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Original
Asynchronous semi-anonymous dynamics over large-scale networks / Ravazzi, C., Como, G., Garetto, M., Leonardi, E., Tarable, A.. - In: SIAM JOURNAL ON APPLIED DYNAMICAL SYSTEMS. - ISSN 1536-0040. - ELETTRONICO. - 22:2(2023), pp. 1300-1343. [10.1137/22M1492155]

Availability:
This version is available at: 11583/2974463 since: 2023-06-26T11:11:59Z

Publisher:
SIAM

Published
DOI:10.1137/22M1492155

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26 November 2026

ASYNCHRONOUS SEMI-ANONYMOUS DYNAMICS OVER LARGE-SCALE NETWORKS

C. RAVAZZI*, G. COMO*†, M. GARETTO‡, E. LEONARDI*§, AND A. TARABLE*

Abstract. We analyze a class of stochastic processes, referred to as *asynchronous* and *semi-anonymous dynamics* (ASD), over directed labeled random networks. These processes are a natural tool to describe general best-response and noisy best-response dynamics in network games where each agent, at random times governed by independent Poisson clocks, can choose among a *finite set of actions*. The payoff is determined by the relative frequency of the different actions among neighbors, while being *independent of the specific identities of neighbors*.

Using a local mean-field approach, we prove rigorously that, under certain conditions on the network and initial node configuration, the evolution of ASD can be approximated, in the large-scale limit, by the solution of a system of non-linear ordinary differential equations. Our framework is very general and applies to a large class of graph ensembles for which the typical random graph is locally tree-like. In particular, we focus on labeled configuration-model random graphs, a generalization of the traditional configuration model which allows different classes of nodes to be mixed together in the network, permitting us, for example, to incorporate a community structure in the system. Our analysis also applies to configuration-model graphs having a power-law degree distribution, an essential feature of many real systems. To demonstrate the power and flexibility of our framework, we consider several examples of dynamics belonging to our class of stochastic processes. Moreover, we illustrate by simulation the applicability of our analysis to realistic scenarios by running our example dynamics over a real social network graph.

Key words. Asynchronous semi-anonymous dynamics, Networks games, Best-response dynamics, Evolutionary game theory, Linear threshold models, Local Weak Convergence.

AMS subject classifications. 68Q25, 68R10, 68U05

1. Introduction.

Many complex systems arising in different domains exhibit cascading phenomena that spread through networks of local interactions. Examples of such cascades include, but are not limited to, infrastructure failures [49], adoption of innovations, conventions and technologies [38, 45, 32], diffusion of beliefs, opinions, fake news [46], memes, and the like [48]. These phenomena can have profound effects on politics [15], social norms [4], financial networks [23], marketing campaigns [24].

The standard mathematical approach to modeling cascading processes is to consider a graph (finite or infinite) in which nodes stand for individuals that can be in one of several (discrete or continuous) states, and edges (directed or undirected, possibly weighted) represent interactions with neighboring nodes. Individuals are supposed to repeatedly update their state over (discrete or continuous) time, depending on the current state of their neighbors [43, 10, 19].

Simple epidemic models in which nodes can change their state as consequence of a single contact with a neighboring node [34] turn out to be too simplistic to describe systems in which individuals tend to react to the joint states of their neighbors. To represent such combined effect, one of the most commonly used models in the literature is the linear threshold model, originally introduced by Granovetter [23] and widely investigated in several variants [50, 17]. The general idea behind such models

*National Research Council of Italy (IEIIT-CNR), c/o Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Torino (Italy)

†Department of Mathematical Sciences "Giuseppe Luigi Lagrange", Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Torino (Italy)

‡Computer Science Department, University of Turin, Via Verdi 8, 10124 Torino, (Italy)

§Department of Electronics and Telecommunications (DET), Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Torino (Italy)

is to assume that a node adopts a given state if the fraction of neighbors (possibly weighted by edges) currently adopting that state exceeds a certain threshold. More in general, researchers have considered so-called networked coordinated games, in which nodes adopt the best-response (according to some payoff matrix) in reaction to the strategies adopted by neighbors [11].

Some fundamental distinctions in this wide class of models are the following. In progressive processes, state transitions are irreversible: once a node joins a given state, it keeps such state indefinitely, irrespective of what happens to neighbors [25, 13, 1, 30, 4]. In non-progressive processes transitions are, instead, reversible, since nodes still remain under the influence of their neighbors after the adoption of a given state [2, 33, 40]. Another crucial distinction concerns the update rule of the nodes: does the future state of a node also depend on the current state of the node, in addition to the states of neighbors, or is it uniquely determined by the neighbors? Indeed the above distinctions, combined to the nature of edges (i.e., directed or undirected), lead to models of widely different nature and analytical tractability.

In this paper we analyze a class of cascading processes, referred to as Asynchronous and Semi-anonymous Dynamics (ASD), with the following characteristics: i) nodes update their (discrete) state over continuous time, according to independent Poisson clocks, following an arbitrary rule that depends on the number (or relative fraction) of neighbors in each possible state, but not on the specific identities of neighbors (which are order-independent); ii) edges are directed; iii) state transitions are reversible (non-progressive model).

In this paper we extends previous work in [40], where authors analyze a two-state, deterministic linear threshold model with synchronous node update over a bounded degree graph, by adopting a mean-field approach. Here, we seek to understand how this approach can be pushed to its greatest generality, extending the class of networks and underlying node dynamics to which it can be rigorously applied. We mention, however, that in [40] authors consider also the progressive variant of their model, while here we focus only on the non-progressive model. The interested reader can refer to [20] for new methods to approximate the dynamics on large networks sampled from a graphon. Although this framework is flexible, it works well on dense network formation models, such as stochastic block models, but not on sparse networks.

One stream of related work [9, 33, 26] analyzes the possible equilibria of a binary-decision game in the case of undirected graphs and synchronous update. Similarly to these works, we study a game where players'payoffs depend on the actions taken by their neighbors in the network but not on the specific identities of these neighbors.

Another huge stream of related work is concerned with the algorithmic aspects of influence maximization [25, 31], where the goal is to find the initial node configuration that maximizes the final size of the cascade. In contrast to such stream of work, here we assume the initial node configuration to be randomly selected according to a given node statistics.

1.1. Overview of main results and paper outline. Our analysis relies on a rigorous proof of a local mean-field approximation result, as we show that the aggregate behavior of ASDs on a large class of locally tree-like random graph ensembles is close to the solution of a finite-dimensional (nonlinear) ODE. Specifically, our results show that the approximation error vanishes in the large-scale limit.

While our results apply over time horizons that remain constant or grow at most logarithmically with the network size, they do have implications to the behavior of the system in the stationary regime. In particular, when combined with, e.g., [7], our

results imply that the weak limit of every converging sequence of stationary probability distributions is an invariant distribution of the ODE. By Poincaré's Recurrence Theorem, the support of all such invariant measures is included in the closure of the recurrent set of the ODE. In particular, when the local mean-field ODE admits a globally attractive equilibrium point x^*, this implies that every sequence of stationary probability distributions for the ODE concentrates on x^* in the large-scale limit.

In Section 2 we formally introduce asynchronous semi-anonymous dynamical processes (ASD) over directed random graphs, presenting some concrete example of ASD. In Section 3 we provide the complete analysis of ASD over a labeled branching process, i.e., an infinite ensemble of labeled graphs with a rooted tree structure. In this case it can be shown that the evolution of the fraction of nodes in a given state indeed corresponds to the solution of some ordinary differential equations (Proposition 2).

In Section 4 we turn our attention to general graph ensembles. The core message is the following: if the graph exhibits a local tree structure, then the analysis on a suitably chosen labeled branching process provides a good approximation of the expected fraction of nodes in a given state (see Proposition 3). A property of Local Weak Convergence is the key feature that provides this link and formalizes the idea that, for large n, the local structure of the graph near a vertex chosen uniformly at random is approximately a branching process. Finally, the analysis of the concentration around the expectation allows us to derive the accuracy of the above approximation.

We will then focus in Section 5 on the labeled configuration-model, a general mix of heterogeneous nodes with class-specific node statistics. This family of graphs is generalization of the traditional configuration model (CM) and allows different classes of nodes to be mixed together in the network, permitting us, for example, to incorporate a community structure in the system. We will explore conditions for Local Weak Convergence (see Theorem 4) and the concentration of the ASD evolution around the expectation (see Theorem 5). In Section 5.3 we will show that the sequence of node degrees is allowed to follow a power-law distribution scaling with the network size. This is particularly important for applications to social network graphs. As a second example, in Section 5.4 we will consider a labeled configuration model with a community structure, which is another fundamental feature found in many real systems. Indeed, by considering as label of a node its membership to a given community, we can represent graphs with a general distribution of in/out degrees among nodes belonging to the same or different communities. This allows us to describe, for example, "assortative" graphs, in which intra-community edges are denser than inter-community edges.

In Section 6 we analytically derive some interesting properties of the ODEs describing the temporal evolution of the system for each of the examples of ASD introduced in Section 2. In particular, we present a detailed analysis on stability of the equilibrium points and discuss the link between the mean-field ODE and the stationary regime. Section 6 presents also numerical results of ASD previously introduced in large but finite networks, considering both synthetically generated graphs and real-world social networks. More precisely, we compare the solutions of the differential equations derived through mean field approximation with results obtained by running Monte-Carlo simulations.

Section 7 summarizes our contribution and collects some concluding remarks. Some of the more technical proofs can be found in Appendix.

1.2. General notation. Throughout this paper, we use the following notational conventions. Let $\mathbb{N}$, $\mathbb{Z}_+$, $\mathbb{R}$ be the set of natural, non-negative integers and real

numbers, respectively. Given $n \in \mathbb{N}$ we use the notation $[n] = \{1, \dots, n\}$.The symbol $|\cdot|$ denotes the absolute value if applied to a scalar value and the cardinality if applied to a set. We denote the indicator function of set A with the notation $\mathbf{1}_A$. Given a finite set $\mathcal{V}$, $\mathbb{R}^{\mathcal{V}}$ denotes the space of real vectors with components labelled by elements of $\mathcal{V}$. If $x \in \mathbb{R}^n$, we denote the ℓ-th entry by x_ℓ and $x_{[\ell]}$ is the projection of x on the sub-space generated by the first ℓ elements, i.e. $x_{[\ell]} = (x_1, x_2, \dots, x_\ell) \in \mathbb{R}^\ell$.

This paper makes frequent use of Landau symbols. The notation "$f(N) = O(g(N))$ when $N \to \infty$" means that positive constants c and N_0 exist, so that $f(N) \leq cg(N)$ for all $N > N_0$. The expression "$f(N) = o(g(N))$ when $N \to \infty$" means that $\lim_{N\to\infty} \frac{f(N)}{g(N)} = 0$.

A labeled directed multigraph is a 6-ple $(\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau)$, where $\mathcal{V}$, $\mathcal{E}$, and $\mathcal{A}$ are the sets of nodes, links, and labels, respectively, all finite; $\lambda : \mathcal{V} \to \mathcal{A}$ is the map giving the label $\lambda(v)$ of a node $v \in \mathcal{V}$; and $\sigma, \tau : \mathcal{E} \to \mathcal{V}$ are the maps giving the tail node $\sigma(e)$ and head node $\tau(e)$ of a link $e \in \mathcal{E}$ so that e is directed from $\sigma(e)$ to $\tau(e)$. The set of in-neighbors and out-neighbors of a node $v \in \mathcal{V}$ are defined as $\mathcal{N}_v^- = \{w \in \mathcal{V} \setminus \{v\} : (w, v) \in \mathcal{E}\}$ and $\mathcal{N}_v^+ = \{w \in \mathcal{V} \setminus \{v\} : (v, w) \in \mathcal{E}\}$, respectively, and the corresponding in-degree and out-degree as $d_v = |\mathcal{N}_v^-|$ and $k_v = |\mathcal{N}_v^+|$. We define its out-degree vector $\mathbf{k}_v \in \mathbb{Z}_+^{\mathcal{A}}$ as the vector whose component $a \in \mathcal{A}$ represents the number of out-neighbors of v belonging to class a. Similarly, we define for node v the in-degree vector $\mathbf{d}_v \in \mathbb{Z}_+^{\mathcal{A}}$.

A path from a vertex $u \in \mathcal{V}$ to a vertex $v \in \mathcal{V}$ (i.e. a path $u \to v$) is a finite sequence of edges $(u_i, v_i)_{1\leq i\leq L}$ with $u_1 = u$, $v_L = v$, $v_i = u_{i+1}$. If there is at least a path from u to v, we say that u is connected to v, and the graph distance from u to v is then defined as the minimum length of a path from u to v. If all (ordered) vertex pairs are connected, the graph $\mathcal{G}$ is said strongly connected. If, instead, for any pair (u, v) either a path $u \to v$ or $v \to u$ exists, we say that the graph is weakly connected. We define a simple path as a path along which all vertices are distinct. A directed tree is a weakly connected graph in which no more than one path exists between every pair of vertices (u, v).

2. Asynchronous semi-anonymous dynamics.

2.1. Mathematical model. Let us consider a finite population of n agents interacting in a connected network, which we map onto the nodes of a labeled directed multigraph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A}, \sigma, \tau, \lambda)$, whereby a link $e \in \mathcal{E}$ represents a direct influence of its head node $\tau(e)$ on its tail node $\sigma(e)$ and each class of nodes $\mathcal{V}_a = \{v \in \mathcal{V} : \lambda(v) = a\}$, for $a \in \mathcal{A}$ may have a different behavior, thus allowing to account for heterogeneity.

Let each agent $v \in \mathcal{V}$ be endowed with a time-varying state $Z_v(t)$ taking values from a finite set $\mathcal{X}$ for every $t \geq 0$. We shall denote the vector of all agents' states by $\mathbf{Z}(t) = (Z_v(t))_{v\in\mathcal{V}}$ and refer to it as the network configuration at time t. We shall consider general *asynchronous* and *semi-anonymous dynamics* (ASD) according to which every agent updates periodically its state in response to the current state of its out-neighbors. The map according to which the new state is selected can be either deterministic or stochastic. In all cases it must be invariant with respect to permutations of such out-neighbors (semi-anonymous). Update times for each user form a Poisson process at rate γ.

Formally, let $\boldsymbol{Z}(t)$ be a continuous-time Markov chain with finite state space equal to the set of configurations $\mathcal{Z} = \mathcal{X}^{\mathcal{V}}$ and the structure illustrated below.

DEFINITION 1 (Asynchronous semi-anonymous dynamics). *Let* $\mathcal{P} = \{\theta \in \mathbb{R}_+^{\mathcal{X}} :$

$\mathbf{1}'\theta = 1\}$ *be the simplex of probability vectors over* $\mathcal{X}$*. For every label* $a \in \mathcal{A}$*, let*

$$\Theta^{(a)} : \mathbb{Z}_+^{\mathcal{A}\times\mathcal{X}} \to \mathcal{P} \tag{1}$$

be a stochastic kernel. It represents the probability distribution of the updated state, for a class-a node, given the state and class profile of its out-neighbors. Also, for every node $v \in \mathcal{V}$*, let* $\Upsilon_v^{\mathcal{G}} : \mathcal{Z} \to \mathbb{Z}_+^{\mathcal{A}\times\mathcal{X}}$ *be formally defined by*

$$\big(\Upsilon_v^{\mathcal{G}}(\boldsymbol{z})\big)_{ax} = \big|\big\{e \in \mathcal{E} : \sigma(e) = v, \lambda(\tau(e)) = a, z_{\tau(e)} = x\big\}\big| \,, \quad a \in \mathcal{A},\, x \in \mathcal{X}\,.$$

In words, $\big(\Upsilon_v^{\mathcal{G}}(\boldsymbol{z})\big)_{ax}$ *is equal to the number of class-a out-neighbors of* v *that are in state* x*. Then,* $\boldsymbol{Z}(t)$ *evolves as a continuous-time Markov chain on* $\mathcal{Z}$ *with transition rates:*

$$\Lambda_{\boldsymbol{z},\boldsymbol{z}^+} = \begin{cases} \gamma\, \Theta_{z_v^+}^{(\lambda(v))}(\Upsilon_v^{\mathcal{G}}(\boldsymbol{z})) & \text{if} \quad \boldsymbol{z} \text{ and } \boldsymbol{z}^+ \text{ differ in the } v\text{-th entry only} \\ 0 & \text{otherwise} \end{cases}$$

where γ *denotes the Poisson rate at which node* v *updates its state.*

The formulation above in Definition 1 is very general. Some remarks are in order. Classes can describe heterogeneous nodes in a variety of ways. In our examples, we will consider the following three cases: i) classes describing different update rules of the nodes; ii) classes describing nodes with different degree distributions; iii) classes describing node membership to different 'communities'. In the most general scenario, a class might represent nodes belonging to a specific community, with a given update rule and a particular degree distribution.

We emphasize that the new state of an agent, when it gets updated, does not need to be a deterministic function of its neighborhood. Indeed, we explicitly allow for a stochastic rule of adopting a certain state. This allows us to model noisy or mixed-strategy best-response dynamics in networked games.

Our main interest in this paper is to track the evolution of some macroscopic features, e.g., the evolution of the fraction of nodes belonging to a specific class that are in a given state at time t. We will demonstrate that a mean-field approximation can yield insight into this analysis for a large class of random networks.

2.2. Examples of ASD dynamics. To clarify the general formulation introduced above, we provide two examples of ASD dynamics that will later be studied in more details Section 6. Since in our examples the node update rule depends only on the total number of neighbors in a given state, and not on their label, we simplify the general notation introduced before and define:

$$\xi_x(\boldsymbol{z}) = \sum_{a\in\mathcal{A}} \big(\Upsilon_v^{\mathcal{G}}(\boldsymbol{z})\big)_{ax} \,, \quad x \in \mathcal{X}\,. \tag{2}$$

The explicit dependence on the Markov-chain state $\boldsymbol{z}$ will be omitted in the following, whenever possible.

2.2.1. Ternary Linear Threshold Model (TLTM). Let $\mathcal{X} = \{-1, 0, 1\}$ be the set of admissible states and let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau)$ be a labeled multigraph. The label $a_v = (a_v^+, a_v^-)$ of node v determines two given (in general, asymmetric) thresholds a_v^+, a_v^-, which trigger the transition to state 1 and -1, respectively. Specifically, when activated, the update of node v is given by

$$Z_v(t) = \begin{cases} 1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) \geq a_v^+ \\ 0 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) \in (-a_v^-, a_v^+) \\ -1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) \leq -a_v^- \end{cases}$$

where $Z_v(t^-) = \lim_{x\uparrow t} Z_v(x)$. The above rule can be encoded in our general formulation by considering the functions:

$$\Theta_1^{(a)}(\xi_1,\xi_{-1},\xi_0) = \mathbf{1}_{\{\xi_1-\xi_{-1}\geq a^+\}},\ \Theta_0^{(a)}(\xi_1,\xi_{-1},\xi_0) = \mathbf{1}_{\{\xi_1-\xi_{-1}\in(-a^-,a^+)\}}$$
$$\Theta_{-1}^{(a)}(\xi_1,\xi_{-1},\xi_0) = \mathbf{1}_{\{\xi_1-\xi_{-1}\leq -a^-\}}$$

which depend only on the numbers ξ_1, ξ_{-1} and ξ_0 of out-neighbors in state 1, -1 and 0, respectively.

REMARK 1 (Applications of the threshold model). *Threshold Models have been widely employed to describing complex dynamics in a variety of systems pertaining to sociology (e.g., spread of ideas in online social networks [25]), economy (e.g., adoption of innovations [47], contagion in financial markets [4]), engineering (e.g., cascading failures in physical infrastructure networks [41]) and biology (e.g., neuronal firing [42]). For the sake of concreteness, in this paper we will primarily focus on applications of the threshold model to opinion dynamics in large social networks. Indeed, the relative popularity of an idea [6, 50] can drive a shift of individual opinions and this model is able to describe situations where individuals have two alternatives and the costs and/or benefits of each depend on how many other actors choose which alternative. The model is of particular interest since individual and small-scale interactions cumulate into larger-scale societal patterns. Here we propose a ternary extension of LTM, which may represents the competition between two opposite ideas.*

2.2.2. Binary Response with Coordinating and Anti-coordinating agents (BRCA). Inspired by the model in [36], we consider a network game where each agent can choose between two actions in $\mathcal{X} = \{-1, 1\}$. The network consists of two classes of nodes, i.e. $\mathcal{A} = \{+,-\}$ and $\mathcal{V} = \mathcal{V}_+ \cup \mathcal{V}_-$. We assume that $\mathcal{V}_+$ and $\mathcal{V}_-$ represent agents following the majority (i.e., coordinating) or the minority (i.e., anti-coordinating) of their out-neighbors, respectively.

Specifically, an agent is updated according to the following rule: if $v \in \mathcal{V}_+$ then

$$Z_v(t) = \begin{cases} 1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) > 0 \\ -1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) < 0 \\ \pm 1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) = 0 \end{cases},$$

and $\forall v \in \mathcal{V}_-$

$$Z_v(t) = \begin{cases} 1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) < 0 \\ -1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) > 0 \\ \pm 1 & \text{if } \sum_{j\in\mathcal{N}_v^+} Z_j(t^-) = 0. \end{cases}$$

In essence, when a node is updated, it counts the number of neighbors in state -1 and 1, and adopts the state of the majority of its neighbors if $v \in \mathcal{V}_+$, or it adopts the state of the minority of its neighbors if $v \in \mathcal{V}_-$. In the case of a tie, it chooses uniformly at random between states 1 and -1.

