Who Should Be My Friends?

Social balance from the perspective of game theory

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Abstract. We define *balance games*, which describe the formation of friendships and enmity in social networks. We show that if the agents give high priority to future profits over short term gains, all Pareto optimal strategies will eventually result in a balanced network. If, on the other hand, agents prioritize short term gains over the long term, every Nash equilibrium eventually results in a network that is stable but that might not be balanced.

Keywords: Structural balance theory · Game theory · Nash equilibrium · Pareto optimality

1 Introduction

A *social network* consists of a number of agents and positive or negative relations between them. The agents could be countries, individuals or groups. A positive relation represents a friendship or alliance, while a negative relation represents an enmity or rivalry. Structural balance theory describes such networks, and was introduced by Heider [15,16] and later generalized by Cartwright and Harary [11,12,3]. It argues that certain patterns are likely to occur while other patterns are unlikely; the likely patterns are referred to as *balanced* while the unlikely ones are *unbalanced*. There is also empirical support for the assertion that networks tend towards balance, see for example [25,27], though a fully balanced network is not always (nor easily) reached [18].

Usually, balance theory describes a network as a whole; it is claimed (quite convincingly) that networks usually become more balanced over time, but relatively little attention is paid to the actions and motivations of individual agents on the way towards balance. Here, we take a different, game-theoretical approach: we explicitly treat the tendency towards balance as evidence for a preference by agents for balanced states over unbalanced ones. This allows us to take a detailed look at how this tendency follows the result of rational choices by the individual agents.

We introduce a class of *balance games*, which are multi-stage games where in each stage one agent updates their relationship with someone else, and all agents prefer being involved in balanced relations over unbalanced ones. We show that if the agents are sufficiently patient (i.e., if the discount factor δ is high enough), any Pareto optimal strategy profile will, with probability 1, eventually result in a balanced network. If the agents are less patient, the end result may not be a balanced network. In fact, we show that for sufficiently impatient agents (i.e., if the discount factor δ is low enough), any subgame perfect Nash equilibrium strategy profile will, with probability 1, result in a network that need not be balanced but that is *stable*. Stability was defined by Van der Hoek et al. [17] and is related to but strictly weaker than balance.

The structure of the paper is as follows. We first give definitions for balance, stability and the balance game in Section 2, where we also present a few useful lemmas, give an example, and discuss related work. Then, in Section 3 we consider the case of patient agents, and show that for them every Pareto optimal strategy profile results in balance. In Sections 4 we study the cases of impatient agents. In Section 5 we discuss some generalizations as well as some limitations of our results. We conclude in Section 6.

2 Definitions and Preliminaries

In this section we first provide definitions of social balance theory, including structural balance and stability. Most of these are from the literature (mainly [3] and [17]). We give examples and introduce some results which will be used in later proofs. We then move on to define a class of balance games and some relevant notions. We use an example to explain the idea of balance games. We then discuss related approaches.

2.1 Structural balance and stability

A *(social) network* is an irreflexive, complete, signed and undirected graph, i.e., a pair (A, E) such that A is a finite set of agents (represented by vertices of a graph), and $E : \{\{i, j\} \subseteq A \mid i \neq j\} \to \{+, -\}$ is an edge function that assigns to each unordered pair of different agents a positive $(+)$ or a negative $(-)$ edge. For simplicity, for pairs of agents we write ij, ik, etc, and for triads we write ijk, ijl, etc. We only consider graphs with at least three agents.

Balance Given a network $N = (A, E)$, a triad ijk of N is called *balanced*, if the labels of its edges are of one of the types $+++$ or $+--$ up to isomorphism. So in a balanced triad there is an even number of negative edges. The *unbalanced* triads therefore have either of the other two types: $++-$ or $---$. A network is *balanced*, if all of its triads are balanced, and *unbalanced* otherwise.

In a triad of the type $---$, all three agents are enemies of one another. In that situation, it is likely that two of them will set aside their differences and unite against their common foe. Doing so would turn the triad into $+--$, which is balanced. In a triad $++-$, there is one agent i that is friends with both j and k, while j and k are enemies. It is then likely that one of two things will happen: either the mutual friendship with i will form a basis for reconciliation between j and k, resulting in the balanced triad $+++$, or the tension between j and k will force i to end its friendship with one of them, resulting in the balanced triad $+--$. So both types of unbalanced triad have a tendency to evolve into a balanced triad.

