

# Opinion Diffusion as Aggregation

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[Based on joint work with Sirin Botan, Markus Brill, Edith Elkind, Ulle Endriss, Emiliano Lorini, Arianna Novaro and Laurent Perrussel]

Have you ever had an opinion?



What should  
we do with Putin?

Have you ever had an opinion?



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we do with Putin?



Relax Angela!  
Let's take a selfie first

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# Have you ever had an opinion?



Michelle Obama  
-1023-  
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Remember you are  
a Nobel laureate  
for peace



Attack  
then think



Leave the  
issue to the  
next president



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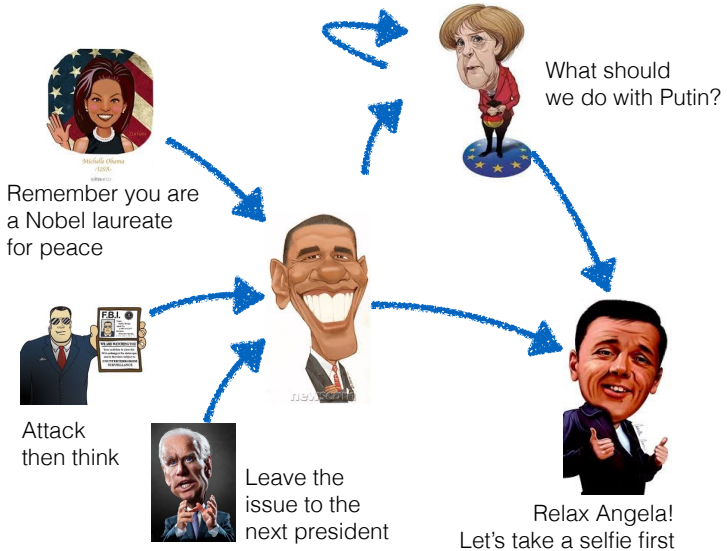


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# Have you ever had an opinion?



# Opinion diffusion in the literature

Established models in mathematical social sciences/social network analysis:

## 1. Discrete models

- First studies by Granovetter and Schelling (1978)
- Threshold models: 0/1 or yes/no opinions, updated if the **proportion of neighbours** with the opposite opinion raises above a certain threshold
- Voter models (Holley and Ligget, 1975, Clifford and Sudbury, 1973): a random individual **takes the opinion of a random neighbour**

## 2. Continuous models

- First studies by De Groot (1974) and Lehrer-Wagner (1981)
- Opinions in  $[0,1]$  on a weighted network. Individuals take the **weighted average** of the opinions of their neighbours
- First recent study involving **logical constraints** by Friedkin et al. (2016)

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Two critical features of this literature:

1. The representation of individual opinions is **too simple**
2. An obsession with reaching **consensus?**



## Opinion diffusion as aggregation

Opinions can be more complex than single 0/1 views or parameters in  $[0,1]$ :

- Vectors of binary views (Grandi et al. 2015)
- Preferences as linear orders over candidates (Brill et al. 2016)
- Belief bases as sets of propositional formulas (Schwind et al. 2015)

How are individuals updating on complex opinions?

A simple idea is to **look at the opinion of one's influencers** and:

- Uses aggregation rules from judgement aggregation (constraints!)
- Uses aggregation rules from preference aggregation (transitivity!)
- Uses belief merging techniques

# Outline

1. A quick summary of related work + diffusion as aggregation (done)
2. Some general but useful definitions
3. The simplest case: vectors of binary opinions
4. Preferences and pairwise updates
5. Let's give life to the network nodes!
6. Conclusions and perspectives

## The architecture of a discrete time iterated diffusion process - Part I

In virtually all settings there are common features:

- A finite set of **individuals**  $\mathcal{N} = \{1, \dots, n\}$
- A **network**  $E \subseteq \mathcal{N} \times \mathcal{N}$  (typically directed)
- Individual **opinions** (unspecified format for now) that we shall denote as  $B_i$

Some further notation:  $Inf(i) = \{j \mid (i, j) \in E\}$  is the set of influencers of individual  $i$  on  $E$ . Profile of opinions are  $\mathbf{B} = (B_1, \dots, B_n)$ .