The above rule corresponds in our general framework to the functions

$$\Theta_1^{(+)}(\xi_1,\xi_{-1}) = \mathbf{1}_{\{\xi_1>\xi_{-1}\}} + \frac{1}{2}\mathbf{1}_{\{\xi_1=\xi_{-1}\}},\ \Theta_{-1}^{(+)}(\xi_1,\xi_{-1}) = 1 - \Theta_1^{(+)}(\xi_1,\xi_{-1})$$
$$\Theta_1^{(-)}(\xi_1,\xi_{-1}) = \mathbf{1}_{\{\xi_1<\xi_{-1}\}} + \frac{1}{2}\mathbf{1}_{\{\xi_1=\xi_{-1}\}},\ \Theta_{-1}^{(-)}(\xi_1,\xi_{-1}) = 1 - \Theta_1^{(-)}(\xi_1,\xi_{-1})$$

which depend only on the number ξ_1 and ξ_{-1} of neighboors in state 1 and -1, respectively. Note that the model in [36] was proposed to represent and analyze real-life situations where a decision between two antithetic actions must be taken by interacting individuals.

2.2.3. Other related examples. Other examples of successful applications of ASD are represented by the analysis of the behaviors of agents in a coordination game [39], fluctuations in stock or other financial data [44], spike patterns in neural networks [16], voter model and many others [12].

At last we wish to mention that ASDs include Glauber dynamics [22] as a special case. In Statistical Physics, Glauber dynamics on undirected graphs is generally used to simulate the Ising model and study ferromagnetism [28]. The model consists of discrete variables (± 1) representing the spin orientation, and the interactions are modeled by a graph. Neighboring spins with the same orientation have lower energy than those that disagree. Generalizations of the model to $q \geq 2$ different states are studied in the Potts model [35]. Recently Glauber dynamics on directed graphs have been proposed to model social phenomena [8].

3. ASD on the labeled branching process. In this section we consider a labeled branching process, i.e. a particular ensemble of infinite labeled directed graphs with rooted tree structure, and then analyze ASD on it. As already said, the reason why we introduce this special graph is that the analysis of ASD on it provides fundamental hints for the analysis of ASD on a general locally tree-like ensemble of graphs.

More precisely, we will consider a labeled branching process completely described by probabilities distributions $p_{\mathbf{k},a} = p_{\mathbf{k}|a} p_a$ and $q^b_{\mathbf{k}|a}$. The first is the joint probability distribution that characterizes the root, i.e. the probability that the root has label $a \in \mathcal{A}$ and out-degree vector $\mathbf{k} \in \mathbb{Z}_+^{\mathcal{A}}$. We recall that the component k_b represents the number of out-neighbors belonging to class $b \in \mathcal{A}$. The latter is the vectorial out-degree distribution for a non-root node with label a, whose parent has label b. In next sections we will show that probability distributions $p_{\mathbf{k},a}$ and $q^b_{\mathbf{k}|a}$ specifying the "approximating" labeled branching process, will be chosen so to exactly match statistics' of the network under investigation. For this reason, we inform the reader that the same notation will be adopted to denote statistics on both the network and the associated labelled branching process.

3.1. Labeled branching process. Recall that in our notation $\mathbf{k}_v \in \mathbb{Z}_+^{\mathcal{A}}$ denotes the out-degree vector of vertex v, whose component $a \in \mathcal{A}$ represents the number of out-neighbors of v belonging to class $a \in \mathcal{A}$.

We will call labeled branching process $\mathcal{T}$ with node set $\mathcal{V} = \{v_0, v_1, ...\}$ and label set $\mathcal{A}$ the rooted tree built through the following procedure:

- Step 0: Start with a root node v_0 and assign to it a random label $A_0 \in \mathcal{A}$ and a random out-degree vector $\mathbf{K}^{(0)} \in \mathbb{Z}_+^{\mathcal{A}}$ with joint probability distribution

$$\mathbb{P}(A_0 = a, \mathbf{K}^{(0)} = \mathbf{k}) = p_{\mathbf{k},a} \,.$$

  For every $a \in \mathcal{A}$, add $\mathbf{K}^{(0)}_a$ out-edges with label (A_0, a) to the root v_0 and declare all these edges active. Note that an edge label is defined as the ordered pair of the labels associated to adjacent nodes.

Then, for $h = 1, 2, \ldots$

- Step h: If there are no active edges, stop. Otherwise, take any active edge e, let (a, b) be its label and declare the edge inactive. Assign to edge e a

head node $\tau(e) = v_h$ with label $\lambda(v_h) = b$ and generate a random vector $\mathbf{K}^{(h)} = \mathbf{k}$ in $\mathbb{Z}_+^{\mathcal{A}}$ with conditional probability distribution $q^a_{\mathbf{k}|b}$, then for every label $c \in \mathcal{A}$ add $\mathbf{K}_c^{(h)}$ new active outgoing edges to v_h with label (b, c).

Note that that labeled branching process is fairly flexible and general. Indeed, several classes of nodes with possibly different network characteristics (such us out-degree distribution etc.) may coexist. Moreover children statistics of a node may depend on the class of node, this permits to represent structures with assortative/dissortative structure, which are commonly met in real-life applications.

3.2. Ordinary differential equations of ASD. Let us now consider the ASD process over the graph $\mathcal{T}$ built above. In the following matrix notation, vectors are meant to be column vectors, unless otherwise specified.

PROPOSITION 2. *Let $\boldsymbol{Z}(t)$, for $t \geq 0$, be the state vector of the ASD on $\mathcal{T}$. Then, for every fixed time $t \geq 0$, the following facts hold*

1. *For every $i \in \mathcal{V}$, the states $\{Z_{\tau(e)}(t) | \, e \in \mathcal{E} \, : \, \sigma(e) = i\}$ of the offsprings j of i in $\mathcal{T}$ are independent and identically distributed random variables with $\zeta_{\omega|a,b}(t) = \mathbb{P}(Z_j(t) = \omega \mid A_j = a, A_i = b)$, $\omega \in \mathcal{X}$, $a, b \in \mathcal{A}$ satisfying*

$$\frac{\mathrm{d}\zeta_{\omega|a,b}(t)}{\mathrm{d}t} = \gamma \left(\phi_{\omega|a,b}(\boldsymbol{\zeta}(t)) - \zeta_{\omega|a,b}(t) \right), \;\; \phi_{\omega|a,b}(\boldsymbol{\zeta}) = \sum_{\boldsymbol{k} \in \mathbb{Z}_+^{\mathcal{A}}} \varphi_\omega^{(\boldsymbol{k},a)}(\boldsymbol{\zeta}) q^b_{\boldsymbol{k}|a} \tag{3}$$

and

$$\varphi_\omega^{(\boldsymbol{k},a)}(\boldsymbol{\zeta}) = \sum_{\substack{\boldsymbol{\xi} \in \mathbb{Z}_+^{\mathcal{A} \times \mathcal{X}}: \\ \boldsymbol{\xi} \mathbf{1} = \boldsymbol{k}}} \Theta_\omega^{(a)}(\boldsymbol{\xi}) \binom{\boldsymbol{k}}{\boldsymbol{\xi}} \prod_{c \in \mathcal{A}} \prod_{g \in \mathcal{X}} [\zeta_{g|c,a}]^{\xi_{cg}}, \quad \binom{\boldsymbol{k}}{\boldsymbol{\xi}} = \prod_c \binom{k_c}{\boldsymbol{\xi}_c},$$

where $\boldsymbol{\xi}_c$ is the c-th row of matrix $\boldsymbol{\xi}$ and ξ_{cg} denotes the (c, g)-th element of matrix $\boldsymbol{\xi}$.

2. *The state $Z_{v_0}(t)$ of the root node v_0 is a random variable with $y_{\omega|a}(t) = \mathbb{P}(Z_{v_0} = \omega \mid A_0 = a)$ satisfying*

$$\frac{\mathrm{d}y_{\omega|a}(t)}{\mathrm{d}t} = \gamma \left(\psi_{\omega|a}(\boldsymbol{\zeta}(t)) - y_{\omega|a}(t) \right), \quad \psi_{\omega|a}(\boldsymbol{\zeta}) = \sum_{\boldsymbol{k} \in \mathbb{Z}_+^{\mathcal{A}}} \varphi_\omega^{(\boldsymbol{k},a)}(\boldsymbol{\zeta}) p_{\boldsymbol{k}|a} \tag{4}$$

Proof. 1. Let v_0 be the root of $\mathcal{T}$. Then, For every $i \in \mathcal{V}$, the states $Z_j(t) : (i, j) \in \mathcal{E}$ of the offsprings of v_i in $\mathcal{T}$ are independent and identically distributed Bernoulli random variables. Define $\zeta_{\omega|a,b}(t) = \mathbb{P}[Z_j(t) = \omega \mid A_j = a, A_i = b]$, $j \in \mathcal{V} \setminus \{v_0\}$, where v_i is the father of v_j, we have

$$\begin{aligned}
&\zeta_{\omega|a,b}(t + \Delta t) \\
&= (\gamma \Delta t + o(\Delta t)) \sum_{\mathbf{k} \in \mathbb{Z}_+^{\mathcal{A}}} \varphi_\omega^{(\mathbf{k},a)}(\boldsymbol{\zeta}(t)) q^b_{\mathbf{k}|a} + (1 - \gamma \Delta t + o(\Delta t)) \, \zeta_{\omega|a,b}(t) + o(\Delta t) \\
&= (\gamma \Delta t + o(\Delta t)) \, \phi_{\omega|a,b}(\boldsymbol{\zeta}(t)) + (1 - \gamma \Delta t + o(\Delta t)) \, \zeta_{\omega|a,b}(t),
\end{aligned}$$

from which we conclude

$$\frac{\mathrm{d}\zeta_{\omega|a,b}(t)}{\mathrm{d}t} = \lim_{\Delta t \to 0} \frac{\zeta_{\omega|a,b}(t + \Delta t) - \zeta_{\omega|a,b}(t)}{\Delta t} = \gamma(\phi_{\omega|a,b}(\boldsymbol{\zeta}(t)) - \zeta_{\omega|a,b}(t)). \quad \square$$

2. Define $y(t) = \mathbb{P}[Z_{v_0}(t) = \omega \mid A_0 = a]$, then with the same arguments we have

$$\frac{\mathrm{d}y_{\omega|a}}{\mathrm{d}t} = \gamma(\psi_{\omega|a}(\boldsymbol{\zeta}(t)) - y_{\omega|a}(t)), \quad \psi_{\omega|a}(\boldsymbol{\zeta}(t)) = \sum_{\mathbf{k}\in\mathbb{Z}_+^{\mathcal{A}}} \varphi_\omega^{(\mathbf{k},a)}(\boldsymbol{\zeta}(t)) p_{\mathbf{k}|a}.$$

REMARK 2. *Whenever labels of neighbor nodes are independent, $p_{\boldsymbol{k}|a}$ and $q^b_{\boldsymbol{k}|a}$ depend on a, b only through $k = \sum_i k_i$, and things become simpler. Indeed, if we define $\zeta_\omega(t) = \mathbb{P}[Z_j(t) = \omega] = \sum_{a,b\in\mathcal{A}} \zeta_{\omega|a,b}(t) p_a p_b$, then, it can be easily shown that, similarly to (3), we can derive an ODE for $\zeta_\omega(t)$ in the form*

$$\frac{\mathrm{d}\zeta_\omega(t)}{\mathrm{d}t} = \gamma\left(\phi_\omega(\boldsymbol{\zeta}(t)) - \zeta_\omega(t)\right), \tag{5}$$

where

$$\phi_\omega(\boldsymbol{\zeta}(t)) = \sum_{a,b\in\mathcal{A}} \sum_{k\in\mathbb{Z}_+} \varphi_\omega^{(k,a)}(\boldsymbol{\zeta}(t)) q_{k|a,b} p_a p_b, \quad q_{k|a,b} = \sum_{\substack{\boldsymbol{k}\in\mathbb{Z}_+^{\mathcal{A}}:\\ \boldsymbol{k}^T\mathbf{1}=k}} q^b_{\boldsymbol{k}|a},$$

and

$$\varphi_\omega^{(k,a)}(\boldsymbol{\zeta}(t)) = \sum_{\substack{\boldsymbol{\xi}\in\mathbb{Z}_+^{\mathcal{X}}:\\ \boldsymbol{\xi}^T\mathbf{1}=k}} \Theta_\omega^{(a)}(\boldsymbol{\xi}) \binom{k}{\boldsymbol{\xi}} \prod_{g\in\mathcal{X}} [\zeta_g(t)]^{\xi_g}.$$

Analogously, defining $y_\omega(t) = \mathbb{P}[Z_0(t) = \omega] = \sum_{a\in\mathcal{A}} y_{\omega|a}(t) p_a$, the ODE replacing (4) can be written as

$$\frac{\mathrm{d}y_\omega(t)}{\mathrm{d}t} = \gamma\left(\psi_\omega(\boldsymbol{\zeta}(t)) - y_\omega(t)\right), \tag{6}$$

where

$$\psi_\omega(\boldsymbol{\zeta}(t)) = \sum_{a\in\mathcal{A}} \sum_{k\in\mathbb{Z}_+} \varphi_\omega^{(k,a)}(\boldsymbol{\zeta}(t)) p_{k|a} p_a, \quad p_{k|a} = \sum_{\substack{\boldsymbol{k}\in\mathbb{Z}_+^{\mathcal{A}}:\\ \boldsymbol{k}^T\mathbf{1}=k}} p_{\boldsymbol{k}|a}.$$

REMARK 3. *The above analysis of ASD over the ensemble $\mathcal{T}$ can be easily extended to the case in which the rate of activation of a vertex depends on its label $a \in \mathcal{A}$. Without loss of generality we will assume $\gamma = 1$ in the following.*

REMARK 4. *Comparing the ODEs obtained in this paper with the finite difference equations derived in [40] for synchronous dynamics (analysis in [40] is restricted to the LTM dynamics), it can be rather immediately checked that the two dynamical systems exhibit the same set of equilibrium points. However synchronous dynamics may exhibit limiting cycles, which are not observed in the asynchronous case.*

4. ASD on labeled random networks. In this section we consider the evolution of ASD process over a multigraph $\mathcal{G}$ taken from a general ensemble of labeled directed graphs $\mathfrak{E}^{(n)}$ of size n. In particular, we show that, under certain conditions on the ensemble and on the initial node configuration, the ASD process over $\mathcal{G}$ can be well approximated by the same process over a labeled branching process $\mathcal{T}$. The ensemble $\mathfrak{E}^{(n)}$ is described by the 'node statistics' $p_{\mathbf{d},\mathbf{k},a,s}$, which provides the probability that a node picked at random has in-degree vector $\mathbf{d}$, out-degree vector

$\mathbf{k}$, label $a \in \mathcal{A}$ and initial state $s \in \mathcal{X}$. We shall assume that $p_{\mathbf{d},\mathbf{k},a,s}$ factorizes as $p_{\mathbf{d},\mathbf{k},a,s} = p_{\mathbf{d},\mathbf{k},a} p_{s|a}$. The above node statistics clearly provides all information needed to compute any marginal or conditional distribution we might be interested in. For example, $p_{\mathbf{d},\mathbf{k},a} = \sum_{s \in \mathcal{X}} p_{\mathbf{d},\mathbf{k},a,s}$ is the distribution of in-degree vector, out-degree vector and label of a generic node. As another example, $p_{\mathbf{k},a} = \sum_{\mathbf{d}} p_{\mathbf{d},\mathbf{k},a}$ provides the distribution of out-degree vector and label of a generic node. We denote $p_a = \sum_{\mathbf{k}} p_{\mathbf{k},a}$ the probability for a node to be associated with label a. With intuitive notation, $p_{\mathbf{k}|a} = p_{\mathbf{k},a}/p_a$ denotes the distribution of out-degree vector of a node with label a, and so on. Note that the ensemble of directed graphs $\mathfrak{C}^{(n)}$ is very general, since it includes (multi)-graphs in which properties of nodes may be arbitrarily correlated. In the following we will restrict our analysis to the sub-class of labeled configuration graphs.

As it always happens in graphs with heterogeneous degrees, we will need to distinguish the probability law of $\mathbf{k}_v$ for a generic node v picked uniformly at random, and the probability law of $\mathbf{k}_v$ for a node v reached by traversing an edge. This because, in general, we could have correlation between in-degree and out-degree. Moreover, when we reach a node by following a certain edge, it is also important to distinguish the label of the node originating the traversed edge picked uniformly at random. To account for the above generality, we need to introduce some additional notation. Specifically, we define $q^a_{\mathbf{d},\mathbf{k}|b} := d_a p_{\mathbf{d},\mathbf{k},b} / \sum_{\mathbf{d},\mathbf{k}} d_a p_{\mathbf{d},\mathbf{k},b}$, which is the distribution of in-degree vector $\mathbf{d}$ and out-degree vector $\mathbf{k}$ of a node with label b, reached by traversing an edge from a node with label a. Similarly, $q^a_{\mathbf{k}|b} = \sum_{\mathbf{d}} q^a_{\mathbf{d},\mathbf{k}|b}$ is the marginal distribution of out-degree vector of a node with label b, reached by traversing an edge from a node with label a.

4.1. Relevant neighborhood at time t. We first observe that, since the process evolves through local interactions, the state of a generic node v on a multigraph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau)$ at time t is determined only by the structure and state of a relatively small neighborhood around v. Given a generic node $v \in \mathcal{V}$, we define the *relevant neighborhood* $\mathcal{N}_t$ of v as the subgraph induced by the set of all nodes in $\mathcal{V}$ having an impact on $Z_v(t)$, i.e., on the state of v at time t. Similarly, we define the *relevant neighborhood* $\mathcal{T}_t$ as the subtree induced by the set of all nodes in $\mathcal{T}$ having an impact on $Z_{v_0}(t)$, where v_0 is the root node of $\mathcal{T}$.

The relevant neighborhood can be built by looking backward in time, identifying dependencies between neighboring nodes. First, observe that the state of v at time t depends on its out-neighbors v' (one-hop away nodes) if and only if v has updated its state in $[0, t]$ at least once, i.e., we can find an update time of v, $\vartheta_v(t) \leq t$. The state of node v depends on a two-hop away node v'', if and only if we can find a common neighbor v' of v and v'', such that $\vartheta_{v'}(t) < \vartheta_v(t) \leq t$. Similarly the state of v depends on a three-hops away node v''' only if we can find two nodes v' and v'' along a directed path from v to v''' such that $\vartheta_{v''}(t) < \vartheta_{v'}(t) < \vartheta_v(t) \leq t$, and so on.

Due to the fact that update times of each node form independent Poisson processes with rate $\gamma = 1$, we can exploit well-known properties of the Poisson process (time-reversibility, memoryless property) to obtain $\mathcal{N}_t$ (or $\mathcal{T}_t$) as the result of a process evolving forward in time, and exploring progressively the neighborhood of v by adding an exponentially distributed delay (of mean 1) on each explored node, up to time t.

More precisely, the relevant neighborhood of v is obtained by the following process. Vertices can be active, neutral or inactive. Initially, the relevant neighborhood is empty.

1. The process starts by activating node v at time $t = 0$. All of the other nodes

are set neutral.
2. Upon the activation of a node, a random timer is associated to it, taken from an exponential distribution of mean $\gamma = 1$. Moreover, the node is added to the relevant neighborhood, together with the outgoing edges.
3. Upon expiration of its associated timer: i) an active node is set inactive; ii) all of its neutral out-neighbors are set active and added to the relevant neighborhood, together with outgoing edges.

For $t \geq 0$, we can stop the above exploration process at time t (i.e., we no longer add nodes to the relevant neighborhood after time t), obtaining a truncated version $\mathcal{N}_t$ of $\mathcal{G}$, composed of all the nodes that have been activated. Similarly, we obtain a truncated version $\mathcal{T}_t$ of $\mathcal{T}$.

4.2. Approximation result. Let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau)$ be a multigraph sampled from a given labeled network ensemble $\mathfrak{E}^{(n)}$ of size n. For $t \geq 0$, let $\mathcal{N}_t$ be the relevant neighborhood at time t of a node v chosen uniformly at random from $\mathcal{V}$, and let $\mu_{\mathcal{N}_t}$ be its distribution on the multigraph space. Let $\mathcal{T}_t$ be a labeled branching process as defined in Sec. 3.1, truncated at time t, and let $\mu_{\mathcal{T}_t}$ be its distribution.

Proposition 3 identifies some sufficient conditions to guarantee that the ASD process over a network is well approximated by the solution of the differential equation in (4).

PROPOSITION 3. *For $t \geq 0$, let $Z(t)$ be the state vector of the ASD at time t on $\mathcal{G}$. Let $z_\omega(t) = \frac{1}{n}|\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ be the fraction of state-ω adopters at time t, and $\overline{z}_\omega(t) = \mathbb{E}[z_\omega(t)]$ be its expectation over the ensemble. For any $\epsilon > 0$,*

$$\mathbb{P}(|z_\omega(t) - y_\omega(t)| \geq \epsilon) \leq \mathbb{P}(|z_\omega(t) - \overline{z}_\omega(t)| \geq \epsilon - \|\mu_{\mathcal{N}_t} - \mu_{\mathcal{T}_t}\|_{\mathrm{TV}})$$

where $y_\omega(t)$ is the solution of (4).

Proof. Notice that

$$\mathbb{P}(|z_\omega(t) - y_\omega(t)| \geq \epsilon) \leq \mathbb{P}(|z_\omega(t) - \overline{z}_\omega(t)| + |\overline{z}_\omega(t) - y_\omega(t)| \geq \epsilon) \tag{7}$$

We prove now that $|\overline{z}_\omega(t) - y_\omega(t)| \leq \|\mu_{\mathcal{N}_t} - \mu_{\mathcal{T}_t}\|_{\mathrm{TV}}$ from which we get the result.