Stability In addition to balance, we will also use the weaker notion of stability, which is defined in terms of mutual and anti-mutual ties. For a pair ij of a network $N = (A, E)$, a *mutual tie* of ij is an agent k of N such that k is a mutual friend or mutual enemy of i and j, i.e., either $E(ik) = E(jk) = +$ or $E(ik) = E(jk) = -$.

An *anti-mutual tie* of ij is an agent k of N such that k is either a friend of i and an enemy of j, or an enemy of i and a friend of j, i.e., if one of the following is true:

- $E(ik) = +$ and $E(jk) = -$
- $E(ik) = -$ and $E(jk) = +$.

We say an pair ij is *stable*, if it is one of the following cases:

- $E(ij) = +$ and ij has at least as many mutual ties as anti-mutual ties;
- $E(ij) = -$ and ij has at least as many anti-mutual ties as mutual ties.

Finally, a network is *stable*, if all of its pairs are stable.

A mutual tie is a reason to stay or become friends, while an anti-mutual tie is a reason to stay or become enemies. A network is therefore stable if every pair of friends has at least as many reasons to remain friends as to become enemies, and every pair of enemies has at least as many reasons to remain hostile as to become friends.

Balance vs. stability If ijk is a balanced triad and $E(ij) = +$, then k is a mutual tie for ij. Specifically, if ijk is of type $+++$ then k is a mutal friend, and if ijk is of type $+--$ then k is a mutual foe. Likewise, if ijk is balanced and $E(ij) = -$, then k is an anti-mutual tie for ij. A balanced network is therefore a stable network with the additional property that for all pairs ij, if $E(ij) = +$ then ij has only mutual ties and if $E(ij) = -$ then ij has only anti-mutual ties.

Not all stable networks are balanced, however. Two typical examples of stable networks that are not balanced are illustrated in Figure 1.

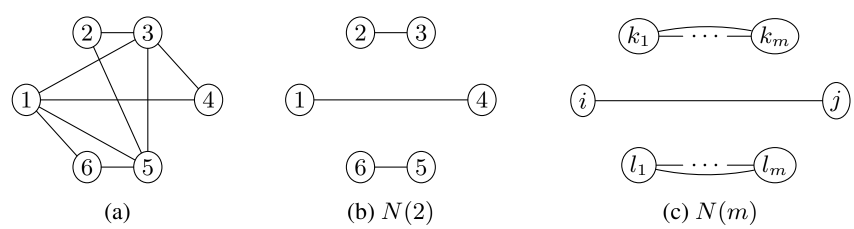


Fig. 1: Stable networks that are unbalanced, where a solid line stands for a positive edge and the lack of a line for a negative edge.

In Figure 1(a), one can verify that every pair has an equal number of mutual and anti-mutual ties. For instance, pair $\{1, 3\}$ has two mutual ties (i.e., agents 4 and 5) and two anti-mutual ties (i.e., agents 2 and 6). It is therefore stable, and so is the entire network. Yet the network is not balanced, for, e.g., the triad $\{1, 2, 3\}$ is not balanced. Similarly, the network of Figure 1(b) is also stable but not balanced.

The benefit of the latter network is that it can be generalized to a class of stable and unbalanced networks illustrated in Figure 1(c). For each natural number $m \geq 2$, the network $N(m)$ can be divided into three cliques: the $\{k_1, \ldots, k_m\}$-party (k-party for short), the $\{l_1, \ldots, l_m\}$-party (l-party for short) which are of equal size, and a small, third party $\{i, j\}$. Agents are friendly towards members of their own clique and hostile towards members of other cliques. The network shown in 1(b) is $N(2)$.