### An aggregation function for individual opinion updates

*Each individual  $i \in \mathcal{N}$  is provided with a suitably defined  $F_i$  that merge a set of opinions into a single one. The updated opinion of  $i$  is  $F_i(B_i, \mathbf{B} \upharpoonright_{Inf(i)})$ .*

*Examples:  $F_i$  is the majority rule, a belief merging operator...*

## The architecture of a discrete time iterated diffusion process - Part II

### Opinion diffusion process

Let  $turn : \mathbb{N} \rightarrow 2^{\mathcal{N}}$  indicate at each point in time the set of agents updating.  
Let  $B_i^t$  be the opinion of agent  $i$  at time  $t \in \mathbb{N}$ , and:

$$B_i^{t+1} = \begin{cases} F_i(B_i, \mathbf{B}^t \upharpoonright_{Inf(i)}) & \text{if } i \in turn(t) \\ B_i^t & \text{otherwise.} \end{cases}$$

If  $turn(t) = \mathcal{N}$  the process is **synchronous**, if  $turn$  selects one individual (typically uniformly at random) the process is **asynchronous**.

Disclaimer: when opinions are complex - multi-issue or preferences - we will also specify at each point in time the issue on which the update is performed.

## Termination

Two forms of termination of the iterative process can be investigated:

### Asymptotic termination

*A diffusion model asymptotically terminates on a class of graphs  $\mathcal{E} \subseteq 2^{N^2}$  if for each graph  $E \in \mathcal{E}$  and for each initial profile of opinions  $\mathbf{B}^0$  we have*

$$\lim_{t \rightarrow +\infty} \mathbb{P}[\mathbf{B}^{t+1} \neq \mathbf{B}^t] = 0.$$

Typically applied to asynchronous models.

### Universal termination

*A diffusion model universally terminates on a class of graphs  $\mathcal{E}$  if there does not exist an infinite sequence of effective updates (ie. such that  $\mathbf{B}^{t+1} \neq \mathbf{B}^t$ ).*

Typically hard to guarantee.

## Convergence

Call a profile  $\mathbf{B}^t$  *stable* if  $F_i(\mathbf{B}^t) = B_i^t$  for all  $i$ , and a *termination profile* for  $\mathbf{B}^0$  any stable profile reachable from  $\mathbf{B}^0$ .

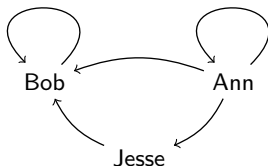
What happens when the process terminates?

- Diffusion **converges to unique profile** if termination profiles coincide
- Diffusion **converges to consensus** if termination profiles are unanimous
- Other notions are of course possible...

The simplest case:  
Multiple binary issues

## A known example revisited

An influence network between Ann, Bob and Jesse:



The three agents need to decide whether to approve the building of a swimming pool (first issue) and a tennis court (second issue) in the residence where they live. Here are their initial opinions and their evolution following **propositional opinion diffusion** with each agent **synchronously** using the majority rule:

Initial opinions	Profile $B^1$	Profile $B^2$
$B_A^0 = (0, 1)$	$B_A^1 = (0, 1)$	$B_A^2 = (0, 1)$
$B_B^0 = (0, 0)$	$B_B^1 = (0, 0)$	$B_B^2 = (0, 1)$
$B_J^0 = (1, 0)$	$B_J^1 = (0, 1)$	$B_J^2 = (0, 1)$



## General termination result

A directed-acyclic graph (DAG) with loops is a directed graph that does not contain cycles involving more than one node.

### Theorem

*If  $F_i$  satisfies ballot-monotonicity for all  $i$  (see paper), then synchronous POD converges on the class of DAG with loops in at most  $\text{diam}(E) + 1$  steps.*

*Proof.* Start from the sources and propagate opinions.

Observations:

- The proof is a **polynomial algorithm** to compute the termination profile
- The theorem is not easy to strengthen: take the example of a circle
- The theorem works for **any aggregator**  $F_i$ , even those that do not treat issues independently

## Summary of results

We show **polynomial algorithms** for the computing POD, and identify classes of graphs on which **termination is guaranteed** (only sufficient conditions):

Aggregation	Class of graphs	Time bound
Any aggregator	DAG with loops	$diam(E) \times Time(F)$
Unanimity rule	No loops, disjoint cycles, $ Inf(i)  > 1$ for one node	$O(n^2m)$
Majority rule	Disjoint cycles $ Inf(i) $ even on cycles	$O(n^2m)$

Where  $n = |\mathcal{N}|$  is the number of individuals,  $m = |E|$  the number of arcs.