Observe that, by definition, the state $Z_v(t)$ of node v depends exclusively on the initial states $Z_j(0) = \sigma_j$ of the agents belonging to the relevant neighborhood $\mathcal{N}_t$ of node v at time t, i.e., $\mathbb{P}(Z_v(t) = \omega) = \chi_\omega(\mathcal{N}_t)$ where χ_ω is a function in the range [0,1]. We thus have

$$\overline{z}_\omega(t) = \mathbb{E}[z_\omega(t)] = \frac{1}{n}\sum_{v \in \mathcal{V}} \mathbb{P}(Z_v(t) = \omega) = \int \chi_\omega(g) \mathrm{d}\mu_{\mathcal{N}_t}(g).$$

On the other hand, considering the state of the root in the labeled branching process $\mathcal{T}$, the output of the ODE (4) satisfies

$$y_\omega(t) = \int \chi_\omega(g) \mathrm{d}\mu_{\mathcal{T}_t}(g).$$

It then follows

$$\begin{aligned}
|\overline{z}_\omega(t) - y_\omega(t)| &\leq \left| \int \chi_\omega(g) \mathrm{d}\mu_{\mathcal{N}_t}(g) - \int \chi_\omega(g) \mathrm{d}\mu_{\mathcal{T}_t}(g) \right| \\
&\leq \left| \int \left(\chi_\omega(g) - \frac{1}{2}\right) \mathrm{d}\mu_{\mathcal{N}_t}(g) - \int \left(\chi_\omega(g) - \frac{1}{2}\right) \mathrm{d}\mu_{\mathcal{T}_t}(g) \right| \\
&\leq \|\mu_{\mathcal{N}_t} - \mu_{\mathcal{T}_t}\|_{\mathrm{TV}}.
\end{aligned}$$

∎

From Proposition 3 we deduce that the evolution of the ASD process is well approximated by the solution of the differential equation in (4) for graph ensembles enjoying the following two fundamental properties:

(a) Topological Property: Local Weak Convergence is required, in the sense that $\|\mu_{\mathcal{N}_t} - \mu_{\mathcal{T}_t}\|_{\mathrm{TV}}$ can be made arbitrarily small by increasing the graph size.
(b) Concentration Property: for large graph size, the fraction of state-ω adopters in the ASD process must concentrate around its expectation with probability close to one.

5. ASD over labeled configuration model. Considering the ensable $\mathfrak{E}^{(n)}$ of all labeled networks with given size n and statistics $p_{\mathbf{d},\mathbf{k},a,s}$, we define the corresponding *labeled configuration model* ensamble $\mathfrak{C}_{n,p}$, on which we will restrict our investigation in the rest of the paper. In particular, we provide general bounds for ASD evolution over $\mathfrak{C}_{n,p}$.

Next we consider two specific examples of labeled configuration model, which we believe are particularly interesting, and apply to them the general bounds above, showing asymptotic convergence to the ODE solution as the network size grows large.

5.1. Labeled configuration model. We first explicitly describe the construction of the labeled configuration model $\mathfrak{C}_{n,p}$. For each $v \in \mathcal{V}$, denote with $\boldsymbol{\kappa}_v = (\kappa_v^a)_{a\in\mathcal{A}}$ and $\boldsymbol{\delta}_v = (\delta_v^a)_{a\in\mathcal{A}}$ the out-degree and in-degree vectors, respectively, such that there is exactly a fraction $p_{\mathbf{d},\mathbf{k},a}$ of nodes $v \in \mathcal{V}$ with $(\boldsymbol{\delta}_v, \boldsymbol{\kappa}_v, a_v) = (\mathbf{d}, \mathbf{k}, a)$. Denote with $\mathcal{L}_{a,a'}$ a set of stubs, and define arbitrary maps $\nu_{a,a'}, \gamma_{a,a'} : \mathcal{L}_{a,a'} \to \mathcal{V}$, satisfying the property: $|\nu_{a,a'}^{-1}(v)| = \delta_v^a$ for nodes v with label $\lambda(v) = a'$ and $|\gamma_{a,a'}^{-1}(v)| = \kappa_v^{a'}$ with $\lambda(v) = a$. For all $a, a' \in \mathcal{A}$, let $\pi_{a,a'}$ be chosen uniformly at random among all permutations of $\mathcal{L}_{a,a'}$ and define multigraph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau)$ with set of nodes $\mathcal{V}$ and $\mathcal{E} = \bigcup_{(a,a')\in\mathcal{A}\times\mathcal{A}} \mathcal{E}_{a,a'}$, where $\mathcal{E}_{a,a'} = (\gamma_{a,a'}(h), \nu_{a,a'}(\pi_{a,a'}(h)) : h \in \mathcal{L}_{a,a'}$, and $\sigma(\gamma_{a,a'}(h), \nu_{a,a'}(\pi_{a,a'}(h))) = \gamma_{a,a'}(h)$ and $\tau(\gamma_{a,a'}(h), \nu_{a,a'}(\pi_{a,a'}(h))) = \nu_{a,a'}(\pi_{a,a'}(h))$.

Denote with $l_{a,a'} = |\mathcal{L}_{a,a'}|$ the total number of edges incoming to nodes with label a', originating from nodes with label a, so that:

$$l_{a,a'} = n \sum_{\mathbf{d},\mathbf{k}} d_a p_{\mathbf{d},\mathbf{k},a'} = n \sum_{\mathbf{d},\mathbf{k}} k_{a'} p_{\mathbf{d},\mathbf{k},a}$$

The total number of edges in the graph is $l = \sum_{a,a'} l_{a,a'}$. The average in-degree of a node, which is equal to the average out-degree, will be denoted by $\bar{d} = l/n$.

We repeat for readers' ease the expression of the fraction of nodes with label a', reached from a node with label a, having in-degree vector $\mathbf{d}$ and out-degree vector $\mathbf{k}$:

$$q^a_{\mathbf{d},\mathbf{k}|a'} = \frac{d_a p_{\mathbf{d},\mathbf{k},a'}}{\sum_{\mathbf{d},\mathbf{k}} d_a p_{\mathbf{d},\mathbf{k},a'}} \tag{8}$$

We emphasize that the graph ensemble defined above extends the classical configuration model, which can be recovered as a particular case by setting $|\mathcal{A}| = 1$. It is fairly general, because, as it will be shown in the following, it permits us to represent graphs with arbitrary degree distributions, and in particular power law/scale free graphs, which are commonly met in most of the applications, as well as social graphs with a community structure.

5.2. Bounds to ASD dynamics. In order to apply the general approximation result stated in Proposition 3 to the labeled configuration model defined above, we need to prove both Local Weak Convergence and Concentration Property of ASD. The following theorems actually provide the main results of our paper:

- Theorem 4 is a topological result and is related exclusively to the properties of the labeled configuration model. More precisely, it provides a useful bound on the total variation distance between the relevant neighborhood of a graph drawn uniformly at random from the labeled configuration model ensemble and the labeled branching process described in Section 3. The proof is rather technical and the interested reader can find the details in Appendix A.1.
- Theorem 5 is related to the ASD evolution and to the specific properties of the labeled configuration model. It provides a bound on the distance between the fraction of state-ω adopters and its expectation. The proof can be found in Appendix A.2.

Let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau)$ be a multigraph sampled from the ensemble $\mathfrak{C}_{n,p}$. For $t \geq 0$, let $\mathcal{N}_t$ be the relevant neighborhood at time t of a node v chosen uniformly at random from $\mathcal{V}$, and let $\mu_{\mathcal{N}_t}$ be its distribution. Let $\mathcal{T}_t$ be the labeled branching process truncated at time t and let $\mu_{\mathcal{T}_t}$ be its distribution. Moreover, let $W_t^{b,a}$ be the number of edges in $\mathcal{T}_t$ from nodes with label $b \in \mathcal{A}$ to nodes with label $a \in \mathcal{A}$ and let $\mathsf{F}_{W_t^{b,a}}(x_{b,a}) = \mathbb{P}(W_t^{b,a} > x_{b,a})$.

THEOREM 4 (Topological Property). *We have*

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq \mathbb{P}(\mathcal{T}_t \neq \mathcal{N}_t) \leq \inf_{\boldsymbol{x} \in (\mathbb{R}^+)^{\mathcal{A}\times\mathcal{A}}} \sum_{a,b\in\mathcal{A}} \Bigg[\mathsf{F}_{W_t^{b,a}}(x_{b,a}) + \frac{x_{b,a}(x_{b,a}+1)}{2} \frac{\sum_{\boldsymbol{d},\boldsymbol{k}} d_b q^b_{\boldsymbol{d},\boldsymbol{k}|a}}{l_{b,a}} + \sum_{b' \neq b} x_{b,a} x_{b',a} \frac{\sum_{\boldsymbol{d},\boldsymbol{k}} d_b q^{b'}_{\boldsymbol{d},\boldsymbol{k}|a}}{l_{b,a}} \Bigg] \tag{9}$$

EXAMPLE 1 (Topological Property for the classical configuration model). *If $|\mathcal{A}| = 1$ then the model ensemble $\mathfrak{C}_{n,p}$ boils down to the classical configuration model and the bound derived in (9) reduces to*

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq \mathbb{P}(\mathcal{T}_t \neq \mathcal{N}_t) \leq \inf_{x>0} \left[\mathsf{F}_{\widetilde{W}_t}(x) + \frac{\sum_{d,k} d q_{d,k} x(x+1)}{2n\overline{d}} \right] \tag{10}$$

where $\widetilde{W}_t$ is the number of nodes in $\mathcal{T}_t$ and $\mathsf{F}_{\widetilde{W}_t}(x) = \mathbb{P}(\widetilde{W}_t > x)$.

We next introduce the concentration result that allows us to estimate to what extent the fraction of state-ω adopters in the ASD process concentrates around its expectation.

THEOREM 5 (Concentration Property). *Let $\mathcal{G}$ be a multigraph sampled from the ensemble $\mathfrak{C}_{n,p}$. We denote with $\mathcal{N}_t^v$ the relevant neighborhood at time t of a node v, sampled with a probability proportional to its in-degree, and with V_t^v the number of nodes in it. For $t \geq 0$, let $Z(t)$ be the state vector of the ASD dynamics on $\mathcal{G}$, $b(t) = |\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ be the number of state-ω adopters at time t conditioned to $\mathcal{G}$. For any $\epsilon > 0, \eta > 0, x > 0, s \geq 1$ we have*

$$\begin{aligned}
&\mathbb{P}(|b(t) - \mathbb{E}[b(t)]| > \eta n) \\
&\quad \leq 4\mathrm{e}^{-\frac{\eta^2 n}{1152(1+\epsilon)tx^2}} + \left(1 + \frac{12}{\eta}\right)(1+\epsilon)tn \frac{2^s \mathbb{E}_v\left[|V_t^v|^s\right]}{x^s} + 2\mathrm{e}^{-\frac{nt\epsilon^2}{2(1+\epsilon)}} + 2\mathrm{e}^{-\frac{\eta^2 n}{288(t+\eta/12)}} \\
&\quad + \left(1 + \frac{4}{\eta}\right) \frac{2^s}{x^s} \sum_{w\in\mathcal{V}} |\boldsymbol{\delta}_w| [\mathbb{E}[|V_t^w|^s] + 2\mathrm{e}^{-\frac{\eta^2 n}{128\overline{d}x^2}}
\end{aligned}$$

REMARK 5. *We emphasize that the bounds presented in Theorem 4 and Theorem 5 represent an important step forward with respect to results already known in literature. In particular, Lemma 5 and Proposition 2 in [40] states a similar result for a different, simplified version of our system dynamics.In contrast to [40], we introduce a much more general result along three different directions:*

1. *We consider asynchronous dynamics (each node is updated by an independent Poisson clock). Hence the neighborhood exploration process in the proof has to take into account this new source of randomness. Specifically, the estimation of the total variation (9) is split into two terms, which are obtained by conditioning on the number of nodes in $\mathcal{T}_t$. The necessity of this refined analysis will be clear in the next section.*
2. *We consider arbitrary semi-anonymous dynamics, with possible random (noisy) response to the state of neighbors. Moreover, we define our dynamics on a much more general ensemble of labelled random graphs, which allows us to differentiate the distribution of incoming/outgoing edges for each pair of classes.*
3. *We allow the maximum in- and out-degree of nodes to possibly scale with n (under some technical constraints). This is crucial for applications to social networks and many other complex systems in which the degree distribution has often been observed to follow a power law. But notice that even in the case of the classic Erdös-Rényi random graph $G(n,p)$, $d_{\max}$ or $k_{\max}$ of course are not independent of n. Note that, in the case of finite $d_{\max}, k_{\max}$, by taking $x = k_{\max}^t$ our bound in (10) leads to*

$$\|\mu_{\mathcal{N}_t} - \mu_{\mathcal{T}_t}\|_{TV} \leq \frac{d_{\max} k_{\max}(k_{\max}^t + 1)}{2n\bar{d}}.$$

recovering the result in [40] (Lemma 5).

In the next section, we show how the bounds derived above for Local Weak Convergence and concentration property can be used to study asymptotic behavior of ASD on a labeled configuration model with power-law degree distribution. More precisely, we will consider a sequence of labeled graphs with size n and described by distributions $p^{(n)}_{\mathbf{k}|a}, q^{(n)}_{\mathbf{k}|a}$ such that $p^{(n)}_{\mathbf{k}|a} \overset{n\to\infty}{\longrightarrow} p_{\mathbf{k}|a}$, $q^{(n)}_{\mathbf{k}|a} \overset{n\to\infty}{\longrightarrow} q_{\mathbf{k}|a}$. Then we will consider the labeled branching process obtained by the construction above with asymptotic distributions. The following proposition quantifies the distance between the solution corresponding to the differential equation with distribution $p^{(n)}_{\mathbf{k}|a}, q^{(n)}_{\mathbf{k}|a}$ and the solution corresponding to the differential equation with asymptotic distribution $p_{\mathbf{k}|a}, q_{\mathbf{k}|a}$.

PROPOSITION 6. *Let*

- $\boldsymbol{\zeta}^{(n)}(t)$ *be the solution of* (3) *with* $q^{(n)}_{\boldsymbol{k}|a}$ *and initial condition* $\boldsymbol{\zeta}^{(n)}_0$*;*
- $\boldsymbol{\zeta}(t)$ *be the solution of* (3) *with* $q_{\boldsymbol{k}|a}$ *and initial condition* $\boldsymbol{\zeta}_0$*.*
- $\boldsymbol{y}^{(n)}(t)$ *be the solution of* (3) *with* $p^{(n)}_{\boldsymbol{k}|a}$ *and initial condition* $\boldsymbol{y}^{(n)}_0$*;*
- $\boldsymbol{y}(t)$ *be the solution of* (3) *with* $p_{\boldsymbol{k}|a}$ *and initial condition* $\boldsymbol{y}_0$*.*

In addition let $\boldsymbol{\phi}(\boldsymbol{z}) - \boldsymbol{z}$ and $\boldsymbol{\psi}(\boldsymbol{z})$ be Lipschitz continuous in $[0,1]^{|\mathcal{A}|}$, and let L and $M > 0$ be the Lipschitz constants corresponding to infinity norm. Then for any $\Delta < 1/L$ we have

$$\sup_{t\in[0,m\Delta]} \|\boldsymbol{\zeta}^{(n)}(t) - \boldsymbol{\zeta}(t)\|_\infty \leq \frac{\|\boldsymbol{\zeta}^{(n)}_0 - \boldsymbol{\zeta}_0\|_\infty}{(1-\Delta L)^m} + \frac{1}{L}\left(\frac{1}{(1-\Delta L)^m} - 1\right)\|q^{(n)}_{\boldsymbol{k}|a} - q_{\boldsymbol{k}|a}\|_{\mathrm{TV}}$$

$$\sup_{t\in[0,m\Delta]} \|\boldsymbol{y}^{(n)}(t)-\boldsymbol{y}(t)\|_\infty \le \frac{\|\boldsymbol{y}_0^{(n)}-\boldsymbol{y}_0\|_\infty}{(1-\Delta)^m}+$$
$$+\left(\frac{1}{(1-\Delta)^m}-1\right)\left[M\sup_{t\in[0,m\Delta]}\|\boldsymbol{\zeta}^{(n)}(t)-\boldsymbol{\zeta}(t)\|_\infty+\|p^{(n)}_{\boldsymbol{k}|a}-p_{\boldsymbol{k}|a}\|_{\mathrm{TV}}\right].$$

The proof is straightforward and is omitted for brevity. In particular, if $p^{(n)}_{\mathbf{k}|a}$ is a truncated version of $p_{\mathbf{k}|a}$, we can apply to the previous bound the following statement of immediate verification:

PROPOSITION 7. *Consider a generic distribution $p_{\boldsymbol{k}|a}$ and its truncated version $p^{(n)}_{\boldsymbol{k}|a}$, i.e. $p^{(n)}_{\boldsymbol{k}|a}=\frac{p_{\boldsymbol{k}|a}\mathbf{1}_{\boldsymbol{k}\in\mathcal{B}_n}}{\sum_{\boldsymbol{k}\in\mathcal{B}_n}p_{\boldsymbol{k}|a}}$ for a generic compact set $\mathcal{B}_n\in\mathbb{N}^{|\mathcal{A}|}$, then we have: $\|p^{(n)}_{\boldsymbol{k}|a}-p_{\boldsymbol{k}|a}\|_{\mathrm{TV}}=1-\sum_{\boldsymbol{k}\in\mathcal{B}_n}p_{\boldsymbol{k}|a}$.*

5.3. Asymptotic behavior on labeled configuration model with power-law degree distribution. In this section we consider the classical configuration model with a *truncated power-law degree distribution*, which is a particular case of labeled configuration model with $|\mathcal{A}|=1$. We simplify the notation: let $p^{(n)}_{d,k}$ be the fraction of nodes with in-degree d and out-degree k, where we have highlighted the number of nodes n, and let $\overline{d}=\sum_{d,k}dp^{(n)}_{d,k}$ be the average degree.

ASSUMPTION 1. *Let us assume that $\sum_{d,k}dq^{(n)}_{d,k}=\Theta(n^\delta)$ with $0\le\delta<1/2$. This means that we allow the average in-degree of a node, reached by an edge selected uniformly at random, to possibly scale with n. Moreover, we will assume that $q^{(n)}_k=O(k^{-\beta})$ follows a power-law of exponent $\beta>2$ and maximum value $k_{\max}=\Theta(n^\zeta)$ with $\zeta<\min\{(1-\delta)/2,1/(\beta-1)\}$.*

Let μ_s be the s-th moment of $q=\{q^{(n)}_k\}_{k\ge0}$. From Assumption 1 we have

$$\mu_s=\begin{cases}\Theta(1) & \text{if } \beta>s+1\\ \Theta(n^{\zeta(s+1-\beta)}) & \text{if } 2<\beta<s+1.\end{cases} \tag{11}$$

Notice that, being $\beta>2$, μ_1 is always finite and, therefore, does not scale with n.

In order to guarantee that the ASD over a network drawn uniformly at random from the configuration model ensemble is well approximated by the solution of ODE, it is sufficient that the terms in the upper bounds derived in (10) (see Example 1), in Theorem 5, and in Proposition 6 go to zero when $n\to\infty$. In the following, let $\mathcal{N}^{(n)}=(\mathcal{V}^{(n)},\mathcal{E}^{(n)})$ be a sequence of networks, each one sampled from the corresponding model ensemble $\mathfrak{C}_{n,p^{(n)}}$, where $\{p^{(n)}\}_n$ is a sequence of truncated versions of a power law distribution of p satisfying Assumption 1. For $t\ge0$, let $\mathcal{N}^{(n)}_t$ be the relevant neighborhood of a node v chosen uniformly at random from the node set $\mathcal{V}^{(n)}$. Moreover, let $\mathcal{T}^{(n)}_t$ be the sequence of truncated Galton-Watson (GW) processes (see [18]) for which the root offspring follows distribution $p^{(n)}$, while the degree of non-root nodes follow law $q^{(n)}$. Finally, let $p^{(n)}\overset{n\to\infty}{\to}p$ and $q^{(n)}\overset{n\to\infty}{\to}q$.

Before presenting the topological result for the configuration model with power-law degree distribution, we present two technical results, whose proofs are given in Appendix B.

LEMMA 8 (Bound on the number of nodes/edges in $\mathcal{T}_t$). *Consider the GW process $\mathcal{T}$ in which the offspring distribution of the root follows law p, while the*

degree of remaining nodes follows law q. Let $\mathcal{T}_t$ be the corresponding random tree obtained by truncating $\mathcal{T}$ at time t, and $\widetilde{W}_t$ be the number of nodes in $\mathcal{T}_t$. Let $h_n = c\log n$ for some $c > 0$ and $t = o(h_n)$ as $n \to \infty$, then for any $s > 0$ we have $\mathsf{F}_{\widetilde{W}_t}(x_n) \leq \mathbb{E}[N_{h_n}^s]/x_n^s + o(1/n)$ for $n \to \infty$ where $\{N_h\}_{h\in\mathbb{N}}$ is the number of nodes in a truncated version of $\mathcal{T}$ with maximal width h.

LEMMA 9. *Let $\{N_h\}_{h\geq 0}$ be a supercritical GW process, in which the offspring distribution of the root follows law p, while the degree of remaining nodes follows law q. We have: $\mathbb{E}[N_h^s] = O(\mu_s \cdot \mu_1^{s(h-1)})$, $\forall \beta > 1$, where μ_j is the j-th moment of q.*

THEOREM 10 (Topological result for configuration model with power-law degree distribution). *With the above definitions, let $\mu_{\mathcal{N}_t^{(n)}}$ and $\mu_{\mathcal{T}_t^{(n)}}$ be the distributions of $\mathcal{N}_t^{(n)}$ and $\mathcal{T}_t^{(n)}$, respectively. Under Assumption 1, for $t = o(\log n)$, we have $\|\mu_{\mathcal{T}_t^{(n)}} - \mu_{\mathcal{N}_t^{(n)}}\|_{\mathrm{TV}} \leq \mathbb{P}(\mathcal{T}_t \neq \mathcal{N}_t) = o(1)$ when $n \to \infty$.*

Proof. From inequality (10), we have

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq \mathbb{P}(\mathcal{T}_t \neq \mathcal{N}_t) \leq \inf_{x>0}\left[\mathsf{F}_{\widetilde{W}_t}(x) + \frac{\sum_{d,k} dq_{d,k}x(x+1)}{2n\overline{d}}\right] \tag{12}$$

where $\widetilde{W}_t$ is the number of nodes in $\mathcal{T}_t$. Let $x_n = n^{(1-\delta)/2-\gamma}$ for some $\gamma > 0$ and $h_n = c\log n$ for some $c > 0$ then

$$\begin{aligned}\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} &\leq \frac{\sum_d dq_{d,k}x_n(x_n+1)}{2n\overline{d}} + \mathsf{F}_{\widetilde{W}_t}(x_n)\\ &\leq \frac{\sum_d dq_{d,k}x_n(x_n+1)}{2n\overline{d}} + \frac{\mathbb{E}[N_{h_n}^s]}{x_n^s} + o(1/n)\end{aligned}$$

where the last inequality holds for any $s > 1$ and $\{N_h\}_{h\in\mathbb{N}}$ is (the number of nodes of) a truncated GW process of maximal width h, in which the offspring distribution of the root follows law p, while the degree of remaining nodes follow law q (see Lemma 8). Under Assumption 1 we prove that there exists s such that $\frac{\mathbb{E}[N_{h_n}^s]}{x_n^s} = o(1/n)$ as $n \to \infty$ and we conclude that for some $\gamma > 0$

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq \frac{1}{2\overline{d}n^{2\gamma}} + o(1/n) = o(1) \qquad n \to \infty.$$

To find a suitable value of s, we distinguish two cases.