One can verify that for any pair $\{k_x, k_y\}$, $\{l_x, l_y\}$ or $\{i, j\}$ in the same party, there are $2m$ mutual ties (i.e., all others are their mutual ties), and is therefore stable. Any pair $\{k_x, l_x\}$ across the two major parties are stable, as there are 2 mutual ties (i.e., i and j) and $(2m-2)$ anti-mutual ties. Any pair $\{i, k_x\}$, $\{i, l_x\}$, $\{j, k_x\}$ or $\{j, l_x\}$ across the third party and a major party has an equal number (i.e., m) of mutual and anti-mutual ties, and is thus stable as well. For every $m \geq 2$, the network $N(m)$ is therefore stable. It is not balanced, however, because it contains triads of the type $---$.

Let us consider a few technical lemmas that will be useful later on. The first lemma is well known in balance theory, and follows immediately from the fact that a triad is balanced if and only if it contains an even number of negative edges.

Lemma 1. *If a triad ijk is balanced, then flipping (the sign of) any single edge of the triad will make it unbalanced. Likewise, if ijk is unbalanced then flipping any single edge of the triad will make it balanced.*

A pair ij is stable if and only if it is part of at least as many balanced triads as unbalanced triads. The following lemma therefore follows from Lemma 1.

Lemma 2. *If a pair ij is stable, then flipping $E(ij)$ does not increase the number of balanced triads containing i, nor does it decrease the number of unbalanced triads containing i.*

If a pair ij is unstable, then flipping $E(ij)$ will strictly increase the number of balanced triads in the network.

Finally, we need a lemma that is new in this paper.

Lemma 3. *For any network, if there is an unbalanced triad, then all agents occur in an unbalanced triad.*

Proof. If ijk contains an odd number of negative edges, then for every agent $l \notin \{i, j, k\}$ at least one of lij, ljk or lik also has an odd number of negative edges.

2.2 Balance games

We study structural balance from the viewpoint of game theory, by introducing a *balance game* which is a type of multi-stage game of infinitely many stages. All the agents in a network are players of a balance game. Each agent is better off if it is involved in more balanced triads.

Valuation Given a network N, the valuation for an agent i in that network is the number of balanced triads i is part of minus the number of unbalanced triads it is part of. This valuation is denoted $val_i(N)$.

Actions At every stage of the game, a single agent (chosen uniformly at random) will be given an opportunity to change one of its relations. This agent can choose to change its relation to one other agent, or it can choose to *pass* and leave all relations unchanged. Note that an agent can only change those relations that it is involved in. Agent i can decide to become enemies with j, but i cannot choose to create an enmity between j and k—although i might be able to create a situation where j and k have an incentive to become enemies.

In a balanced network all triads are balanced, so balance is a *global* optimum of val_i for every i. In a stable network no single change to any relation ij would result in an increase in the number of balanced triads for either i or j (see Lemma 2). So stability is a *local* optimum of val_i for every i.

Cost of change If an agent decides to change a relation, it will incur a cost of change. This cost represents the effort and social cost associated with changing one's relation to another agent. For example, deciding to end an enmity might require an apology and a good bottle of wine, whereas ending a friendship may reduce one's social capital.

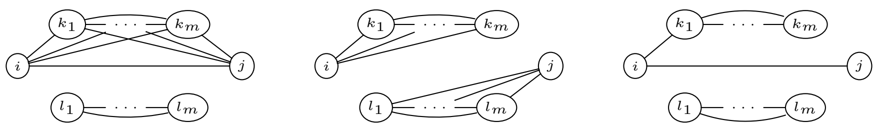
The exact value that this cost of change should have can be debated. We believe that it should lie in the open interval $(0, 2)$. In order to keep all calculations as simple as possible we prefer to have an integer cost of change, so we set it to be 1. See Section 5 for a discussion of why we believe that the cost of change should be between 0 and 2, and an overview of how any cost of change in the interval $[0, \infty)$ would influence our results.

Discount factor At every stage of the game, the agents immediately receive utility equal to their valuation of the current network. This rewards them for having more balanced relations and punishes them for unbalanced ones. Additionally, they receive utility from future game stages. A reward today is worth more than the same reward tomorrow, however, so the agents multiply their future utility by a discount factor $\delta \in (0, 1)$. The value of δ indicates the kind of agents that are being modeled; patient agents place (relatively) high value on the future and therefore have a high value for δ, impatient agents prioritize short term gain and therefore have a low value for δ. The utility for agent i in a network N therefore equals $val_i(N)$ plus δ times the expected utility in the successor network (minus the cost of change, if applicable).