## Follow-up work I

Many of the previous termination results are subsumed by the following paper:

Zoé Christoff and Davide Grossi. *Stability in Binary Opinion Diffusion*. Under submission.

Their result in a nutshell:

### Definition - Winning and veto coalitions

$C \subset \mathcal{N}$  is a **winning** coalition for  $p$  and  $F$  if  $C$  can force **acceptance** of  $p$  by accepting it unanimously.  $C \subset \mathcal{N}$  is a **veto** coalition for  $p$  and  $F$  if  $C$  can force **rejection** of  $p$  by rejecting it unanimously.

### Theorem

*Propositional opinion diffusion for independent and monotonic  $F$  terminates universally from profile  $\mathbf{B}$  if and only if a specific condition relating winning and veto coalitions of  $F$  with profile  $\mathbf{B}$  and network  $G$  holds.*

## Follow-up work II

What happens when issues are connected by an **integrity constraint** IC?  
To avoid discursive dilemmas we could restrict updates to subsets of issues.

### Definition - $F$ -consistency

*An opinion diffusion process is  $F$ -consistent if for all termination profiles  $\mathbf{B}$  and all agents  $i \in \mathcal{N}$ , if  $F(B_i, \mathbf{B} \upharpoonright_{\text{Inf}(i)}) \in \text{IC}$ , then  $B_i = F(B_i, \mathbf{B} \upharpoonright_{\text{Inf}(i)})$ .*

### Definition - Open structure

*IC has open structure if any two models of IC at Hamming distance  $k$  are connected by a sequence of at most  $k$  models at distance  $\leq 1$  from each other.*

### Theorem

*Propositionwise diffusion is  $F$ -consistent if and only if IC has open structure.*

Sirin Botan, Umberto Grandi and Laurent Perrussel. Propositionwise Opinion Diffusion with Constraints. In *Proceedings of EXPLORE-2017*, 2017.

## Follow-up work III

What if an external agent want to manipulate the diffusion process?

Asynchronous majoritarian diffusion on **undirected** graphs and one single issue:

- **Bribing individuals to change their opinions** to obtain at least  $k$  zeros (or ones) at optimistic termination is NP-complete,  $W[2]$ -hard on number of vertices to bribe,  $W[1]$ -hard on tree-width of  $G$ .
- **Removing edges** to obtain at least  $k$  zeros (or ones) at optimistic termination is NP-complete (+ same parametrised results as above).
- **Controlling the update sequence** to get a specific profile at termination is NP-complete and  $W[1]$ -hard in tree-width of  $G$ .

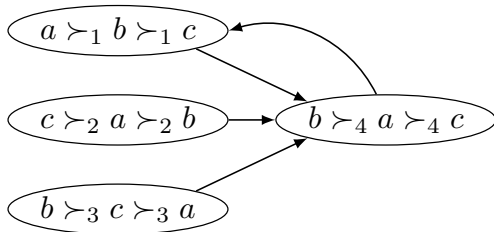
*Proofs.* Reductions to TARGET SET SELECTION.

Robert Brederick and Edith Elkind. Manipulating Opinion Diffusion in Social Networks. To appear in *Proceedings of IJCAI-2017*.

## Preferences as linear orders over a set of candidates

## The influence of a Condorcet cycle

An influence network with 4 agents and 3 alternatives. The preferences 1, 2, and 3 form a *Condorcet cycle*: the majority relation of their preferences is cyclic:



A possible branching of **asynchronous pairwise preference diffusion (PPD)**:

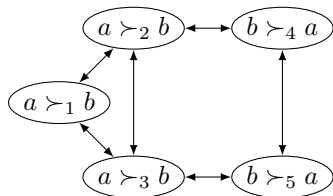
- agent 4 updates on  $ab$ , moving to  $a \succ_4 b \succ_4 c$
- no further updates possible:  $ac$  is no longer adjacent in  $\succ_4$

A possible branching of **synchronous PPD**:

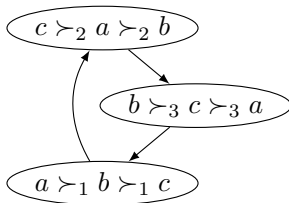
- agents 1 and 4 update repeatedly on pair  $ab$
- an infinite update sequence starts

## Convergence (or not) to consensus

A strongly connected network and a stable profile. PPD does not converge to consensus despite acyclic transitive majority:



A simple cycle influence network and a preference profile with a cyclic majority relation. PPD **converges to consensus**:





## One interesting result and two open problems

Formalising the argument that mutual influence leads to aligned profiles:

### Convergence to aligned profiles

*If the sources of a DAG are **aligned** (single-peaked, single-crossing, Sen's restriction) then under mild conditions **termination profiles are also aligned**.*

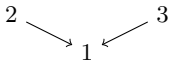
A number of problems are left open in pairwise opinion diffusion:

1. We show that asymptotic termination is **guaranteed on all graphs** (even cyclic ones) though under restrictive conditions (basically that **no Condorcet cycle** can ever occur). Can we relax this assumption?
2. We show that for less than three alternatives, a simple cycle can terminate on any linear order that does not conflict with a unanimous accepted pair in  $B^0$ . How about the case when  $|A| > 3$ ?

Let's give life to the network nodes!

## An example: things get more complicated

Take a very simple network:



$F_i$  is unanimity (change if all influencers agree). Consider two **action profiles**:

- $\mathbf{a}_0 = (\text{skip}, \text{skip}, \text{reveal}(p))$ : agent 3 reveals her opinion
- $\mathbf{a}_1 = (\text{skip}, \text{hide}(p), \text{skip})$ : agent 2 hides her opinion

Let a **state** be a profile of opinions (on one single issue  $p$  in this example), and a profile of **visibilities**. The two action profiles above generate a **history**:

$$\begin{array}{ccccc} ((0, 1, 1), (1, 1, 0)) & \xrightarrow{\mathbf{a}_0} & ((1, 1, 1), (1, 1, 1)) & \xrightarrow{\mathbf{a}_1} & ((1, 1, 1), (1, 0, 1)) \\ H_0 & & H_1 & & H_2 \end{array}$$

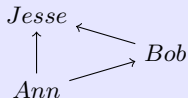
## Strategic disclosure of opinions on a social network

We define a simple notion of **influence games**:

- Individuals have private opinions on issues
- The actions at their disposal are  $\text{reveal}(p)$  and  $\text{hide}(p)$  for all issues  $p$
- Each agent is endowed with an **LTL goal**

### Example

*Ann, Bob and Jesse have opinions (1,0,0) on a single issue  $p$ :*



- *Ann's goal is  $\diamond \square \text{op}(\text{Jesse}, p)$*
- *Memory-less winning strategy: play  $\text{reveal}(p)$*

## Outline of results

It is very hard to **explore the existence of game-theoretic solution concepts** restricting the structure of the networks and/or the goals: only limited results.

If we want to **automate the search**, then we need (lower bounds):

- LTL for memory-less strategies (PSPACE)
- ATL for perfect-recall winning strategy existence (EXPTIME)
- Graded strategy logic for Nash equilibrium existence (2EXPTIME)

A final observation: influence games are an interesting generalisation of iterated boolean games where **propositional control is not exclusive!**

## Conclusions

To summarize:

- Opinion diffusion can be seen as **iterated aggregation** on a network
- The same idea can be applied to binary evaluations (eventually with constraints), preferences, or belief bases
- **Problems** to study: termination (asymptotic or universal), convergence (to consensus, to unanimity, to aligned profiles....)

**Lots of open problems** to be attacked. But (my) main interest is to go further:

### Strategic aspects of collective decisions on networks

*Recent papers showed that providing users with only local information (=looking at neighbouring nodes) generates processes that are resistant to a number of strategic actions by internal or external players (mostly on personalised recommender systems). How about voting rules?*

## References

This talk is based on the following papers:

Umberto Grandi, Emiliano Lorini and Laurent Perrussel. Propositional Opinion Diffusion. In *Proceedings of the 14th International Conference in Autonomous Agents and Multiagent Systems (AAMAS)*, 2015.

Markus Brill, Edith Elkind, Ulle Endriss, and Umberto Grandi. Pairwise Diffusion of Preference Rankings in Social Networks. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence (IJCAI)*, 2016.

Sirin Botan, Umberto Grandi and Laurent Perrussel. Propositionwise Opinion Diffusion with Constraints. In *Proceedings of the 4th AAMAS Workshop on Exploring Beyond the Worst Case in Computational Social Choice (EXPLORE)*, 2017.

Umberto Grandi, Emiliano Lorini, Arianna Novaro and Laurent Perrussel. Strategic Disclosure of Opinions on a Social Network. In *Proceedings of the 16th International Conference in Autonomous Agents and Multiagent Systems (AAMAS)*, 2017.