(i) If $\beta > \lfloor\frac{2}{1-\delta}\rfloor + 2$ we can simply choose $s = \lfloor\frac{2}{1-\delta}\rfloor + 1$. By so doing, we stay in the case $\beta > s+1$, and from (11) and Lemma 9 we get: $\mathbb{E}[N_{h_n}^s] = \Theta(n^{cs\log\mu_1})$ and

$$\frac{\mathbb{E}[N_{h_n}^s]}{x_n^s} = \Theta(n^{-s\left(\frac{1-\delta}{2}-\gamma-c\log\mu_1\right)}) = o(1/n) \qquad n \to \infty$$

(ii) If $\beta \leq \lfloor\frac{2}{1-\delta}\rfloor + 2$, we choose instead a sufficiently large value of s, falling in the case $s > \beta - 1$ in which μ_s scales with n as in (11). In particular, from Lemma 9 we have $\mathbb{E}[N_{h_n}^s] = \Theta(n^{\zeta(s+1-\beta)+cs\log\mu_1})$. Thus

$$\mathbb{E}[N_{h_n}^s]/x_n^s = \Theta\left(n^{\zeta(s+1-\beta)+cs\log\mu_1 - s\left(\frac{1-\delta}{2}-\gamma\right)}\right).$$

We now observe that if there exists $s \in \mathbb{N}$ such that

$$s\left(\frac{1-\delta}{2} - \zeta - c\log\mu_1 - \gamma\right) > 1 - \zeta(\beta-1) \tag{13}$$

then $\mathbb{E}[N^s_{h_n}]/x^s_n = o(1/n)$ for $n \to \infty$. Since $\zeta < 1/(\beta-1)$, the right hand side in (13) is positive, and since $\zeta < \min\{\frac{1-\delta}{2}\}$, we can always find two sufficiently small constants γ and c such that $\left(\frac{1-\delta}{2} - \zeta - c\log\mu_1 - \gamma\right)$ is also positive. Therefore, there exists an integer s large enough such that both $s > \beta - 1$ and (13) are satisfied. ∎

COROLLARY 11. *For $t \geq 0$, let $\boldsymbol{Z}(t)$ be the state vector of the ASD dynamics on $\mathcal{N}^{(n)}$ and $z^{(n)}_\omega(t) = \frac{1}{n}|\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ be the fraction of state-ω adopters at time t. Under Assumptions 1 for $t = o(\log n)$, for any $\eta > 0$ $\mathbb{P}(|z^{(n)}_\omega(t) - y_\omega(t)| > \eta) = o(1)$for $n \to \infty$, where $y_\omega(t)$ is the solution of (4) over a GW tree $\mathcal{T}_t$ with the asymptotic degree statistics p and q.*

Proof. Let $\mathcal{T}^{(n)}_t$ be the continuous-time branching process truncated up to time t, $\mu_{\mathcal{T}^{(n)}_t}$ be its distribution. Denote by $\boldsymbol{y}^{(n)}(t)$ the solution of (4) with $p^{(n)}_{\mathbf{k}|a}$ and initial condition $\boldsymbol{y}^{(n)}_0$. We have

$$\mathbb{P}(|z^{(n)}_\omega(t) - y_\omega(t)| \geq \eta) \leq \mathbb{P}(|z^{(n)}_\omega(t) - y^{(n)}_\omega(t)| \geq \eta/2) + \mathbb{P}(|y^{(n)}_\omega(t) - y_\omega(t)| \geq \eta/2)$$

From Theorem 10 we obtain that if $t = o(\log n)$ as $n \to \infty$ we have $\|\mu_{\mathcal{T}^{(n)}_t} - \mu_{\mathcal{N}^{(n)}_t}\|_{\mathrm{TV}} = o(1)$ when $n \to \infty$. We conclude that for any $\eta > 0$ there exists a sufficiently large n_0 such that, if $n \geq n_0$, then $\|\mu_{\mathcal{N}^{(n)}_t} - \mu_{\mathcal{T}^{(n)}_t}\|_{\mathrm{TV}} \leq \mathbb{P}(\mathcal{T}_t \neq \mathcal{N}_t) \leq \eta$. Using Proposition 3, it follows that for any $\eta > 0$ and large enough n:

$$\mathbb{P}(|z^{(n)}_\omega(t) - y_\omega(t)| \geq \eta) \leq \mathbb{P}(|z^{(n)}_\omega(t) - \overline{z}^{(n)}_\omega(t)| \geq \eta/4) + \mathbb{P}(|y^{(n)}_\omega(t) - y_\omega(t)| \geq \eta/2)$$

From Theorem 5, by choosing $x = n^{4/9}$, $s = 3$, and $\epsilon > 0$, we get

$$\mathbb{P}(|z^{(n)}_\omega(t) - y_\omega(t)| \geq \eta) \leq \mathbb{P}(|y^{(n)}_\omega(t) - y_\omega(t)| \geq \eta/2) + o(1)$$

where, we have applying jointly Corollary 25 and Corollary 27 in Appendix B to bound the third moment of V^v_t. Finally Propositions 6 and 7 guarantee that $|y^{(n)}_\omega(t) - y_\omega(t)| \to 0$ and $\mathbb{P}(|y^{(n)}_\omega(t) - y_\omega(t)| \geq \eta/2) = 0$ for large enough n. ∎

5.4. Asymptotic behavior on Configuration Block Model. In this section, we apply the bounds derived for Local Weak Convergence and Concentration Property in Section 4 to study the asymptotic ASD on a labeled configuration model with community structure, which is a key feature of many real systems. In particular, we consider a Configuration Block Model (CBM) with K communities of sizes $\{n_i\}_{i=1}^K$, which are mapped into corresponding classes with labels $\{a_i\}_{i=1}^K$.

When the maximum in/out degree of nodes is finite both Local Weak Convergence and Concentration property can be easily proven by taking the simple worst-case in which all nodes have in/out degree equal to the maximum in/out degree, so we will consider here a more challenging case, where in/out degree of nodes is allowed to scale with n.

However, to simplify the analysis, we assume no correlation between in-degree and out-degree of a node. As a consequence, the law of p is the same as the law of q, and $\zeta_{\omega|a,a'}(t) = y_{\omega|a}(t)$ (see Proposition 2).

Moreover, we assume that the number of edges established from a node of community i towards nodes of community j is independent for any pair (i,j), including the special case $i = j$, i.e., intra-community edges. Therefore, $p_{\mathbf{d},\mathbf{k}|a}$ factorizes into:

$$p_{\mathbf{d},\mathbf{k}|a} = \prod_{i\in\mathcal{A}} p^{\mathtt{in}}_{i,a}[d_i] \prod_{j\in\mathcal{A}} p^{\mathtt{out}}_{a,j}[k_j]$$

We will require that in/out degree sequences of the nodes, although possibly dependent on the network size n, generate empirical distributions $p^{\mathtt{in}}_{i,a}[d]$ and $p^{\mathtt{out}}_{a,j}[k]$ with a light tail, for any pair (i,a) or (a,j), thus having finite moments of any order.

In order to guarantee that the ASD over a network drawn uniformly at random from the CBM ensemble is well approximated by the solution of the ODE, it is sufficient that the terms in the upper bound derived in (9) and in Theorem 5 go to zero when $n \to \infty$. In the following, let $\mathcal{N}^{(n)} = (\mathcal{V}^{(n)}, \mathcal{E}^{(n)})$ be a sequence of networks, each one sampled from the corresponding CBM ensemble $G^{(n)} = G(\{n_i\}_{i=1}^K, p^{(n)}_{\mathbf{d},\mathbf{k},a})$, and, for $t \geq 0$, let $\mathcal{N}^{(n)}_t$ be the relevant neighborhood of a node v chosen uniformly at random from the node set $\mathcal{V}^{(n)}$. Moreover, let $\mathcal{T}^{(n)}_t$ be the sequence of GW processes with offspring distribution following law $p^{(n)}$. Finally, let $p^{(n)} \overset{n\to\infty}{\to} p$.

THEOREM 12. *Under above definitions and assumptions on the CBM ensemble, let $\mu_{\mathcal{N}^{(n)}_t}$ and $\mu_{\mathcal{T}^{(n)}_t}$ be the distributions of $\mathcal{N}^{(n)}_t$ and $\mathcal{T}^{(n)}_t$, respectively. For $t = o(\log n)$, we have $\|\mu_{\mathcal{T}^{(n)}_t} - \mu_{\mathcal{N}^{(n)}_t}\|_{\mathrm{TV}} = o(1)$ when $n \to \infty$.*

Proof. First observe that the number of edges $W^{b,a}_t$ in $\mathcal{T}_t$ between any pair of classes (a,b) con be upper bounded by the total number of edges in $\mathcal{T}_t$, which itself can be bounded by the total number of nodes in $\mathcal{T}_t$.

Recall that the number of edges between a node of community a and nodes of community j conforms to the empirical distribution $p^{\mathtt{out}}_{a,j}[k]$.

Let $P^{\mathtt{out}}_{a,j}$ be the cumulant of $p^{\mathtt{out}}_{a,j}$, and define $P^{\mathtt{out}}_*[k] = \min_{a,j} P^{\mathtt{out}}_{a,j}[k]$. Then, let $p^{\mathtt{out}}_*[k]$ be the distribution whose cumulant is $P^{\mathtt{out}}_*[k]$.

The outgoing degree of a generic node is then stochastically dominated by a r.v. distributed as $p^{\mathtt{out}}_*$ which has, by construction, all finite moments. Indeed note that, since all $p^{\mathtt{out}}_{a,j}$ have, by assumption, an exponential tail, $p^{\mathtt{out}}_*$ has an exponential tail as well. Therefore, we can bound the number of edges in $\mathcal{T}_t$ with those in a truncated GW tree $\overline{\mathcal{T}}_t$ in which the outgoing degree distribution of nodes is $p^{\mathtt{out}}_*$.

Then, setting $x_{b,a} = x_n = n^{\frac{1}{2}-\gamma}$, for any $(a,b) \in \mathcal{A} \times \mathcal{A}$, from (9) and Lemma 8 we have, for any $s > 1$:

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq S\,\frac{x_n(x_n+1)}{2n\bar{d}} + |\mathcal{A}|^2\frac{\mathbb{E}[\overline{N}^s_{h_n}]}{x^s_n} + o(1/n) \quad n \to \infty \tag{14}$$

where $\overline{N}^s_{h_n}$ is the number of nodes in a truncated GW process of maximum depth h_n, in which the offspring distribution of every node is $p^{\mathtt{out}}_*$. Moreover, we have introduced $S = \sum_{a,b\in\mathcal{A}}\sum_d d\, p^{\mathtt{in}}_{a,b}[d]$ which is by assumption a finite constant since the number of classes is finite and the average number of edges going into a node of class b from nodes of class a is finite.

Now we can apply Corollary 28 to bound $\mathbb{E}[\overline{N}^s_{h_n}]$, since all moments of $p^{\mathtt{out}}_*$ are finite.

In particular, from Corollary 28 we have $\mathbb{E}[\overline{N}^s_{h_n}] = \Theta(n^{cs\log\mu_1})$, therefore:

$$\frac{\mathbb{E}[\overline{N}^s_{h_n}]}{x^s_n} = \Theta(n^{-s\left(\frac{1}{2}-\gamma-c\log\mu_1\right)}) = o(1/n) \qquad n \to \infty$$

and we can conclude

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq \frac{|\mathcal{A}|^2 S}{2\bar{d}n^{2\gamma}} + o(1/n) = o(1) \qquad n \to \infty.$$

COROLLARY 13. *Under above definitions and assumptions on the CBM ensemble, for $t \geq 0$, let $\boldsymbol{Z}(t)$ be the state vector of the ASD dynamics on $\mathcal{N}^{(n)}$ and $z_\omega^{(n)}(t) = \frac{1}{n}|\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ be the fraction of state-ω adopters at time t. For $t = o(\log n)$ and any $\eta > 0$: $\mathbb{P}(|z_\omega^{(n)}(t) - y_\omega(t)| > \eta) = o(1)$ for $n \to \infty$, where $y_\omega(t)$ is the solution of (4) over a GW tree $\mathcal{T}_t$ with the asymptotic degree statistics p and q.*

The proof follows exactly the same lines of Corollary 11.

6. The missing link between the mean-field ODE and the stationary regime. Our main result implies that the weak limit of every converging sequence of stationary probability distributions of ASDs on a large class of locally tree-like random graph converges, when the size of networks tends to infinity, to a deterministic limit which is the solution of a nonlinear ODE. This convergence is guaranteed over finite time horizons or for time windows that scale logarithmically with the size of the network. However, some form of convergence of the stationary regimes can be guaranteed, by combining the approximation derived in 4.2 with results in [7]. In particular, if the deterministic process has a unique limit point $y^\star$ and the sequence of invariant probabilities is tight, then the sequence of invariant probabilities will converge to the Dirac mass at $y^\star$.

In this section we consider regular random graphs, where all nodes have the same out-degree, and we analytically derive some interesting properties of the ODEs describing the temporal evolution of the system (see Proposition 2), for each of the three examples of ASD introduced in Section 2.2. In particular, we can characterize the equilibrium points of the system and their stability.

6.1. Ternary Linear Threshold Model (TLTM).

6.1.1. Mean field analysis. We assume that all agents have the same out-degree k and symmetric thresholds, i.e., $k_v = k$ and $a_v^\pm = r$ for all $v \in \mathcal{V}$. In this case, there is a single class $a = r$ for which $p_{k|r} = q_{k|r} = 1$, and

$$\begin{aligned}
\Theta_1^{(r)}(\xi_1, \xi_{-1}, k - \xi_1 - \xi_{-1}) &= \mathbf{1}_{\{\xi_1 - \xi_{-1} \geq r\}} \\
\Theta_0^{(r)}(\xi_1, \xi_{-1}, k - \xi_1 - \xi_{-1}) &= \mathbf{1}_{\{\xi_1 - \xi_{-1} \in (-r, r)\}} \\
\Theta_{-1}^{(r)}(\xi_1, \xi_{-1}, k - \xi_1 - \xi_{-1}) &= \mathbf{1}_{\{\xi_1 - \xi_{-1} \leq -r\}}
\end{aligned}$$

From Proposition 2 we have that, given an initial distribution $(y_1(0), y_{-1}(0))$, the dynamics over the continuous-time branching process is described by

$$\begin{cases} \frac{\mathrm{d}y_1}{\mathrm{d}t} = \phi_+^{(k,r)}(y_1(t), y_{-1}(t)) - y_1(t), \\ \frac{\mathrm{d}y_{-1}}{\mathrm{d}t} = \phi_-^{(k,r)}(y_1(t), y_{-1}(t)) - y_{-1}(t), \end{cases} \tag{15}$$

and $y_0 = 1 - y_1 - y_{-1}$, where

$$\phi_+^{(k,r)}(x, z) = \sum_{v=0}^{\lfloor \frac{k-r}{2} \rfloor} \sum_{u=v+r}^{k-v} \binom{k}{u} \binom{k-u}{v} x^u z^v (1 - x - z)^{k-u-v} \tag{16}$$

and $\phi_-^{(k,r)}(x, z) = \phi_+^{(k,r)}(z, x)$.

Some analytical properties of the dynamical system can be deduced from the analysis of $\phi_+^{(k,r)}(x, z)$ and $\phi_-^{(k,r)}(x, z)$. In particular, we are interested in finding stationary points, and analysing their stability properties. Before presenting the main result we give some preliminary lemmas.

LEMMA 14. *Let $\phi_+^{(k,r)}(x,z)$ be as defined in (16). Then*

1. *$\phi_+^{(k,r)}(x,z)$ is non decreasing in x and strictly increasing if $0 < r \leq k$;*
2. *$\phi_+^{(k,r)}(x,z)$ is non increasing in z and strictly decreasing if $0 \leq r < k$;*
3. *$\phi_+^{(k,r)}(0,z) = 0$ for $0 < r \leq k$, $\phi_+^{(k,0)}(x,0) = 1$, $\phi_+^{(k,r)}(1,0) = 1$, for $0 \leq r \leq k$;*
4. *$\nabla_x \phi_+^{(k,r)} = \sum_{v=0}^{\lfloor \frac{k-r}{2} \rfloor} \chi(v+r-1,v) x^{v+r-1} z^v (1-x-z)^{k-2v-r}$ with $\chi(u,v) = \binom{k}{u}\binom{k-u}{v}(k-u-v)$*
5. *$\nabla_z \phi_+^{(k,r)} = -\sum_{u=r}^{k} \chi(u,v') x^u z^{v'} (1-x-z)^{k-u-v'-1}$ with $v' = (k-u) \wedge (u-r)$.*

The proof is trivial and we omit it for brevity.

PROPOSITION 15. *If $2 \leq r < k$, then*

1. *the equation $\phi_+^{(k,r)}(x,0) = x$ has three solutions $\{0, x^\star, 1\}$ with $x^\star \in (0,1)$;*
2. *for every $x \in (x^\star, \bar{x})$ with $0 < x^\star < \bar{x} \leq 1$ there exists a unique value $z(x)$ such that $\phi_+^{(k,r)}(x, z(x)) = x$.*
3. *the equation $\phi_-^{(k,r)}(0,z) = z$ has exactly three solutions $\{0, z^\star, 1\}$ with $z^\star \in (0,1)$;*
4. *for every $z \in (z^\star, \bar{z})$ with $0 < z^\star < \bar{z} \leq 1$, there exists a unique value $x(z)$ such that $\phi_-^{(k,r)}(x(z), z) = z$.*

Proof. If $2 \leq r < k$, the function $\phi_+^{(k,r)}(x,0)$ has a lazy-S-shaped graph, i.e., it is increasing, with a unique inflection point at $\widetilde{x} = (r-1)/(k-1)$, it is convex on the left-hand side of $\widetilde{x}$ and concave on the right-hand side of $\widetilde{x}$ (see Lemma 4 in [40]). From this fact and the observation that $\phi_+^{(k,r)}(0,0) = 0$ and $\phi_+^{(k,r)}(1,0) = 1$ we get the assertion at Point 1. It can also be proved that $x^\star \in [(r-1)/k, r/k]$. Denoting $F(x,z) = \phi_+^{(k,r)}(x,z) - x$ and observing that $F(x^\star, 0) = \phi_+^{(k,r)}(x^\star, 0) - x^\star = 0$ and $\nabla_z F(x^\star, 0) \neq 0$ (see expression in Point 14 of Lemma 14), the statement in Point 2. is obtained by the implicit function theorem [5]. Point 3. and 4. are straightforward from the relation $\phi_-^{(k,r)}(x,z) = \phi_+^{(k,r)}(z,x)$. ∎

In Figure 1 the functions $z(x)$ such that $\phi_+^{(k,r)}(x, z(x)) = x$ and $x(z)$ such that $\phi_-^{(k,r)}(x(z), z) = z$ are depicted for threshold values $r = 2$ (left) and $r = 3$ (right) and degree $k = 10$. In addition to stationary points $\{(0,0), (x^\star, 0), (1,0), (0, z^\star), (0,1))\}$, as derived in Lemma 14, extra stationary points are placed at intersections between curves $z(x)$ and $x(z)$. In the specific case with $k = 10$ it can be noticed that if $r = 2$ then there are two additional stationary points.

The following proposition gives sufficient conditions guaranteeing that the set of stationary points only contains the trivial points $\{(0,0), (x^\star, 0), (1,0), (0, z^\star), (0,1))\}$.

PROPOSITION 16. *If $r \geq (k+1)/2$, $\{(0,0), (x^\star, 0), (1,0), (0, z^\star), (0,1))\}$ are the only fixed points of the system.*

Proof. Notice that $\phi_+^{(k,r)}(x,x) = \phi_-^{(k,r)}(x,x) \leq \sum_{u=r}^{k} \binom{k}{u} x^u (1-x)^{k-u} = \varphi^{(k,r)}(x)$. If $r \geq (k+1)/2$, we have $\varphi^{(k,r)}(x) < x$ for all $x < 1/2$ and, consequently, $\phi_+^{(k,r)}(x,x) < x$ from which we conclude the assertion. ∎

The following corollary can be proved by linearization.