We consider only memoryless pure strategies, so a strategy for an agent i can be represented by a function that maps every network to either a single change in a relation for i or to no change. Below we introduce the formal definitions. We assume a fixed set of agents $A = \{1, \ldots, n\}$ with $n \geq 3$, and use $\mathcal{N}$ to denote the set of all social networks over A.

Definition 1. *The* balance game *over a network* $N = (A, E)$ *is a pair* (N, s) *given by*

- (Players) A *is the set of players.*
- (Strategies) $s = (s_1, \ldots, s_n)$ *is a strategy profile, such that for every player* i*,* $s_i : \mathcal{N} \to \{(+, i, j), (-, i, j) \mid j \in A \backslash \{i\}\}$ *is a strategy for* i*.*



(a) A balanced outcome of $N(m)$ where i and j take the same side.

(b) A balanced outcome of $N(m)$ where i and j take different sides.

(c) A successor of $N(m)$ where i and k_1 become friends.

Fig. 2: Possible evolutions of the network $N(m)$ from Figure 1(c).

- (Outcomes) *The outcome of* (N, s) *is one of* $\{(N^{s_i}, s) \mid i \in A\}$*, chosen uniformly at random, where* $N^{s_i} = (A, E^{s_i})$ *is given by*

$$E^{s_i}(kl) = \begin{cases} +, & \textit{if } s_i(N) = (+, i, j) \textit{ and } kl = ij, \\ -, & \textit{if } s_i(N) = (-, i, j) \textit{ and } kl = ij, \\ E(kl), & \textit{otherwise}. \end{cases}$$

- (Utility) *The utility function* $u = (u_1, \ldots, u_n)$*, where* u_i *is the utility of player* i*, is given recursively by*

$$u_i(N, s) = val_i(N) + \delta \cdot \frac{1}{n} \cdot (\textstyle\sum_{j \in A} u_i(N^{s_j}, s) - c_j),$$

where $c_j = 1$ *if* $i = j$ *and* $N \neq N^{s_j}$*, and* $c_j = 0$ *otherwise.*

The recursive definition of utility does not immediately provide a practical way to compute $u_i(N, s)$. It is therefore useful to also have a direct characterization of $u_i(N, s)$. For this purpose, we use the concept of *timelines*. Given a strategy profile s, an s*-timeline* is an infinite sequence $l = \langle N_0, N_1, \ldots \rangle$ such that for every $t \in \mathbb{N}$, $N_{t+1} \in \{N_t^{s_i} \mid i \in A\}$. The utility of agent i in such a timeline is given by $u_i(l) = \sum_{t=0}^{\infty} \delta^t (val_i(N_t) - c)$, where $c = 1$ if i brought about a change from N_{t-1} to N_t and $c = 0$ otherwise. The utility $u_i(N, s)$ is then simply the expected value of $\{u_i(l) \mid l = \langle N, N_1, \ldots \rangle$ is an s-timeline$\}$.

For a given s-timeline $l = \langle N_0, N_1, \ldots \rangle$, if there is a natural number T such that $N_{t_1} = N_{t_2}$ for all $t_1, t_2 \geq T$, then we say l *finalizes* in N_T, or N_T is the *final* of l.

We write $N \rightsquigarrow_i N'$ if there is a strategy s_i for agent i such that $N' = N^{s_i}$, and we write $N \rightsquigarrow N'$ if there is at least one i such that $N \rightsquigarrow_i N'$.

As usual, we say a strategy profile is *Pareto optimal* (or simply, *optimal*) if there is no other strategy profile with which all players receive no less utility and at least one player gets a higher utility. A strategy profile is called a *subgame perfect Nash equilibrium* (or simply, an *equilibrium*), if no player could obtain a higher utility in any network by unilaterally changing its strategy.

