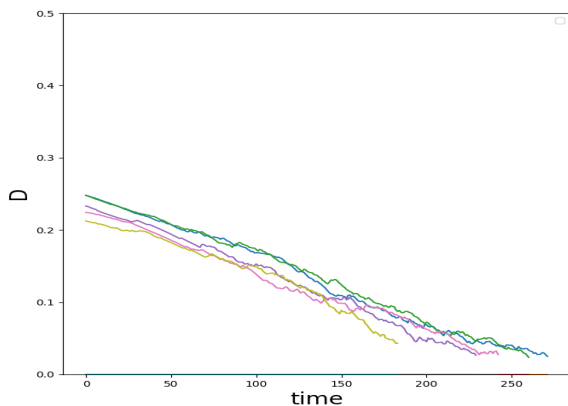
If $\mathcal{D}(x, a) = 0$, then we almost surely reach an AS (since the flip process stops).

Simulations



Five trajectories of the discordance with $K = 500$, $(\beta, \gamma) = (1, 4)$ and $\phi = 6$.

Simulations



Five trajectories of the discordance with $K = 500$, $(\beta, \gamma) = (1, 4)$ and $\phi = 1$.

Discussions and future works

- 1 External entities (advertisers, political campaigns etc.) controlling the opinions or graph dynamics
- 2 Consider non-VM OD models: continuous OD and a discrete graph dynamics: studied by Krause, Frasca etc..
So why not a continuous evolving graph?
- 3 Application of similar models to other frameworks like epidemics.

Questions?

Section 7

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