COROLLARY 17. *The following properties hold*

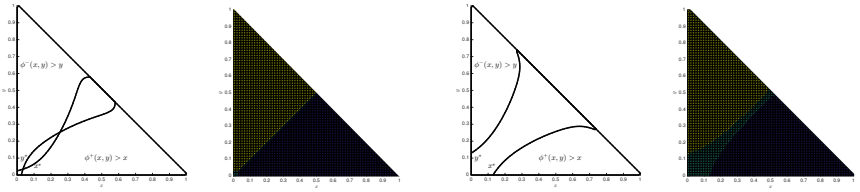
1. *$(0,0)$ is a locally stable stationary point for $2 \leq r \leq k$, unstable if $r = 1$.*
2. *$(0,1)$ and $(1,0)$ are locally stable stationary points for $1 \leq r < k$, unstable otherwise.*

3. $(x^\star, 0)$ *and* $(0, z^\star)$ *are unstable stationary points.*
4. *The set of points* $\{(x, z) \in \mathbb{R}^2 : x = z\}$ *is invariant.*

PROPOSITION 18. *Let us consider the dynamical system in* (15)*. Then there are no periodic orbits.*

Proof. The set of points $M_1 = \{(x, z) : x = 0\}$, $M_2 = \{(x, z) : z = 0\}$, and $M_3 = \{(x, z) : x = z\}$ are positively invariant. From Proposition 16 and by applying the Poincaré-Bendixson theorem we conclude that there are no periodic orbits. ∎

The basins of attraction for the ODE in (15) are shown in Figure 1 for degree $k = 10$ and threshold $r \in \{2, 3\}$. Basins are evaluated numerically, by solving the ODE system for a wide set of initial conditions. More specifically, for each initial condition x_0, z_0 the color in the picture represents the asymptotically stable equilibrium point (yellow for (0,1), green for (0,0) and blue for state $(1, 0)$) to which the trajectory tends. As to be expected by Corollary 17, we have that points $(0, 0)$, $(0, 1)$ and $(1, 0)$ are locally stable stationary points.



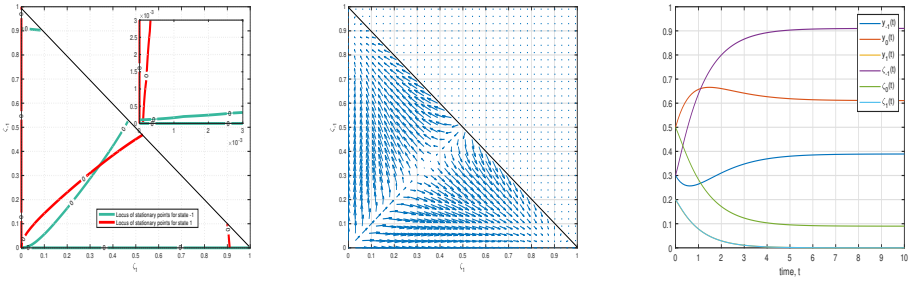
(a) (b)

FIGURE 1. *Basins of attraction for the ODE in* (15)*:* (a) $k = 10$ *and* $r = 2$ (b) $r = 3$

6.1.2. TLTM on the Epinions graph. The online social network Epinions was a consumer website operating from 1999 to 2014, where the users can review different kind of items and rank the reviews of others to be trusted. The available dataset [27] contains the who-trust-whom relationships of all members. The network consists of $|\mathcal{V}| = 75879$ nodes and $|\mathcal{E}| = 508837$ directed edges, it is highly connected and contains cycles. The average clustering coefficient is 0.1378. The maximum in-degree is 3035, maximum out-degree is 1801, the average in/out-degree is 6.7. In and out degrees follow an approximate power law distribution with exponent 1.7.

We assume that all nodes have symmetric threshold $a_v^{\pm} = 2$. In Figure 2, we show on the left the loci of the stationary solution of (3) in the plane (ζ_{-1}, ζ_1), and on the right an arrow plot representing the gradient of the system of the two ODEs in each possible point for which $\zeta_{-1} + \zeta_1 \leq 1$. As it can be seen from the combinations of the two plots, there are three stable stationary points, which are located at $(\zeta_{-1}, \zeta_1) = (0, 0)$, $(\zeta_{-1}, \zeta_1) = (\bar{\zeta}, 0)$ and $(\zeta_{-1}, \zeta_1) = (0, \bar{\zeta})$, with $\bar{\zeta} \simeq 0.91$ while there are four *unstable* stationary points at values $(\zeta_{-1}, \zeta_1) = (\widetilde{\zeta}, 0)$, $(\zeta_{-1}, \zeta_1) = (0, \widetilde{\zeta})$, $(\zeta_{-1}, \zeta_1) = (\widetilde{\zeta_1}, \widetilde{\zeta_1})$ and $(\zeta_{-1}, \zeta_1) = (\widetilde{\zeta_2}, \widetilde{\zeta_2})$, where $\widetilde{\zeta} \simeq 1.02 \times 10^{-4}$, $\widetilde{\zeta_1} \simeq 1.066 \times 10^{-4}$ and $\widetilde{\zeta_2} \simeq 0.341$. The arrow plot allows also to verify that the boundary of the two basins of attraction for the stationary points coincides with the line $\zeta_{-1} = \zeta_1$ for $\widetilde{\zeta_1} \leq \zeta_1 \leq 1/2$.

In Figure 2, we show the evolution over time of the variables $\zeta_\omega(t)$ and $y_\omega(t)$, $\omega \in \{-1, 0, 1\}$, obtained through the numerical solution of ODEs in equations (3)-(4). In particular, $y_\omega(t)$ represents the fraction of nodes in state ω at time t, while $\zeta_\omega(t)$ represents the fraction of edges connected to a node in state ω at time t. At time $t = 0$, the fraction of nodes of any degree in states $-1, 0, 1$ is $0.3, 0.5, 0.2$, respectively.



(a) (b) (c)

FIGURE 2. *TLTM in the Epinions social network with symmetric thresholds* $r^{\pm} = 2$*.: (a) Stationary solution of ODEs in* (3)*. (b) Gradient of ODE system in* (3) *(c) Transient solution of ODEs in* (3)-(4)*.*

As it can be seen, the fraction of nodes in state 1 decreases exponentially with time (the curve of $\zeta_1(t)$ is superimposed on that of $y_1(t)$). Instead, the curve for $\zeta_{-1}(t)$ reaches the fixed point $\overline{\zeta} = 0.91$, as predicted by Figure 2. The fixed point for $y_{-1}(t)$ is lower, at about 0.39, implying that the fraction of nodes with higher degree that asymptotically reach state -1 is larger than for nodes with lower degree.

6.1.3. TLTM on the Configuration Block Model. In this subsection, we show results for a network with $n = 10^7$ nodes divided into two equal-size communities (classes), with size $n/2 = 5 \cdot 10^6$. We consider the TLTM with symmetric thresholds $a_v^{\pm} = 2$. We put 10^5 seeds in state 1 in community 1, and 10^5 seeds in state -1 in community 2. The out-degree distribution of the first class is given by $p_{(k_1,k_2)|1} = p_{11}(k_1)p_{12}(k_2)$ where

$$p_{11}(k_1) = \binom{n/2-1}{k_1} p_A^{k_1}(1-p_A)^{1-k_1}, \qquad p_{12}(k_2) = \binom{n/2}{k_2} p_B^{k_2}(1-p_B)^{1-k_2}$$

p_A and p_B being chosen so that the average degree toward community 1 is 20, while the average degree toward community 2 is 6. Analogously, the out-degree distribution of the second class is given by $p_{(k_1,k_2)|2} = p_{21}(k_1)p_{22}(k_2)$ where

$$p_{21}(k_1) = \binom{n/2}{k_1} p_C^{k_1}(1-p_C)^{1-k_1}, \qquad p_{22}(k_2) = \binom{n/2-1}{k_2} p_A^{k_2}(1-p_A)^{1-k_2}$$

p_C being chosen so that the average degree toward community 1 is 5. The network shows a slight asymmetry, since nodes in community 1 have slightly more edges directed towards nodes of community 2 than viceversa.

Figure 3 compares the fraction of nodes in state 1 and -1 in either community, averaged across 100 simulation runs, against analytic results. We observe very good agreement between analysis (thin curves) and simulation (thick curves). Interestingly, in the beginning we have two weakly interfering percolation processes in the two communities, producing a significant increase of nodes in state -1 in community 2, and a significant increase of nodes in state 1 in community 1. However, the percolation process in community 2 grows faster, because nodes in community 2 receive less influence from nodes in community 1 than viceversa. As a consequence, the percolation process of nodes in state -1 eventually invades also community 1, while nodes in state 1 vanish to zero throughout the network.

6.2. Binary Response with Coordinating and Anti-coordinating agents.

6.2.1. Mean field analysis. We consider the homogenous case in which all nodes have out-degree k. For simplicity, in the following, we will suppose that k is odd,

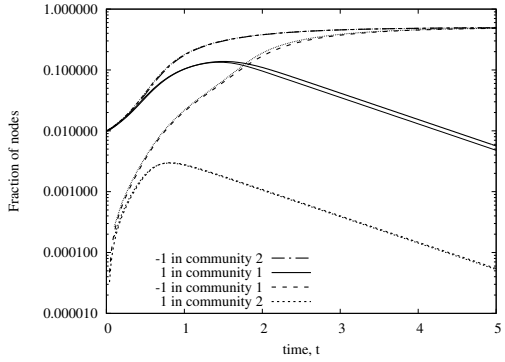


FIGURE 3. *Evolution over time of the fraction of nodes in states 1 and -1 in the two communities, according to analysis (thin curves) and simulation (average of 100 runs) (thick curves).*

in order to avoid ties, although the extension to the case of even k is straightforward. Let α be the fraction of coordinating nodes. From Proposition 2, the evolution of the node states is governed by the following ODE:

$$\frac{\mathrm{d}y_1(t)}{\mathrm{d}t} = \alpha\phi_1\left(y_1(t)\right) + (1-\alpha)\left(1-\phi_1\left(y_1(t)\right)\right) - y_1(t), \tag{17}$$

where $\phi_1\left(y_1(t)\right)$ is the probability with which a coordinating node enters state 1, given by

$$\phi_1\left(y_1\right) = \sum_{k_1=\lceil k/2\rceil}^{k} \binom{k}{k_1} y_1^{k_1}(1-y_1)^{k-k_1}. \tag{18}$$

The above ODE derives from the fact that the probability of stepping to state $+1$ for an anti-coordinating node is equal to the probability of stepping to state -1 for a coordinating node.

PROPOSITION 19. *Let us consider the dynamical system in* (17)*. There exists* $\alpha_{\mathrm{th}} \in (0,1)$ *such that*

- *if* $\alpha \leq \alpha_{\mathrm{th}}$*, then the only stationary point is* $y_1 = 1/2$*, which is stable and has a basin of attraction equal to* $[0,1]$*;*
- *if* $\alpha > \alpha_{\mathrm{th}}$*, then there are three stationary points:* $z_1 = 1/2$ *is unstable and the other two are symmetric with respect to* $z_1 = 1/2$ *and stable, with basins of attraction* $[0,1/2)$ *and* $(1/2,1]$*.*

Proof. Let us define $\ell_1\left(y_1(t)\right)$ the RHS of (17). It is to verify that $\phi_1\left(1/2\right) = 1/2$, $\ell_1\left(1/2\right) = 0$, so that $y_1 = 1/2$ is a stationary point for every α.

The derivative of ℓ_1 with respect to y_1 is given by:

$$\frac{\mathrm{d}\ell_1}{\mathrm{d}y_1} = (2\alpha-1)\frac{\mathrm{d}\phi_1}{\mathrm{d}y_1} - 1 = (2\alpha-1)k\tbinom{k-1}{\lfloor \frac{k}{2}\rfloor}\left(y_1(1-y_1)\right)^{\lfloor \frac{k}{2}\rfloor} - 1$$

From the above equation, it turns out that we have two distinct regimes, according to whether $\alpha \leq \alpha_{\mathrm{th}}$ or $\alpha > \alpha_{\mathrm{th}}$, with $\alpha_{\mathrm{th}} = \frac{1}{2}\left(1 + \frac{2^{k-1}}{k\binom{k-1}{\lfloor \frac{k}{2}\rfloor}}\right)$

- If $\alpha \leq \alpha_{\mathrm{th}}$, then $\frac{\mathrm{d}\ell_1}{\mathrm{d}y_1} \leq 0$ for $0 < y_1 < 1$. It then turns out that the only stationary point is $y_1 = 1/2$, which is stable and has a basin of attraction equal to $[0,1]$.

- If $\alpha > \alpha_{\text{th}}$, then $\frac{\mathrm{d}\ell_1}{\mathrm{d}y_1}$ has two zeros, symmetric with respect to $z_1 = 1/2$, in the solutions of the quadratic equation $y_1(1-y_1) = ((2\alpha-1)k\binom{k-1}{\lfloor \frac{k}{2} \rfloor})^{-\lfloor \frac{k}{2} \rfloor}$ Because of that, there are three stationary points, out of which the one in $z_1 = 1/2$ becomes unstable. The other two are symmetric with respect to $z_1 = 1/2$, i.e., $y^{\pm} = 1/2 \pm \epsilon$, and stable, with basins of attraction $[0, 1/2)$ and $(1/2, 1]$.

6.2.2. BRCA on the regular graph. Here we consider a simple regular graph where all nodes have fixed out-degree $k = 21$ and fixed in-degree $d = 21$. Note that, since the out-degree is odd, the best response is always deterministic (i.e., there are no ties). We run a single simulation with $n = 10^5$, with the following initial configuration: 30,000 coordinating nodes in state 1, 10,000 coordinating nodes in state -1, 40,000 anti-coordinating nodes in state 1, 20,000 anti-coordinating nodes in state -1.

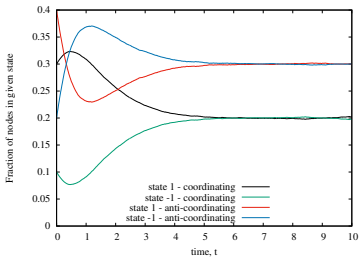


FIGURE 4. *Evolution over time of the fraction of nodes in the ABRD game, according to a single simulation run.*

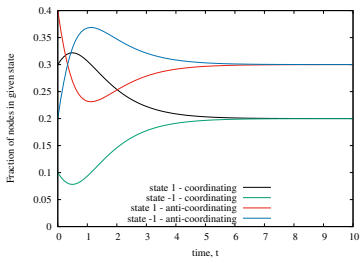


FIGURE 5. *Evolution over time of the fraction of nodes in the ABRD game, according to analysis.*

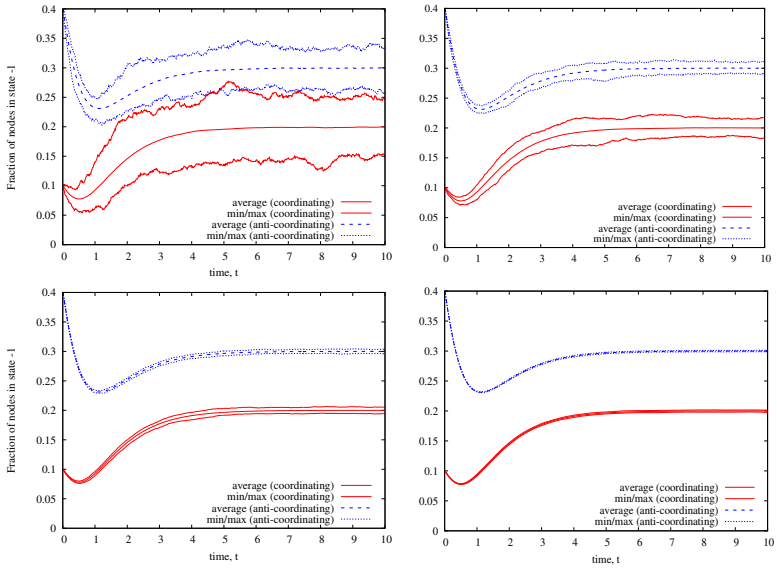


FIGURE 6. *Evolution over time of the fraction of nodes in state -1 in the ABRD game, across 400 simulation runs.*

In Figures **??** and **??** we show the fraction of nodes in each of the possible states

as function of time, according to simulation and analysis, respectively. We notice a perfect agreement between analytical prediction and simulation. Small fluctuations around the equlibrium configuration appear on the (single) simulation sample path.

To assess the degree of concentration of the process around its average, we carried out the following experiment: we performed 400 runs of the system, where the variability across runs is due to multiple reasons: i) the network topology generated by the configuration model; ii) the initial selection of nodes in the various states; iii) the temporal dynamics of the process (Poisson clocks). We then sampled the system with time granularity $\Delta t = 0.01$, and at each time instant we evaluated the average, the minimum, and the maximum fraction of nodes in each state, across the 400 runs. In Figure 6 we show the results of the above experiment for the fraction of nodes in state -1 (either coordinating or anti-coordinating), with $n = 10^3$ (top-left), $n = 10^4$ (top-right), $n = 10^5$ (bottom-left), $n = 10^6$ (bottom-right). Thin curves above and below the thicker line (denoting the average), correspond to maximum and minimum values. Results for the fraction of nodes in state 1 are not shown, and they exhibit a similar variability. We observe that results become more concentrated passing from $n = 10^3$ to $n = 10^6$ nodes.

6.2.3. BRCA on the Epinions graph. We now investigate BRCA dynamics on the Epinions graph with a fraction of coordinating nodes equal to $\alpha = 0.7$, evenly distributed among nodes of any degree. Our main goal in this section will be to understand better the origin of possible discrepancies between analysis and simulation.

A numerical analysis of (3)-(4) shows that, similarly to the regular case, the stationary points for the Epinions degree distribution are three, out of which the one in $\zeta_1 = 1/2$ is unstable. The other two are positioned at $\zeta_1 \simeq 0.33$ and $\zeta_1 \simeq 0.67$ and are stable. Such stationary points correspond to fractions of nodes in state 1 given by $y_1 \simeq 0.426$ and $y_1 \simeq 0.574$, respectively.

Let us now move to the time evolution of fractions of nodes in a given state. We consider the following initial condition: 42% of coordinating nodes in state 1, 28% of coordinating nodes in state -1, 10% of anti-coordinating nodes in state 1, 20% of anti-coordinating nodes in state -1. The left plot in Figure 7 shows the fraction of

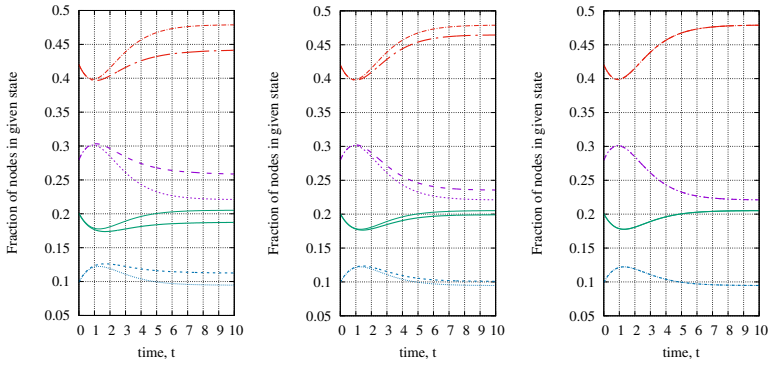


FIGURE 7. *BRCA dynamics: evolution over time of the fraction of nodes in each possible state, according to simulation (thick curves) and analysis (thin curves). From top curve to bottom curve: coordinating nodes in state 1, coordinating nodes in state -1, anti-coordinating nodes in state 1, anti-coordinating nodes in state -1. From left to right plot: original Epinions graph (left); configuration model matched to the Epinions graph (middle); configuration model matched to the Epinions graph, with* $10n$ *nodes (right).*

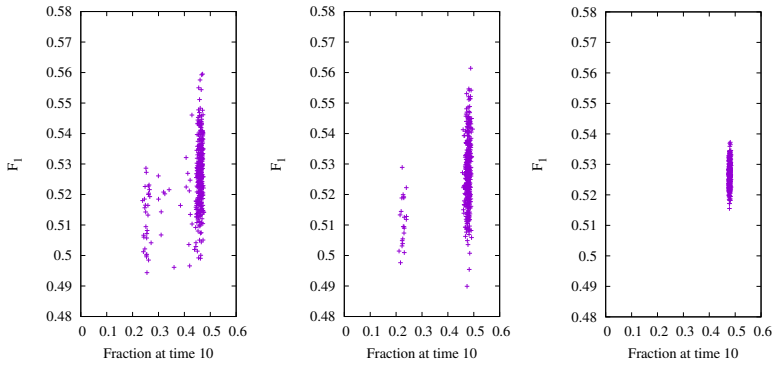


FIGURE 8. *F_1 metric vs fraction of coordinating node in state 1 (sampled at time $t = 10$): original Epinions graph (left); configuration model matched to the Epinions graph (middle); configuration model matched to the Epinions graph, with $10n$ nodes (right).*

nodes in each possible state as function of time, comparing simulation (thick curves) and analysis (thin curves). For simulations, we have plotted the average of 400 runs, where in each run we randomly select a different seed set. We observe that, after a very similar initial behavior, simulations results tend to a different equilibrium point with respect to analysis, as one can see by looking at the fraction of nodes at time $t = 10$. We have identified two main reasons for the observed discrepancies: i) the first one due to the fact that the structure of the Epinions graph is not captured by the configuration model; ii) the second one due to the fact that the network size is not large enough to converge to a unique equilibrium point across different runs, due to random effects.

To separate out the impact of the above two reasons, we have performed the following experiments. First, we have run simulations in which, in each run, we randomly reshuffle the edges while maintaining the same node statistics. Note that, by so doing, we generate graph according to the configuration model matched to the Epinions graph. The results of this experiment are shown in the middle plot of Fig. 7. As expected, now we observe a much better agreement between analysis and simulation. Still, there are non negligible discrepancies in the final fraction of nodes in each possible state.

An in-depth inspection of simulation results revealed that about 5% of simulation runs tend to a completely different equilibrium than the remaining 95% of the runs. This fact is illustrated by the middle plot in Figure 8, where we have put a mark for each of the 400 runs, showing on the x axes the fraction of coordinating nodes in state 1, sampled at time $t = 10$. For each run, we also computed the fraction of coordinating nodes that would transit to state 1 if their clock would fire at time $t = 0$. This fraction, denoted as F_1, is plotted on the y axes, and it is meant to capture a possible initial bias towards entering state 1, due to the initial network condition, which is especially dependent on the random seed allocation.