2.3 Example

Consider the network $N(m)$ for a given $m \geq 2$ as depicted in Figure 1(c). In this network, most triads are balanced, but some remain unbalanced: the triads ikl and jkl

are unbalanced for every $k \in \{k_1, \ldots, k_m\}$ and every $l \in \{l_1, \ldots, l_m\}$, since those triads are of the form $---$.

The agents could choose to pass, leaving the network in the state $N(m)$ forever. Alternatively, the agents could take actions that change the network. Taking such an action would incur a cost of change, however, so a rational agent will only do so in the expectation of a sufficiently high reward later. The main reward which all agents would like to obtain (although they may or may not be willing to pay the price for doing so) would be a balanced network.

There are many ways in which $N(m)$ can be changed to a balanced network. For example, all agents could decide to become friends with one another. That change would be very costly, however. Rational agents would instead aim for a balanced state that is easier to reach. A more feasible way to reach balance would be for the agents i and j to join the k-party or l-party, as shown in Figures 2(a) and 2(b).

Suppose that i joins the k-party. So eventually i will become friends with every agent k_x. Then at first, a friendship between i and some agent k_x must form. Without loss of generality, we can assume that this first friendship is with k_1, as shown in Figure 2(c). Consider the effect this has on the valuation of the different agents. Triads ik_1k_y and ik_1j used to be of the form $+--$ but are now $++-$. So they have turned from balanced to unbalanced. Triads ik_1l_y, on the other hand, used to be $---$ and have become $+--$, so they have turned from unbalanced to balanced. All other triads are unaffected. In total, there are $m-1$ triads ik_1k_y, 1 triad ik_1k_y and m triads ik_1l_y. So the number of triads that become balanced and the number of triads that become unbalanced are both m.

The agents i and k_1 are part of all triads that change, so their valuation is unchanged. One of them does have to pay the cost of change, but they suffer no harm from the change in the network. Agents l_y are part of one triad that changes, and it turns balanced. So their valuation increases, without them having to take any action. They quite like this change. The agents j and k_y are less happy, however: they too are part of one triad that changes, but theirs turns unbalanced. So they lose out due to this new friendship.

Once this first friendship has been established, all other members of the k-clique have an incentive to follow k_1 and become friends with i as well: currently, k_1k_yi if of the type $++-$, but by becoming friends with i they can turn this into the balanced type $+++$. So the first friendship ik_1 is likely to be followed by a flood of new friendships between i and the members of the k-party. Every such new friendship will be welcomed by the l-party, by i and by all k_y that are already friends with i, since it makes their relations more balanced. For those k_y that are not yet friends with i, the situation turns even worse, however. Every time an agent k_x becomes friends with i, the triad ik_yk_x becomes unbalanced, depriving k_y of another 2 points of valuation. In particular, if k_m is the last agent to become friends with i then just before they do so their valuation is $2(m-1)$ lower than it was in $N(m)$. Eventually, however, the network reaches one of the balanced states depicted in Figure 2, at which point all temporary losses are wiped away and replaced by the benefits of being part of a balanced network.

For highly impatient agents, paying the initial cost of change is not worth it, so remaining in $N(m)$ is the only rational option. If agents are more patient, however, aiming for balance may be the only rational choice. How patient agents have to be in order for remaining in $N(m)$ not to be an option depends on whether we are considering optimal strategy profiles or equilibria. The fact that the agents who are late to become friends with i (or j) suffer until balance is achieved means that remaining in $N(m)$ remains optimal until δ becomes very high. But the agents that experience a loss in valuation are not the ones that take action, it's the ones that have not yet taken action. So if the agents are even a little bit patient ($\delta = 0.5$ suffices, for example), the agents who decide to initiate the friendships will benefit by doing so, thereby making the strategy of remaining in $N(m)$ not an equilibrium.