We can observe that simulations converge to two main equilibria, and that simulations runs where the final fraction of coordinating nodes in state 1 is smaller (around 0.2) have smaller values of the F_1 metric specified above, suggesting that the initial seed allocation is the main responsible for driving the system into a different configuration. We emphasize that a similar behavior can be observed also on the original Epinions graph, for which an analogous investigation of single simulation runs pro-

duced the left plot in Fig. 8.

To remove the bi-stable outcome of simulations, we performed the following additional experiment: we considered again the node statistics of the original Epinions graph, but this time we generated graphs of size ten times larger than the original one (i.e., with $n = 758790$ nodes), using the configuration model.

The right plot in Fig. 8 shows that simulation results are now much more concentrated around a unique equilibrium. Moreover, in the right plot of Fig. 7 we observe an almost perfect agreement between analysis and simulation for the evolution over time of the fraction of nodes in each possible state (in this plot thick and thin curves are essentially overlapped and thus indistinguishable).

We conclude that, when our analytic approach is used to predict the behavior of ASD dynamics on realistic (finite) graph, one must be aware of two main sources of errors: one due to the fact that real graphs are not completely described by the configuration model; the other due to the fact that, in finite graphs, randomness can possibly drive the system to different equilibria, especially when initial conditions are close to the border of the attraction basin of the expected equilibrium. However, our experiments with the Epinions graph suggest that our approach has remarkable accuracy even in realistic graphs. Moreover, when the number of nodes exceeds, say, one million, results are sufficiently concentrated around their average to justify our mean-field approach, at least for the types of ASD dynamics that we have examined so far.

7. Conclusions. In this paper we have proposed a mathematical framework showing that general semi-anonynoums dynamics in large scale random graphs converge to the solution of ordinary differential equations, allowing fast numerical prediction of the transient behavior of many cascading processes in complex systems and, in some cases, analytical estimation of their points of equilibrium. With respect to existing literature, we have extended the above mean-field approximation along several directions: i) asynchronous node activation; ii) arbitrary semi-anonymous dynamics, including noisy best-response and class-dependent behavior; iii) general random graph exhibiting a local tree-structure, possibly mixing heterogeneous nodes and unbounded in/out degrees. Our main contribution is a rigorous mathematical proof of convergence, which requires a careful combination of many independent results related to the different framework components. Despite the generality of our approach, we have not considered important variations of semi-anonynoums dynamics such as non-reversible transitions. Moreover, it remains still largely open how to analytically characterize in a tractable way the behavior of ASD in undirected network.

Appendix A. Proofs of Section 5.2.

A.1. Topological result: Proof of Theorem 4. Let $\mathcal{N}_t$ be the relevant neighborhood of a node chosen uniformly at random from $\mathcal{V}$, respectively. Moreover, Let $\mathcal{T}_t$ be the truncated branching process at time t. In order to compare the distributions $\mu_{\mathcal{N}_t}$ and $\mu_{\mathcal{T}_t}$ of these two random variables, we define a coupling between them.

Definition of coupling. As a starting point, we define two different sequences of random variables. For $a, a' \in \mathcal{A}$, let $(L_h^{a,a'})_{h\in\mathbb{N}}$ be a sequence of i.i.d. random variables distributed according to a uniform distribution on the finite set $\mathcal{L}_{a,a'}$. Let $(M_h^{a,a'})_{h\in\mathcal{L}_{a,a'}}$ be a finite sequence of random variables such that

$$\mathbb{P}(M_h^{a,a'} = L_h^{a,a'} | L_h^{a,a'} \notin \{M_1^{a,a'}, \dots, M_{h-1}^{a,a'}\}) = 1$$

while $M_h^{a,a'}$ is uniformly distributed on the set $\mathcal{L}_{a,a'} \setminus \{M_1^{a,a'}, ..., M_{h-1}^{a,a'}\}$, if $L_h^{a,a'} \in \{M_1^{a,a'}, \ldots, M_{h-1}^{a,a'}\}$. Notice that the marginal distribution of the sequences $(L_h^{a,a'})_{h\in\mathbb{N}}$ and $(M_h^{a,a'})_{h\in\mathcal{L}_{a,a'}}$ are equivalent to sampling with replacement and sampling without replacement, respectively, from the set $\mathcal{L}_{a,a'}$. We thus have

$$\mathbb{P}(L_{h+1}^{a,a'} \neq M_{h+1}^{a,a'} | (L_1^{a,a'}, \ldots, L_h^{a,a'}) = (M_1^{a,a'}, \ldots, M_h^{a,a'})) = \frac{h}{l_{a,a'}}. \tag{19}$$

We build the neighborhood $\mathcal{N}_t$ with a dynamic exploration procedure driven by variables $(M_h^{a,a'})_{h\in\mathbb{N}}$. Our procedure starts adding to $\mathcal{N}_t$ the root v_0 alone (chosen uniformly at random over $\mathcal{V}$), then $\mathcal{N}_t$ grows through the addition of new edges/nodes, according to the following mechanism. Upon insertion, a newly added node is declared unexplored and its out-degree is initialized to 0. Then some of the unexplored nodes in $\mathcal{N}_t$ are sequentially explored at random times (smaller than t). Upon its exploration, a node acquires a non-null out-degree and its out-neighbors are introduced in the network (if not already in the network).

Before describing in detail the algorithm, we introduce the following variables:

- i denotes the iteration, which is determined by the number of explored nodes in the network;
- $h_i^{a,a'}$ denotes the number of (a, a') edges at iteration i;
- h_i denotes the total number of edges in $\mathcal{N}_t$ at iteration i,
- $\mathcal{S}_i$ denotes the set of nodes (except for the root v_0) in $\mathcal{N}_t$ at iteration i;
- $\mathcal{S}'_i$ denotes the set of unexplored nodes in $\mathcal{N}_t$ at iteration i;
- T_i denotes the time at which the i-th node activates (i.e., it is explored).
- Γ_i denotes the time lag between the $(i-1)$-th and the i-th exploration.
- V_i denotes the identity of the i-th explored node.
- A_i denotes the class of the i-th explored node.

Then $\mathcal{N}_t$ is generated according to the following procedure:

1. Set $i = 0$. Start from the root v_0 (chosen uniformly at random from $\mathcal{V}$). Assign it label $A_0 = \lambda(v_0)$ and out-degree vector $\mathbf{J}_0 = \mathbf{0}$, and declare it unexplored. Set $h_0^{a,a'} = 0$, for all $a, a' \in \mathcal{A}$, $h_0 = 0$, $\mathcal{S}_0 = \mathcal{S}'_0 = \emptyset$ and extract $T_0 \sim \text{Exp}(1)$.
2. If $T_0 > t$, stop the process. If $T_0 \leq t$: declare v_0 explored, change its out-degree vector to $\mathbf{J}_0 = \mathbf{K}_{v_0}$, and add $J_0 = \sum_{a'\in\mathcal{A}} J_0^{a'}$ new edges to $\mathcal{N}_t$. In particular, for all $a' \in \mathcal{A}$, add exactly $J_0^{a'}$ out-going edges $M_{h'}^{A_0,a'}$, $h' \in \{1, \ldots J_0^{a'}\}$, from v_0, pointing to nodes $\nu_{A_0,a'}(M_{h'}^{A_0,a'})$. Note that such nodes are not necessarily different from each other. Newly introduced nodes are declared unexplored and their out-degree is set to 0.
   Then, counters are updated as: $i = 1$, $h_1^{A_0,a'} = J_0^{a'}$ for all $a' \in \mathcal{A}$ and $h_1^{a,a'} = 0$ for $a \neq A_0$, $h_1 = \sum_{a,a'} h_1^{a,a'}$, $\mathcal{S}_1 = \cup_{a',h'}\{\nu_{A_0,a'}(M_{h'}^{A_0,a'})\}$ and $\mathcal{S}'_1 = \mathcal{S}_1$.
3. Let us define $T_i = T_{i-1} + \Gamma_i$ and let $\Gamma_i \sim \text{Exp}(|\mathcal{S}'_i|)$ where $|\mathcal{S}'_i|$ represents the number of unexplored nodes in $\mathcal{N}_t$ at iteration i; and let V_i be chosen uniformly at random from $\mathcal{S}'_i$.
4. If $T_i > t$, stop the process. If $T_i \leq t$: declare the node V_i explored, assign it a degree $\mathbf{J}_i = \mathbf{K}_{V_i}$ and add $J_i = \sum_{a'\in\mathcal{A}} J_i^{a'}$ new edges to $\mathcal{N}_t$. In particular, add for all $a' \in \mathcal{A}$ exactly $J_i^{a'}$ out-going edges $M_{h'}^{A_i,a'}$ from V_i pointing to nodes $\nu_{A_i,a'}(M_{h'}^{A_i,a'})$ with $h' \in \{h_i^{A_i,a'} + 1, \ldots, h_i^{A_i,a'} + J_i^{a'}\}$. Note that such nodes are not necessarily all distinct, nor they are distinct from other nodes

already inserted in $\mathcal{N}_t$. Among them, those that are not already in $\mathcal{N}_t$ are added and declared unexplored and their out-degree is set to 0.
Then, $h_{i+1}^{A_i,a'} = h_i^{A_i,a'} + J_i^{a'}$, and, for all $a \neq A_i$, $h_{i+1}^{a,a'} = h_i^{a,a'}$. Then $h_{i+1} = h_i + \sum_{a'} J_i^{a'}$, $\mathcal{S}_{i+1} = \mathcal{S}_i \bigcup \{\cup_{a',h'} \{\nu_{A_i,a'}(M_{h'}^{A_i,a'})\}$ and
$\mathcal{S}'_{i+1} = \mathcal{S}'_i \backslash \{V_i\} \bigcup (\cup_{a',h'} \{\nu_{A_i,a'}(M_{h'}^{A_i,a'})\}$. Finally, increment i and go back to Point 3.

Note that by construction, Point 4 is repeated for all $i \leq i_M$ where $i_M = \max\{i \geq 0 | T_i \leq t\}$. Observe that the random network $\mathcal{N}_t$ generated in this way has, by construction, the same structure and desired distribution $\mu_{\mathcal{N}_t}$, of the relevant neighborhood of a random node in $\mathcal{G}$. Let $E_t^{a,a'}$ be the total number of edges in $\mathcal{N}_t$ from nodes with label a to nodes with label a'. Notice that $E_t^{a,a'} = h_{i_M}^{a,a'}$.

Now we build the tree $\mathcal{T}_t$ with a similar dynamic exploration procedure driven by variables $(L_h^{a,a'})_{h\in\mathbb{N}}$, which starts from a root $\widetilde{v}_0$ alone and sequentially adds new edges/nodes $\widetilde{v}_h$, $h = 1, 2, \ldots$, to the tree. Nodes $\{\widetilde{v}_h\}_{h\geq 0}$ are assumed to be pairwise different. However a correspondence between node $\{\widetilde{v}_h\}_h$ in the tree and nodes in the graph $\mathcal{G}$ is dynamically established. We emphasize that this correspondence is, in general, non bijective: the same node in the network may correspond to several distinct nodes of $\mathcal{T}_t$, which are replicas of it.

More in detail, first we define the following variables:

- i denotes the iteration, i.e., the number of activated nodes in the tree;
- $\widetilde{h}_i^{a,a'}$ denotes the number of (a, a') edges at iteration i;
- $\widetilde{h}_i$ denotes the total number of edges in the tree at iteration i, which, by construction, equals the total number of non-root nodes S_i in the tree;
- $\widetilde{\mathcal{S}}_i$ denotes the set of nodes (except for the root $\widetilde{v}_0$) in $\mathcal{T}_t$ at iteration i;
- $\widetilde{\mathcal{S}}'_i$ denotes the set of unexplored nodes in $\mathcal{T}_t$ at iteration i;
- $\widetilde{T}_i$ denotes the time at which the i-th node activates.
- $\widetilde{\Gamma}_i$ denotes the time lag between the $(i-1)$-th and the i-th exploration.
- $\widetilde{V}_i$ denotes the identity of the i-th explored node.
- $W(\cdot)$ represents the function that maps the nodes of the tree into $\mathcal{V}$.
- $\widetilde{A}_i$ is the class of the i-th activated node.

Then $\mathcal{T}_t$ is generated according to the following procedure:

1. Set $i = 0$. Start from the root $\widetilde{v}_0$. Establish a correspondence between $\widetilde{v}_0$ and v_0 (i.e., $W(\widetilde{v}_0) = v_0$). Assign it label $\widetilde{A}_0 = \lambda(v_0)$ and out-degree vector $\widetilde{\mathbf{J}}_0 = \mathbf{0}$. Set $\widetilde{h}_0^{a,a'} = \widetilde{h}_0 = 0$, for all $a, a' \in \mathcal{A}$, $\widetilde{\mathcal{S}}_0 = \emptyset$ and $\widetilde{T}_0 = T_0$.
2. If $\widetilde{T}_0 > t$, stop the process. If $\widetilde{T}_0 \leq t$: change the out-degree vector of $\widetilde{v}_0$ to $\widetilde{\mathbf{J}}_0 = \mathbf{K}_{v_0}$, and add $\widetilde{J}_0 = \sum_{a'\in\mathcal{A}} \widetilde{J}_0^{a'}$ new nodes to $\mathcal{T}_t$ (as children of $\widetilde{v}_0$). In particular, for all $a' \in \mathcal{A}$, add exactly $\widetilde{J}_0^{a'}$ out-going edges from $\widetilde{v}_0$, pointing to different nodes $\widetilde{v}_h$, $h \in \{1, \ldots, \sum_{a'} \widetilde{J}_0^{a'}\}$. Establish a correspondence between newly inserted tree nodes and graph nodes as $W(\widetilde{v}_h) = \nu_{A_0,a'}(L_{h'}^{A_0,a'})$, for $h = h' + \sum_{a'<a} \widetilde{J}_0^{a'}$. Set their out-degree to 0.Then, counters are updated as: $i = 1$, $\widetilde{h}_1^{A_0,a'} = \widetilde{J}_0^{a'}$ for all $a' \in \mathcal{A}$ and $\widetilde{h}_1^{a,a'} = 0$ for $a \neq A_0$, $\widetilde{h}_1 = \sum_{a,a'} \widetilde{h}_1^{a,a'}$, $\widetilde{\mathcal{S}}_i = \cup_h \{\widetilde{v}_h\}$ and $\widetilde{\mathcal{S}}'_i = \widetilde{\mathcal{S}}_i$.
3. Let us define $\widetilde{T}_i = \widetilde{T}_{i-1} + \widetilde{\Gamma}_i$ with $\widetilde{\Gamma}_i = \Gamma_i$ if $|\widetilde{\mathcal{S}}'_i| = |\mathcal{S}'_i|$, otherwise $\Gamma'_i \sim \text{Exp}\left(|\widetilde{\mathcal{S}}'_i|\right)$; moreover, let $\widetilde{V}_i = V_i$ if $\widetilde{\mathcal{S}}'_i = \widetilde{\mathcal{S}}_i$, otherwise let $\widetilde{V}_i$ be chosen uniformly at random from $\widetilde{\mathcal{S}}'_i$.

4. If $\widetilde{T}_i > t$, stop the process. If $\widetilde{T}_i \leq t$: declare the node $\widetilde{V}_i$ explored, assign it a degree $\widetilde{\mathbf{J}}_i = \mathbf{K}_{W(\widetilde{V}_i)}$ and add $\widetilde{J}_i = \sum_{a' \in \mathcal{A}} \widetilde{J}_i^{a'}$ new nodes to $\mathcal{T}_t$ (as children of $\widetilde{V}_i$). In particular, for all $a' \in \mathcal{A}$, add exactly $\widetilde{J}_i^{a'}$ out-going edges from $\widetilde{V}_i$, pointing to different nodes $v_{\widetilde{h}_i+h}$, $h \in \{1, \dots, \sum_{a'} \widetilde{J}_i^{a'}\}$. Establish a correspondence between newly inserted tree nodes and graph nodes as $W(\widetilde{v}_{\widetilde{h}_i+h}) = \nu_{A_i,a'}(L^{A_i,a'}_{\widetilde{h}_i^{A_i,a'}+h'})$, for $h = h' + \sum_{a'<a} \widetilde{J}_i^{a'}$. Set their out-degree to 0.Then, $\widetilde{h}_{i+1}^{A_i,a'} = \widetilde{h}_i^{A_i,a'} + \widetilde{J}_i^{a'}$, and for all $a \neq A_i$, $\widetilde{h}_{i+1}^{a,a'} := \widetilde{h}_i^{a,a'}$, $\widetilde{h}_i = \widetilde{h}_{i-1} + \sum_{a'} \widetilde{J}_i^{a'}$, $\widetilde{\mathcal{S}}_{i+1} = \widetilde{\mathcal{S}}_i \bigcup (\cup_h \{\widetilde{v}_{\widetilde{h}_i+h}\}$ and $\widetilde{\mathcal{S}}'_{i+1} = \widetilde{\mathcal{S}}'_i \backslash \widetilde{V}'_i \bigcup (\cup_h \{\widetilde{v}_{\widetilde{h}_i+h}\})$. Finally, increment i and go back to Point 3.

Note that by construction, Point 4 is repeated for all $i \leq \widetilde{\imath}_M$ where $\widetilde{\imath}_M = \max\{i \geq 0 | \widetilde{T}_i \leq t\}$. Observe that the random tree $\mathcal{T}_t$ generated in this way has, by construction, the same structure and desired distribution $\mu_{\mathcal{T}_t}$, of the relevant neighborhood over a labeled branching process. Let $\widetilde{E}_t^{a,a'}$ be the total number of edges in $\mathcal{T}_t$ from nodes with label a to nodes with label a'. Notice that $\widetilde{E}_t^{a,a'} = \widetilde{h}_{\widetilde{\imath}_M}^{a,a'}$.

A.1.1. Proof of Theorem 4. Using the coupling inequality (see Proposition 4.7 in [29]) we have

$$\|\mu_{\mathcal{T}_t} - \mu_{\mathcal{N}_t}\|_{\mathrm{TV}} \leq \mathbb{P}(\mathcal{N}_t \neq \mathcal{T}_t). \tag{20}$$

Define the two events

$$\mathcal{B}_1 = \bigcap_{a,a' \in \mathcal{A}} \left\{ (L_1^{a,a'}, L_2^{a,a'}, \dots, L^{a,a'}_{\widetilde{E}_t^{a,a'}}) = (M_1^{a,a'}, M_2^{a,a'}, \dots, M^{a,a'}_{\widetilde{E}_t^{a,a'}}) \right\}$$

$$\mathcal{B}_2 = \bigcap_{a \in \mathcal{A}} \left\{ \bigcap_{(b,h) \neq (b',h'): b,b' \in \mathcal{A}, h \in \{1,\dots,\widetilde{E}_t^{b,a}\}, h' \in \{1,\dots,\widetilde{E}_t^{b',a}\}} \{\nu_{b,a}(L_h^{b',a})) \neq \nu_{b',a}(L_h^{b,a}))\} \right\}$$

$$\bigcap \left\{ \bigcap_{b \in \mathcal{A}} \bigcap_{h \in \{1,\dots,\widetilde{E}_t^{b,a_0}\}} \{\nu_{b,A_0}(W(\widetilde{v}_h)) \neq v_0\} \right\},$$

which are, in words, the event that there are no repeated edges in $\mathcal{T}_t$ and that the map $W(\cdot)$ is bijective (i.e., just a single node in $\mathcal{T}_t$ corresponds to every node in $\mathcal{N}_t$).

We are going to show that $\{\mathcal{B}_1 \cap \mathcal{B}_2\} \subseteq \{\mathcal{N}_t = \mathcal{T}_t\}$. The assertion, indeed, can be easily checked by induction over the iteration i. First observe that at the end of iteration 0, by construction, under $\mathcal{B}_1$ and $\mathcal{B}_2$ the structure of $\mathcal{T}_t$ and $\mathcal{N}_t$ are necessarily equal. Indeed by construction they can be different only if either some $L_{h'}^{A_0,a'} \neq, M_{h'}^{A_0,a'}$ for $h' \leq J_0^{A_0,a'} = \tilde{J}_0^{A_0,a'}$ or there are h' and h'' such that $\nu_{A_0,a}(L_{h'}^{A_0,a'}) = \nu_{A_0,a'}(M_{h'}^{A_0,a'}) = \nu_{A_0,a'}(M_{h''}^{A_0,a'}) = \nu_{A_0,a'}(L_{h''}^{A_0,a'})$. Now suppose that the structure of $\mathcal{N}_t$ is equal to the structure of $\mathcal{T}_t$ at the end of iteration $i-1$ (for $i \geq 1$). Then, by construction $\mathcal{S}_i = \widetilde{\mathcal{S}}_i$ and $\mathcal{S}'_i = \widetilde{\mathcal{S}}'_i$ $h_i^{a,a'} = \widetilde{h}_i^{a,a'}$; therefore $V_i = \widetilde{V}_i$ and $\Gamma_i = \widetilde{\Gamma}_i$ and $A_i = \widetilde{A}_i$ $J_i^{A_i,a'} = \widetilde{J}_i^{A_i,a'}$. During iteration i we add to $\mathcal{N}_t$ nodes $\nu_{A_i,a'}(M^{A_i,a'}_{h_i^{A_i,a'}+h'}) = \nu_{A_i,a'}(L^{A_i,a'}_{h_i^{A_i,a'}+h'})$ for $h' \in \{1, \dots, J_i^{a'}\}$ (where the equality descends from $\mathcal{B}_1$), which, from $\mathcal{B}_2$, are all different and different from nodes already in $\mathcal{N}_t$. In $\mathcal{T}_t$ we add brand-new replicas of nodes $\nu_{A_i,a'}(L^{A_i,a'}_{h_i^{A_i,a'}+h'}) = \nu_{A_i,a'}(M^{A_i,a'}_{h_i^{A_i,a'}+h'})$. Therefore the structures of $\mathcal{N}_t$ and $\mathcal{T}_t$ are still equal at the end of iteration i.

Thus:

$$\mathbb{P}\left(\mathcal{N}_t \neq \mathcal{T}_t\right) \leq \mathbb{P}\left(\mathcal{B}_1^C \cup \mathcal{B}_2^C \middle| \bigcap_{b,a}\left\{\widetilde{E}_t^{b,a} \leq x_{b,a}\right\}\right) + \mathbb{P}\left(\bigcup_{b,a}\left\{\widetilde{E}_t^{b,a} > x_{b,a}\right\}\right)$$

$$\leq \mathbb{P}\left(\mathcal{B}_1^C \middle| \bigcap_{b,a}\left\{\widetilde{E}_t^{b,a} \leq x_{b,a}\right\}\right) + \mathbb{P}\left(\tilde{\mathcal{B}}_2^C \middle| \tilde{\mathcal{B}}_1, \bigcap_{b,a}\left\{\widetilde{E}_t^{b,a} \leq x_{b,a}\right\}\right) + \sum_{b,a}\mathbb{P}\left(\widetilde{E}_t^{b,a} > x_{b,a}\right)$$

where in the first inequality we have let out the probability that the number of nodes exceeds a fixed threshold.

Define the event $\mathcal{E}_h^{b,a} = \left\{(L_1^{b,a}, \ldots, L_h^{b,a}) = (M_1^{b,a}, \ldots, M_h^{b,a}))\right\}$. The first term of (A.1.1) is upper bounded by

$$\mathbb{P}\left(\mathcal{B}_1^C \middle| \bigcap_{b,a}\left\{\widetilde{E}_t^{b,a} \leq x_{b,a}\right\}\right) = \mathbb{P}\left(\bigcup_{b,a\in\mathcal{A}}\left(\mathcal{E}^{b,a}_{\widetilde{E}_t^{b,a}}\right)^c \middle| \bigcap_{b,a}\left\{\widetilde{E}_t^{b,a} \leq x_{b,a}\right\}\right)$$

$$\leq \sum_{b,a\in\mathcal{A}}\mathbb{P}\left(\left(\mathcal{E}^{b,a}_{\widetilde{E}_t^{b,a}}\right)^c \middle| \widetilde{E}_t^{b,a} \leq x_{b,a}\right) \leq \sum_{b,a\in\mathcal{A}}\sum_{h_{b,a}=0}^{x_{b,a}-1}\mathbb{P}(L^{b,a}_{h_{b,a}+1} \neq M^{b,a}_{h_{b,a}+1} | \mathcal{E}^{b,a}_{h_{b,a}})$$

$$= \sum_{b,a\in\mathcal{A}}\sum_{h_{b,a}=0}^{x_{b,a}-1}\frac{h_{b,a}}{l_{b,a}} \tag{21}$$

where the first inequality is the union bound, the second inequality is the chain rule, while the last equality comes from (19). Using the same arguments, the second term of (A.1.1) becomes

$$\mathbb{P}\left(\mathcal{B}_2^C \middle| \mathcal{B}_1, \bigcap_{b,a}\left\{\widetilde{E}_t^{b,a} \leq x_{b,a}\right\}\right)$$

$$\leq \sum_{a,b\in\mathcal{A}}\sum_{h_{b,a}=1}^{x_{b,a}}\mathbb{P}(\nu_{b,a}(M^{b,a}_{h_{b,a}}) \in \{w_0, \nu_{b,a}(M_1^{b,a}), ..., \nu_{b,a}(M^{b,a}_{h_{b,a}-1})\} | \mathcal{E}^{b,a}_{h_{b,a}})$$

$$+ \sum_{a,b\in\mathcal{A}}\sum_{b'\neq b}\sum_{h_{b,a}=1}^{x_{b,a}}\sum_{h_{b',a}=1}^{x_{b',a}}\mathbb{P}\left(\nu_{b,a}(M^{b,a}_{h_{b,a}}) = \nu_{b',a}(M^{b',a}_{h_{b',a}}) \middle| \mathcal{E}^{b,a}_{h_{b,a}}, \mathcal{E}^{b',a}_{h_{b',a}}\right) \tag{22}$$

where the first term above gives the probability that two edges from the same class point to the same node or that a given edge points to the root, while the second term computes the probability that two edges from two different classes point to the same node. From the definition in (8), we have that the first term is upper bounded by

$$\sum_{a,b\in\mathcal{A}}\sum_{h_{b,a}=1}^{x_{b,a}}\mathbb{P}(\nu_{b,a}(M^{b,a}_{h_{b,a}}) \in \{w_0, \nu_{b,a}(M_1^{b,a}), ..., \nu_{b,a}(M^{b,a}_{h_{b,a}-1})\} | \mathcal{E}^{b,a}_{h_{b,a}})$$

$$\leq \sum_{a,b\in\mathcal{A}}\sum_{h_{b,a}=1}^{x_{b,a}}\frac{(h_{b,a}-1)\sum_{\mathbf{d},\mathbf{k}}(d_b-1)q^b_{\mathbf{d},\mathbf{k}|a} + \sum_{\mathbf{d},\mathbf{k}} d_b q^b_{\mathbf{d},\mathbf{k}|a}}{l_{b,a}}$$

$$\leq \sum_{a,b\in\mathcal{A}}\frac{x_{b,a}(x_{b,a}+1)}{2}\frac{\sum_{\mathbf{d},\mathbf{k}} d_b q^b_{\mathbf{d},\mathbf{k}|a}}{l_{b,a}} - \sum_{a,b\in\mathcal{A}}\sum_{h=0}^{x_{b,a}-1}\frac{h}{l_{b,a}}. \tag{23}$$

Using similar arguments, we get

$$\sum_{a,b\in\mathcal{A}}\sum_{b'\neq b}\sum_{h_{b,a}=1}^{x_{b,a}}\sum_{h_{b',a}=1}^{x_{b',a}}\mathbb{P}\left(\nu_{b,a}(M^{b,a}_{h_{b,a}})=\nu_{b',a}(M^{b',a}_{h_{b',a}})\middle|\mathcal{E}^{b,a}_{h_{b,a}},\mathcal{E}^{b',a}_{h_{b',a}}\right)$$

$$\leq\sum_{a,b\in\mathcal{A}}\sum_{b'\neq b}x_{b,a}x_{b',a}\frac{\sum_{\mathbf{d},\mathbf{k}}d_b q^{b'}_{\mathbf{d},\mathbf{k}|a}}{l_{b,a}}. \tag{24}$$

Combining these bounds and inequalities in (20) and (21) we conclude the thesis.

A.2. Concentration property: Proof of Theorem 5. Before presenting the proof of the main result we fix some notations and we state some preliminary lemmas. First, we recall a simple variant of Azuma's inequality which will be useful in our arguments. Let $\{Y_k : k = 0,1,2,3,\ldots\}$ be a martingale. The classical Azuma's inequality [3, Theorem 7.2.1] states that if $|Y_k - Y_{k-1}| \leq c_k$ with probability one, then

$$\mathbb{P}(|Y_N - Y_0| \geq \eta) \leq 2\mathrm{e}^{-\frac{\eta^2}{2\sum_{\ell=0}^{N} c_\ell^2}}.$$

The following martingale concentration result generalizes the Azuma inequality to the case in which $|Y_k - Y_{k-1}|$ is not bounded.

LEMMA 20 (Lemma 1 in [14]). *Let $\{Y_k : k = 0,1,2,3,\ldots\}$ be a martingale. Then for all sequences of positive numbers (c_ℓ) and $\eta > 0$, we have the following inequality*

$$\mathbb{P}(|Y_N - Y_0| \geq \eta) \leq 2\mathrm{e}^{-\frac{\eta^2}{32\sum_{\ell=1}^{N} c_\ell^2}} + \left(1 + \frac{2\Delta^\star}{\eta}\right)\sum_{\ell=1}^{n}\mathbb{P}(|Y_\ell - Y_{\ell-1}| \geq c_\ell),$$

with $\Delta^\star = \sup_i |Y_i - Y_{i-1}|$.

We recall that we consider three sources of randomness: the dynamics defined by Θ in (1), the activation process and the labeled network. The concentration property is proved in two steps. First, we study concentration by sequentially unveiling the edges in the labeled network (Lemma 21) and then we consider the other sources of randomness for a fixed graph (see Lemma 23).

We recall that for any $\ell \in \mathbb{N}$ we use the notation $[\ell] = \{1,\ldots,\ell\}$. Let $\Pi_{a,a'}$ be the set of all permutations of $\mathcal{L}_{a,a'} = \{1,\ldots,l_{a,a'}\}$ for any $a, a' \in \mathcal{A}$ and denote by $\Pi = \times_{a,a'\in\mathcal{A}}\Pi_{a,a'}$. Since each of permutation $\pi_{a,a'} \in \Pi_{a,a'}$ defines a specific pairing of out-links from nodes with label a and in-links of nodes with label a', there are exactly $\prod_{a,a'\in\mathcal{A}} l_{a,a'}!$ distinct elements in Π. We define the following cylinder sets:

$$\mathcal{C}_\ell(\pi_{[\ell]}) = \{\upsilon \in \Pi : \upsilon_{[\ell]} = \pi_{[\ell]}\}, \qquad \forall \pi_{[\ell]} \tag{25}$$

We notice that $\mathcal{C}_\ell(\cdot)$ are disjoint and exhaustive events, i.e., $\mathcal{C}_\ell(\pi_{[\ell]}) \cap \mathcal{C}_\ell(\pi'_{[\ell]}) = \emptyset$ if $\pi_{[\ell]} \neq \pi'_{[\ell]}$ and $\cup_{\pi_{[\ell]}}\mathcal{C}_\ell(\pi_{[\ell]}) = \Pi$.

LEMMA 21 (Unveiling network). *Let $\mathcal{N} = ((\mathcal{V},\mathcal{E},\mathcal{A},\lambda,\sigma,\tau))$ be a network sampled from the model ensemble $\mathfrak{C}_{n,p}$ of all labeled networks with given size n and statistics p. We denote the induced graph obtained in the exploration process of the neighborhood of a node v by $\mathcal{N}_t^v$, and with V_t^v the number of nodes in it. For $t \geq 0$, let $Z(t)$ be the state vector of the ASD dynamics on $\mathcal{N}$, $b(t) = |\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ be the*

number of state-ω adopters at time t. We denote the expectation over the ensemble of labeled graphs by $\widetilde{b}(t)$. For any $s \geq 1$ we have

$$\mathbb{P}\left(|b(t) - \widetilde{b}(t)| \geq \eta n\right) \leq \inf_{x>0} \left\{ 2\mathrm{e}^{-\frac{\eta^2 n}{32\bar{d}x^2}} + \left(1 + \frac{2}{\eta}\right) \frac{2^s}{x^s} \sum_{v \in \mathcal{V}} |\boldsymbol{\delta}_v| [\mathbb{E}[|V_t^v|^s] \right\}$$

Proof. Let $\pi \in \Pi$ be the random element of Π (uniformly extracted by Π) which describes the network $\mathcal{N} = ((\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau))$. We denote with $\mathcal{F}_\ell$ the natural filtration generated by $\pi_{[\ell]}$, with $\mathcal{F}_0$ equal to the trivial σ-algebra. Let $\pi^\ell \in \Pi$, for any given $\ell \in \{1 \cdots |\mathcal{E}|\}$, a random element in Π satisfying the following properties: i) $\pi^\ell_{[\ell]} = \pi_{[\ell]}$; ii) $\pi^\ell_{\ell+1}$ and $\pi_{\ell+1}$ are conditionally independent given $\pi_{[\ell]}$; iii) for any $i > 1$, $\pi^\ell_{\ell+i} = \pi_{\ell+i}$ if $\pi_{\ell+i} \neq \pi^\ell_{\ell+1}$ and $\pi^\ell_{\ell+i} = \pi_{\ell+1}$ if $\pi_{\ell+i} = \pi^\ell_{\ell+1}$. Observe that by construction π^ℓ is extracted uniformly from Π, as well. Furthermore the conditional law of both π and π^ℓ, given $\pi_{[\ell]}$ with $\pi_{[\ell]} = \pi^\ell_{[\ell]}$ is uniform in $C_\ell(\pi_{[\ell]})$. Let $\mathcal{G}^\ell_{\ell'}$ be the natural filtration induced by $\pi^\ell_{[\ell']}$. Observe that by construction $\mathcal{G}^\ell_{\ell'} = \mathcal{F}_\ell$ for $\ell' \leq \ell$. At last let $\hat{\mathcal{F}}_{\ell+1}$ and $\hat{\mathcal{G}}^\ell_{\ell+1}$ the natural filtration induced by $\pi_{\ell+1}$ and $\pi^\ell_{\ell+1}$. Of course $\mathcal{F}_{\ell+1} = \sigma(\mathcal{F}_\ell \cup \hat{\mathcal{F}}_{\ell+1})$ and $\mathcal{G}^\ell_{\ell+1} = \sigma(\mathcal{G}^\ell_\ell \cup \hat{\mathcal{G}}^\ell_{\ell+1})$.

We have $\mathbb{P}(|b_\pi(t) - \widetilde{b}(t)| \geq \eta n) = \mathbb{P}\left(\left|\mathbb{E}[b_\pi(t)|\mathcal{F}_{|\mathcal{E}|}] - \mathbb{E}[b_\pi(t)|\mathcal{F}_0]\right| \geq \eta n\right)$. Let us emphasize the dependence of the number of ω-adopters $b(t)$ on a specific graph $\pi \in \Pi$ with notation $b_\pi(t)$ and define $A_\ell = \mathbb{E}[b_\pi(t)|\mathcal{F}_\ell]$. Note, indeed, that $\{A_\ell\}_\ell$ is a martingale.

In order to estimate the above probability we apply Lemma 20. First, we compute

$$\mathbb{P}\left(|A_{\ell+1} - A_\ell| \geq c_\ell\right) = \mathbb{P}\left(|A_{\ell+1} - A_\ell|^s \geq c_\ell^s\right) \leq \mathbb{E}\left[|A_{\ell+1} - A_\ell|^s\right]/c_\ell^s$$

Notice that by construction $A_\ell = \mathbb{E}[b_\pi(t)|\mathcal{F}_\ell] = \mathbb{E}[b_{\pi^\ell}(t)|\mathcal{F}_\ell] = \mathbb{E}[b_{\pi^\ell}(t)|\mathcal{F}_{\ell+1}]$ where the first equation holds because π and π^ℓ are both uniform on $\mathcal{C}_\ell(\pi_{[\ell]})$, and last equation descends from the fact that $\hat{G}^\ell_{\ell+1}$ and $\hat{F}^\ell_{\ell+1}$ are conditionally independent given $\mathcal{F}_\ell = \mathcal{G}^\ell_\ell$. Furthermore we have $A_{\ell+1} = \mathbb{E}[b_\pi(t)|\mathcal{F}_{\ell+1}]$. Therefore

$$\begin{aligned} A_{\ell+1} - A_\ell &= \mathbb{E}[b_\pi(t) \mid \mathcal{F}_{\ell+1}] - \mathbb{E}[b_\pi(t) \mid \mathcal{F}_\ell] = \mathbb{E}[b_\pi(t) \mid \mathcal{F}_{\ell+1}] - \mathbb{E}[b_{\pi^\ell}(t) \mid \mathcal{F}_{\ell+1}] \\ &= \mathbb{E}[b_\pi(t) - b_{\pi^\ell}(t) \mid \mathcal{F}_{\ell+1}] \end{aligned} \tag{26}$$

Now observing that by construction π and π^ℓ differ in at most two positions, hence we have:

$$\mathbb{E}[b_\pi(t) - b_{\pi^\ell}(t) \mid \mathcal{F}_{\ell+1}] \leq 2\mathbb{E}[|\mathcal{N}_t^{\mathrm{v}(\pi_{\ell+1})}| \mid \mathcal{F}_{\ell+1}]$$

and

$$\mathbb{E}\left[|A_{\ell+1} - A_\ell|^s\right] \leq 2^s \mathbb{E}\left[\left(\mathbb{E}[|\, \mathcal{N}_t^{\mathrm{v}(\pi_{\ell+1})} \mid |\mathcal{F}_{\ell+1}]\right)^s\right] \leq 2^s \mathbb{E}\left[|V_t^{\mathrm{v}(\pi_\ell+1)}|^s\right]$$

where $\mathrm{v}(\pi_\ell)$ is the in-node of edge π_ℓ. We conclude that $\mathbb{P}\left(|A_{\ell+1} - A_\ell| \geq c_\ell\right) \leq 2^s \left[\mathbb{E}[|V_t^{\mathrm{v}(\pi_{\ell+1})}|^s\right]/c_\ell^s$. For any $x > 0$ let $c_\ell = x$ for all ℓ. Then, by applying Lemma 20 and observing that $\Delta^\star \leq n$, we obtain

$$\begin{aligned} \mathbb{P}\left(|b(t) - \widetilde{b}(t)| \geq \eta n\right) &\leq 2\mathrm{e}^{-\frac{\eta^2 n}{32\bar{d}x^2}} + \left(1 + \frac{2}{\eta}\right) \frac{2^s}{x^s} \sum_{\ell=1}^{\bar{d}n} \left[\mathbb{E}[|V_t^{v(\pi_\ell)}|^s\right] \\ &= 2\mathrm{e}^{-\frac{\eta^2 n}{32\bar{d}x^2}} + \left(1 + \frac{2}{\eta}\right) \frac{2^s}{x^s} \sum_{v \in \mathcal{V}} |\boldsymbol{\delta}_v| [\mathbb{E}[|V_t^v|^s] \end{aligned}$$

from which the thesis. ∎

REMARK 6. *The approach followed in Lemma 21 can be potentially extended to more general classes of random graphs, with a variable number of edges, as long as: i) the number of edges in the graph is sufficiently concentrated around its expectation; ii) random variables associated to the presence of different edges in the graph are sufficiently weakly correlated, so that we can effectively bound* $\mathbb{E}[|A_{\ell+1} - A_\ell|]$*, through a coupling argument similar to the one established between* π *and* π^ℓ *in Lemma 21.*

Let $\mathcal{N} = ((\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau))$ be a labeled graph. We denote the random times at which the opinion update occurs, random node sequence activated, and the random state, by $\{T_\ell\}_{\ell\in\mathbb{N}}, \{w_\ell\}_{\ell\in\mathbb{N}}$, $\{z_\ell\}_{\ell\in\mathbb{N}}$, respectively. For $t \geq 0$, let $Z(t)$ be the state vector of the ASD dynamics on $\mathcal{N}$ and $b(t) = |\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ be the number of state-ω adopters at time t.

LEMMA 22. *Let* $\{T_\ell\}_{\ell\in\mathbb{N}}$ *be the random times at which the opinion update occurs. For* $t > 0$ *define the random variable* $\iota(t) = \sup\{k \in \mathbb{N} : T_k \leq t\}$*. Then for any* $\epsilon > 0$ *and* $\Delta_n < tn$ *the following bounds hold*

$$\mathbb{P}(\iota(t) \geq (1+\epsilon)tn) \leq \mathrm{e}^{-\frac{nt\epsilon^2}{2(1+\epsilon)}}, \quad \mathbb{P}(|\iota(t) - tn| \geq \Delta_n) \leq 2\mathrm{e}^{-\frac{\Delta_n^2}{2(tn+\Delta_n)}}.$$

Proof. This is a straightforward consequence of Chernoff bound [21]. ∎

LEMMA 23 (Unveiling dynamics). *Let* $\mathcal{N} = ((\mathcal{V}, \mathcal{E}, \mathcal{A}, \lambda, \sigma, \tau))$ *be a labeled graph. Let* $\{T_\ell\}_{\ell\in\mathbb{N}}, \{w_\ell\}_{\ell\in\mathbb{N}}, \{z_\ell\}_{\ell\in\mathbb{N}}$ *be the random times at which the opinion update occurs, random node sequence activated, and random state of activated sequence, respectively. We denote the size of the induced graph obtained in the exploration process of the neighborhood of a node* v *with* V_t^v *at time* t*. For* $t \geq 0$*, let* $Z(t)$ *be the state vector of the ASD dynamics on* $\mathcal{N}$*,* $b(t) = |\{v \in \mathcal{V} : Z_v(t) = \omega\}|$ *be the number of state-*ω *adopters at time* t *conditioned to* $\mathcal{N}$*. We denote the expectation over the activation process by* $\bar{b}(t) = \mathbb{E}[b(t)|\mathcal{N}]$*. For any* $\epsilon > 0$ *we have*

$$\mathbb{P}(|b(t) - \bar{b}(t)| > \eta n) \leq 2 \inf_{x>0} \left\{ 2\mathrm{e}^{-\frac{\eta^2 n}{288(1+\epsilon)tx^2}} + \left(1 + \frac{6}{\eta}\right)(1+\epsilon)tn\frac{2^s \mathbb{E}_v\left[|V_t^v|^s\right]}{x^s} \right\}$$
$$+ 2\mathrm{e}^{-\frac{nt\epsilon^2}{2(1+\epsilon)}} + 2\mathrm{e}^{-\frac{\eta^2 n}{72(t+\eta/6)}}$$

with v *chosen uniformly at random in* $\mathcal{V}$*.*

Proof. For $t \in \mathbb{R}^+$ let $\iota(t) = \sup\{k \in \mathbb{N} : T_k \leq t\}$, w and z be the random sequences of activated nodes and the corresponding random state. We recall that for any $\ell > 0$ the sequence $w_{[\ell]}$ is uniformly distributed over $\mathcal{V}^{[\ell]}$. We denote by $\mathcal{F}_{\ell,s}$ the natural filtration generated by $w_{[\ell]}$ and $z_{[s]}$. Given $\iota(t)$, let w be a random vector uniformly distributed in $\mathcal{V}^{[\iota(t)]}$ (let $w_{\ell+1} = v$) and $\hat{w}^\ell$ be a random vector in $\mathcal{V}^{[\iota(t)]}$ which is obtained by choosing some v' uniformly at random from the set of nodes $\mathcal{V}$ and putting $\hat{w}^\ell_{\ell+1} = v'$ and $\hat{w}^\ell_i = w_i$ for all $i \in [\iota(t)] \setminus \{\ell+1\}$. It should be noticed that $w_{\ell+1}$ and $\hat{w}^\ell_{\ell+1}$ are conditionally independent given $w_{[\ell]}$. Furthermore, by construction $\hat{w}^\ell$ is uniformly distributed over $\mathcal{V}^{[\iota(t)]}$.

In an analogous way, recall that $z_s = Z_{w_s}$ is a random variable distributed as defined in Definition 1. Given $\iota(t)$, let z be a vector of length $\iota(t)$, whose components are independent with the ℓ-component distributed as $\Theta^{(\lambda(w_\ell))}$ in Definition 1 (let $z_{s+1} = \omega$) and, let $\tilde{z}^s$ be a random vector which is obtained by choosing some ω'

according to $\Theta^{(\lambda(w_\ell))}$ in Definition 1 and putting $\tilde{z}^s_{s+1} = \omega'$ and $\tilde{z}^s_i = z_i$ for all $i \in [\iota(t)] \setminus \{s+1\}$.

Let us emphasize the dependence of the number of ω-adopters $b(t)$ on a specific sequence of activated nodes w and states z with notation $b_{w,z}(t)$. Given $\iota(t)$, we define for any $(\ell, s) \in [\iota(t)] \times [\iota(t)]$ the conditional expectetion $B^{\iota(t),\mathcal{N}}_{\ell,s} = \mathbb{E}[b(t)|\iota(t), \mathcal{F}_{\ell,s}, \mathcal{N}]$, then

$$\mathbb{P}\left(|b_{w,z}(t) - \bar{b}(t)| \geq \eta n\right) \leq \underbrace{\mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\iota(t),\iota(t)} - B^{\iota(t),\mathcal{N}}_{\iota(t),0}| > \frac{\eta n}{3}\right)}_{\text{(T1)}} +$$
$$+ \underbrace{\mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\iota(t),0} - B^{\iota(t),\mathcal{N}}_{0,0}| > \frac{\eta n}{3}\right)}_{\text{(T2)}} + \underbrace{\mathbb{P}\left(\left|B^{\iota(t),\mathcal{N}}_{0,0} - \mathbb{E}[b_{w,z}(t)|\mathcal{F}_{0,0}, \mathcal{N}]\right| \geq \frac{\eta n}{3}\right)}_{\text{(T3)}}$$

We now evaluate (T1) and (T2) by applying Lemma 20 and (T3).

- In order to estimate (T1) we first consider

$$\begin{aligned} B^{\iota(t),\mathcal{N}}_{\ell+1,0} - B^{\iota(t),\mathcal{N}}_{\ell,0} &= \mathbb{E}[b_{w,z}(t)|\iota(t), \mathcal{F}_{\ell+1,0}, \mathcal{N}] - \mathbb{E}[b_{w,z}(t)|\iota(t), \mathcal{F}_{\ell,0}, \mathcal{N}] \\ &= \mathbb{E}[b_{w,z}(t)|\iota(t), \mathcal{F}_{\ell+1,0}, \mathcal{N}] - \mathbb{E}[b_{\hat{w}^{\ell+1},z}(t)|\iota(t), \mathcal{F}_{\ell+1,0}, \mathcal{N}] \\ &= \mathbb{E}[b_{w,z}(t) - b_{\hat{w}^\ell,z}(t)|\iota(t), \mathcal{F}_{\ell+1,0}, \mathcal{N}]. \end{aligned}$$

  By observing that, by construction, w and $\hat{w}^{\ell-1}$ differ in at most one position, we get

$$\mathbb{E}[b_{w,z}(t) - b_{\hat{w}^\ell,z}(t)|\iota(t), \mathcal{F}_{\ell+1,0}, \mathcal{N}] \leq 2\mathbb{E}[|V^v_t||\mathcal{F}_{\ell,0}]$$

  where v is chosen uniformly at random in $\mathcal{V}$. We thus have for any $x > 0$

$$\begin{aligned} &\mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\ell+1,0} - B^{\iota(t),\mathcal{N}}_{\ell,0}| > x\right) = \mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\ell+1,0} - B^{\iota(t),\mathcal{N}}_{\ell,0}|^m > x^m\right) \\ &\leq \frac{\mathbb{E}\left[|B^{\iota(t),\mathcal{N}}_{\ell+1,0} - B^{\iota(t),\mathcal{N}}_{\ell,0}|^m\right]}{x^m} \leq \frac{2^m\mathbb{E}\left[(\mathbb{E}[|V^v_t||\mathcal{F}_{\ell+1,0}])^m\right]}{x^m} \leq \frac{2^m\mathbb{E}\left[|V^v_t|^m\right]}{x^m} \end{aligned}$$

  where v is chosen uniformly at random. We thus have for any $\epsilon > 0$

$$\begin{aligned} &\mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\iota(t),0} - B^{\iota(t),\mathcal{N}}_{0,0}| > \frac{\eta n}{3}\right) \\ &\leq \mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\iota(t),0} - B^{\iota(t),\mathcal{N}}_{0,0}| > \frac{\eta n}{3}|\iota(t) < (1+\epsilon)tn\right) + \mathbb{P}\left(\iota(t) \geq (1+\epsilon)tn\right) \\ &\leq \inf_{x>0}\left\{2\mathrm{e}^{-\frac{\eta^2 n}{288(1+\epsilon)tx^2}} + \left(1 + \frac{6}{\eta}\right)(1+\epsilon)tn\frac{2^m\mathbb{E}\left[|V^v_t|^m\right]}{x^m}\right\} + \mathrm{e}^{-\frac{nt\epsilon^2}{2(1+\epsilon)}} \end{aligned} \tag{27}$$

  with v chosen uniformly at random in $\mathcal{V}$.

- (T2): Following the same arguments used in the previous point and observing that $\tilde{z}^s_s$ differs from $z_{[\iota(t)]}$ only at position $s+1$, we get

$$\begin{aligned} &\mathbb{P}\left(|B^{\iota(t),\mathcal{N}}_{\iota(t),\iota(t)} - B^{\iota(t),\mathcal{N}}_{\iota(t),0}| > \frac{\eta n}{3}\right) \leq \\ &\inf_{x>0}\left\{2\mathrm{e}^{-\frac{\eta^2 n}{288(1+\epsilon)tx^2}} + \left(1 + \frac{6}{\eta}\right)(1+\epsilon)tn\frac{2^m\mathbb{E}\left[|V^v_t|^m\right]}{x^m}\right\} + \mathrm{e}^{-\frac{nt\epsilon^2}{2(1+\epsilon)}}. \end{aligned} \tag{28}$$

- (T3): Let now $\hat{\iota}(t)$ a random variable taking values in $\mathbb{Z}^+$, distributed as $\iota(t)$, and independent of it; let $w_{[\iota(t)]} \in \mathcal{V}^{\iota(t)}$ and $\hat{w}_{[\hat{\iota}(t)]} \in \mathcal{V}^{\hat{\iota}(t)}$ random uniform sequences of activation of length $\iota(t)$ and $\hat{\iota}(t)$ respectively and $b(t)$ and $\hat{b}_\ell(t)$ the corresponding the numbers of state-ω adopters at time t on the network $\mathcal{N}$:
  For any Δ_n we have

$$\begin{aligned}
&\mathbb{P}\left(|\mathbb{E}[b(t)|\iota(t),\mathcal{F}_{0,0},\mathcal{N}] - \mathbb{E}[b(t)|\mathcal{F}_{0,0},\mathcal{N}]| \geq \frac{\eta n}{3}\right) \qquad (29)\\
&= \mathbb{P}\left(\left|\mathbb{E}[b(t)|\iota(t),\mathcal{F}_{0,0},\mathcal{N}] - \mathbb{E}[\hat{b}_\ell(t) \mid \iota(t),\mathcal{F}_{0,0},\mathcal{N}]\right| \geq \frac{\eta n}{3}\right)\\
&\leq \mathbb{P}\left(|\iota(t)-\hat{\iota}(t)| \geq \frac{\eta n}{3}\middle||\hat{\iota}(t)-tn| \leq \Delta_n, |\iota(t)-tn| \leq \Delta_n\right)\\
&+ 2\mathbb{P}\left(|\iota(t)-tn| > \Delta_n\right) \leq 2\mathrm{e}^{-\frac{\Delta_n^2}{2(tn+\Delta_n)}} \qquad (30)
\end{aligned}$$

  where the second inequality descend from the fact that we can establish a coupling between the sequences of activation $w_{[\iota(t)]}$ and $\hat{w}_{[\hat{\iota}(t)]}$ by forcing them to have common initial part of length $\min(\iota(t),\hat{\iota}(t))$ while the last inequality follows from Lemma 22. Choosing $\Delta_n = \frac{\eta n}{6}$ we get

$$\mathbb{P}\left(|\iota(t)-\hat{\iota}(t)| \geq \frac{\eta n}{3}\middle||\hat{\iota}(t)-tn| \leq \Delta_n, |\iota(t)-tn| \leq \Delta_n\right) = 0$$

  and we conclude the proof combining with (28). ∎

Proof of Theorem 5 For any $\epsilon > 0$ we have

$$\mathbb{P}(|b(t)-\mathbb{E}[b(t)]| > \eta n) \leq \mathbb{P}(|b(t)-\mathbb{E}[b(t)|\mathcal{N}]| > \eta n/2) + \mathbb{P}(|\mathbb{E}[b(t)|\mathcal{N}]-\mathbb{E}[b(t)]| > \eta n/2)$$

Let v is sampled with a probability proportional with its in-degree. Combining Lemma 23 with Lemma 21 we get that for any $\epsilon > 0$, $\eta > 0$ and $x > 0$ we have

$$\begin{aligned}
\mathbb{P}(|b(t)-\mathbb{E}[b(t)]| > \eta n) &\leq 4\mathrm{e}^{-\frac{\eta^2 n}{1152(1+\epsilon)tx^2}} + \left(1+\frac{12}{\eta}\right)(1+\epsilon)tn\frac{2^s\mathbb{E}_v\left[|V_t^v|^s\right]}{x^s}\\
&+ 2\mathrm{e}^{-\frac{nt\epsilon^2}{2(1+\epsilon)}} + 2\mathrm{e}^{-\frac{\eta^2 n}{288(t+\eta/12)}} + \left(1+\frac{4}{\eta}\right)\frac{2^s}{x^s}\sum_{w\in\mathcal{V}}|\boldsymbol{\delta}_w|[\mathbb{E}[|V_t^w|^s] + 2\mathrm{e}^{-\frac{\eta^2 n}{128\bar{d}x^2}}.
\end{aligned}$$

Appendix B. Proofs of Sections 5.3 and 5.4.

Proof of Lemma 8 Let $\mathrm{d}(w_1,w_2)$ be the geodesic distance (i.e. the number of edges in a shortest path) between nodes w_1 and w_2. We denote the maximum number of hops traversed from the root v to a node w in $\mathcal{T}_t$ with $H_v(t) = \max_{w\in\mathcal{T}_t}\mathrm{d}(v,w)$. Equivalently, $H_v(t)$ is the depth of the tree $\mathcal{T}_t$. Let us fix $h_n = c\log n$ with $c > 0$ then

$$\begin{aligned}
\mathsf{F}_{\widetilde{W}_t}(x_n) &\leq \mathbb{P}(\widetilde{W}_t > x_n | H_v(t) < h_n) + \mathbb{P}(H_v(t) \geq h_n)\\
&= \mathbb{P}(\widetilde{W}_t > x_n | H_v(t) < h_n) + \mathbb{P}\left(\exists w \in \mathcal{T}_t : \mathrm{d}(v,w) = h_n\right)\\
&\leq \mathbb{P}(N_{h_n} > x_n) + n\mathbb{P}(\widetilde{P}(t) \geq h_n)
\end{aligned}$$

where $\{N_h\}_{h\in\mathbb{N}}$ is a truncated GW process of maximum depth h, in which the offspring distribution of the root follows law p, while the degree of remaining nodes follow law q, and $\widetilde{P}(t)$ is a variable representing the number of points falling in $[0,t)$ according to

a homogeneous Poisson process with constant parameter $\gamma = 1$. Note that $n\mathbb{P}(\widetilde{P}(t) \geq h_n)$ represents an obvious upper-bound to the probability that the depth of $\mathcal{T}_t$ exceeds h_n, since by conduction $\mathbb{P}(\widetilde{P}(t) \geq h_n)$ is equal to the probability that a given branch of $\mathcal{T}_t$ has depth larger than h_n.

We have

$$\begin{aligned}\mathbb{P}(\widetilde{P}(t) \geq h_n) &\leq \sum_{h=h_n}^{\infty} \frac{\mathrm{e}^{-t}t^h}{h!} = \frac{\mathrm{e}^{-t}t^{h_n}}{h_n!} \sum_{h \geq h_n} \frac{t^{h-h_n}}{h(h-1)\dots(h_n+1)} \\ &\leq \frac{\mathrm{e}^{-t}t^{h_n}}{h_n!} \sum_{s \geq 0} \left(\frac{t}{h_n}\right)^s = \frac{\mathrm{e}^{-t}t^{h_n}}{h_n!} \left(1 - \frac{t}{h_n}\right)^{-1} \quad \text{for } h_n \to \infty\end{aligned}$$

where the last inequality follows from $t/h_n < 1$ definitely, being $t = o(h_n)$ for $h_n \to \infty$. Using Stirling's approximation [21]

$$\mathbb{P}(\widetilde{P}(t) \geq h_n) \leq \mathrm{e}^{-t+h_n \log t - h_n(\log h_n) + h_n - \frac{1}{2}\log(2\pi h_n) - \log(1-t/h_n)}. \tag{31}$$

Using bound in (31), we obtain for any $s > 0$

$$\mathsf{F}_{\widetilde{W}_t}(x_n) \leq \mathbb{P}(N_{h_n} > x_n) + n\mathrm{e}^{-h_n \log h_n + o(h_n \log h_n)} \leq \frac{\mathbb{E}[N_{h_n}^s]}{x_n^s} + o(1/n) \quad n \to \infty,$$

where the second last inequality follows from the Markov inequality [21]. At last, we emphasize that the an analogous bound holds for the number W_t of edges, since $\widetilde{W}_t = W_t + 1$.

LEMMA 24. *Let $\mathcal{N} = (\mathcal{V}, \mathcal{E})$ be a network sampled from the configuration model ensemble $\mathfrak{C}_{n,p}$ of compatible size n and statistics p and q, $\mathcal{N}_h^{w_0}$ be the induced graph obtained by the exploration process of the h-depth neighborhood of a node w_0 chosen uniformly at random from the node set $\mathcal{V}$. Let $\dot{q}$ be the distribution defined as follows: $\sum_{h=0}^{k} \dot{q}_h = \min(\sum_{h=0}^{k} p_h, \sum_{h=0}^{k} q_h)$, $\forall k$. Note that $\dot{q}$ stochastically dominates both p and q. Moreover, let $\widehat{q}_k$ be the distribution related to $\dot{q}_k$ as follows: $\widehat{q}_{k+k_0} = \dot{q}_k$, with $k_0 = \min_k : \sum_{j=1}^{k} \dot{q}_j > \epsilon$. Let $N_h^{w_0}$ be the number of nodes in $\mathcal{N}_h^{w_0}$. We have that for every $x_n \leq \lfloor \epsilon n \rfloor$: $\mathbb{P}(N_h^{w_0} > x_n) \leq \mathbb{P}(\overline{N}_h^{w_0} > x_n)$ where $\overline{N}_{h_0}^{w_0}$ is the total number of nodes over a tree of depth h_0, in which the degree of all the nodes follow law $\widehat{q}$.*

The proof is omitted for brevity and we refer the reader to [37] for details.

COROLLARY 25. *For any h_0 and $s \geq 1$ we have: $\mathbb{E}[(N_{h_0}^{w_0})^s] = O(\mathbb{E}[(\overline{N}_{h_0}^{w_0})^s])$.*

Now we introduce a technical result that characterizes the moments of the total number of nodes generated in a GW process in which the offspring distribution follows a generic law $\widehat{q}$. Such result will later on be used to prove more specific results valid when $\widehat{q}$ either follows a truncated power law distribution (Corollary 27) or it has all finite moments (Corollary 28). The proof is obtained through a coupling argument and using induction. We omit the details for brevity, but the interested reader can find the mathematical details in [37].

LEMMA 26. *Let $\{N_h\}_{h \geq 0}$ be a supercritical GW process with power-law degree distribution $\widehat{q} = \{\widehat{q}_k\}_{k \geq 0}$ (with $\sum_{k=0}^{\infty} k\widehat{q}_k > 1$). Let n_h be the number of nodes at depth h, and N_h be the total number of nodes generated up to generation h. These quantities are defined recursively as follows: $n_{h+1} = \sum_{i=1}^{n_h} D_i$; $N_{h+1} = N_h + n_{h+1}$ where D_i are*

i.i.d. according to $\widehat{q}$, and we start with $n_0 = N_0 = 1$. Let $\widetilde{\mu}_j = \mathbb{E}[(D+1)^j]$, with D distributed according to $\widehat{q}$. We have

$$\mathbb{E}[N_h^s] = O\left(\sum_{(k_1,\dots,k_s)\in\mathcal{K}_s} \widetilde{\mu}_k \widetilde{\mu}_1^{k_1} \widetilde{\mu}_2^{k_2} \dots \widetilde{\mu}_s^{k_s} \widetilde{\mu}_1^{s(h-2)}\right). \tag{32}$$

where $k = \sum_{j=1}^s k_j$, and the summation is over $\mathcal{K}_s = \{(k_1,\dots,k_s) : \sum_{j=1}^s j k_j = s\}$.

Corollary 27 (**Proof of Lemma 9**). *Let $\{N_h\}_{h\geq 0}$ be a supercritical GW process with power-law degree distribution $\widehat{q} = \{\widehat{q}_k\}_{k\geq 0}$ of exponent $\beta > 1$, truncated at $\widehat{k}_{\max} = \Theta(n^\zeta)$, $\zeta > 0$. We have: $\mathbb{E}[N_h^s] = O(\widehat{\mu}_s \cdot \widehat{\mu}_1^{s(h-1)})$, $\forall \beta > 1$, where $\widehat{\mu}_j$ is the j-th moment of q.*

Proof. Let's first consider the extreme case in which all moments $\widehat{\mu}_j$ of $\widehat{q}$ are infinite, including the first one, which happens for $1 < \beta < 2$. From (11) we have $\widetilde{\mu}_j = \Theta(\widehat{\mu}_j) = \Theta(n^{\zeta(j+1-\beta)})$, $\forall j \geq 1$. Plugging the above expression of $\widetilde{\mu}_s$ into (32), we obtain:

$$\begin{aligned} F_h^s &= O\left(\sum_{(k_1,\dots,k_s)\in\mathcal{K}_s} \mu_k n^{\zeta(k_1(1+1-\beta)+k_2(2+1-\beta)+\dots k_s(s+1-\beta))} \mu_1^{s(h-2)}\right) \\ &= O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-2)} n^{\zeta s(2-\beta)}\right) = O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-2)} \widehat{\mu}_1^s\right) = O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-1)}\right) \end{aligned} \tag{33}$$

where we have used the fact that, since we are assuming $\beta < 2$, the dominant term in the summation is the one associated to the largest possible value of k, obtained when $k_1 = s$, while all others $k_i = 0$, $i > 1$.

Let us now assume that all moments of the degree distribution are finite up to moment $j-1$, whereas moments of order j or higher are infinite. This happens when $\beta > j$. Repeating the same passages as before, adding and subtracting the 'missing' terms corresponding to finite moments, we get:

$$\begin{aligned} F_h^s &= O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-2)} \sum_{(k_1,\dots,k_s)\in\mathcal{K}_s} n^{\zeta((k-k_1)(2-\beta)-k_2(3-\beta)-\dots-k_{j-1}(j-\beta))}\right) = \\ &= O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-2)}\right) = O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-1)}\right) \end{aligned} \tag{34}$$

where we have used the fact that, since $\beta > j$, the dominant term is obtained again by choosing $k = k_1 = s$, while all others $k_i = 0$, $i > 1$. ∎

Remark 7. *In our application to the single-class configuration-model with (truncated) power law distribution (Section 5.3), we are only interested to the case $\beta > 2$ (so that the average degree is finite), for which we could obtain the stricter bound $F_h^s = O\left(\widehat{\mu}_s \widehat{\mu}_1^{s(h-2)}\right)$. However, since we take $h = c \log n$, we are not penalized by using looser bound stated in Corollary 27.*

Remark 8. *To apply Corollary 27 to the single-class configuration-model with (truncated) power law distribution (Section 5.3), one should also consider the fact that the first generation of nodes in the GW process follows law $p_k^{(n)}$, while the following generations follow law $q_k^{(n)}$. However, by Assumption 1, we have that $p_k^{(n)}$ and $q_k^{(n)}$*

are both $O(k^{-\beta})$, hence $p_k^{(n)}$ and $q_k^{(n)}$ are both stochastically dominated by a power law distribution $\widehat{q}$ of exponent β, which allows us to apply Corollary 27 and obtain a valid bound for our configuration-model. In particular we can define $\widehat{q}$ as follows: $\sum_{h=0}^{k} \widehat{q}_h = \min(\sum_{h=0}^{k} p_h, \sum_{h=0}^{k} q_h)$.

COROLLARY 28. *Let $\{N_h\}_{h\geq 0}$ be a supercritical GW process with degree distribution $\widehat{q} = \{\widehat{q}_k\}_{k\geq 0}$ (with $\sum_{k=0}^{\infty} k\widehat{q}_k > 1$) having all finite moments. Let N_h be the total number of nodes generated up to generation h. We have $\mathbb{E}[N_h^s] = O(\widehat{\mu}_1^{s(h-2)})$, where $\widehat{\mu}_1$ is the first moment of $\widehat{q}$.*

Proof. By assumption we have $\widetilde{\mu}_j = \Theta(\widehat{\mu}_j) = \Theta(1)$ for any $j \geq 1$. As direct application of Lemma 26 we get $\mathbb{E}[N_h^s] = O\left(\widehat{\mu}_1^{s(h-2)}\right)$. ∎

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