2.4 Related work

Our definition of balance is called *3-balance* in the classical literature (e.g., [3]), where the number 3 refers to the length of the cycles to be examined – 3-cycles for triangles. In general, *k-balance* of a network requires that all cycles of length up to k contain an even number of negative edges. There is also pressure of balance from longer cycles, but it is considered of less effect. This leads to a difference between viewing balance of networks as a *property* or a *process*. Taking the former view, as in the classical literature, all cycles of all lengths are examined before we can determine the balance of the whole network. The lesser effect of longer cycles is modeled by assigning a *weight* or *strength* to each length [3,23]. In the latter view as proposed in [17] and adopted in this paper, however, the balance of a network lies in the balance of its local parts. The balance of longer cycles is achieved gradually over time by the constraints of balance among shortest cycles (triads in the case of undirected graphs).

The *structure theorem* [3,13] states that a balanced network can be partitioned into two mutually antagonistic and self-solidary components. The structure theorem was later generalized in [5] to consider a weaker version of balance which corresponds to more than two partitions. This gives a different way of studying the tendency of balance: it can be viewed as a process of partitioning a network. This approach has been developed in [7,8,24].

In recent years the study of link formation has drawn much attention in various fields including social network analysis, economics, information and computer science. Some of these are empirical studies that investigate into, say, the formation of social networks or how technology is adopted in a network [28,4], and some are theoretical studies that focus on, say, the prediction, formal model, statistical and computational results of network formation [21,30,29,6]. This paper falls into theoretical side, and we focus on the formal model of a type of link formation from the viewpoint of game theory.

The study of structural balance theory has not been limited to a single field since the very beginning. It was initiated in Heider's work [15,16] in social psychology and reinvented by Harary et al. [11,12,3,13] using graph theory. Empirical studies on the impact of structural balance theory was carried out in the area of social network analysis (see, e.g., [25,26]). The trend to study and adopt the theory from new perspectives and in new fields has not come to an end. For example, the impact of structural balance on opinion formation has been evaluated in the framework of evolutionary games [20]. In our paper we also have structural balance and games in the same framework, but we focus more on the theoretical aspects of the structural balance of social networks.

Another area of related work is that of games on networks, a sub-discipline of game theory concerned with networks. See for example [22,9,19]. Balance games can be considered part of this field, but they differ significantly from the games that have been studied before. Other disciplines of game theory, such as coalition formation and evolutionary games (see, e.g., [31]), are also related to balance games but very different from a technical point of view.

3 Patient Players

We show that for sufficiently patient players, a Pareto optimal strategy profile finalizes in a balanced network with probability 1.

Lemma 4. *Let s be a strategy profile, N_0 a network and L the set of s-timeline starting in N_0 that do not finalize in balance. If L occurs in the game (N_0, s) with probability greater than 0, then there is a $\delta_{high} < 1$ such that for all $\delta > \delta_{high}$, s is not Pareto optimal.*

Proof. Every agent is part of $b := \frac{(n-1)\cdot(n-2)}{2}$ different triads. In a balanced network, all triads are balanced so every agent has a valuation of b. In every non-balanced network, every agent has a valuation of at most $b - 2$, since by Lemma 3 every agent is part of at least one unbalanced triad.

Let s be any strategy profile that finalizes in a balanced network with probability 1, and s' any strategy profile that does not. Then after some number of time steps, the expected valuation under s will be higher than under s'. For sufficiently patient agents, s therefore Pareto dominates s'.

Theorem 1. *For a given number of players, there exists a discount factor δ_{high} such that for every $\delta > \delta_{high}$ and every Pareto optimal strategy profile s the following hold:*

1. *every s-timeline that contains a balanced network finalizes in that network;*
2. *for every N, the game (N, s) reaches a balanced network with probability 1.*

Note that the bound δ_{high} depends on the number of agents. In fact, it can be seen that $\lim_{n\to\infty} \delta_{high} = 1$, so the required amount of patience approached 1 as the number of agents increases.

This can, for example, be seen from the network $N(m)$ depicted in Figure 1(c). In order for $N(m)$ to become balanced, the central two agents i and j need to join either the clique $k_1, \ldots, k_m$ or the clique $l_1, \ldots, l_m$. While i is in the process of joining a clique, those members of the clique that are not yet friends with i experience a loss in valuation equal to twice the number of agents that are already friends with i. This loss is temporary, but both its magnitude and its duration increase with the number of agents. The amount of patience needed for any "go to balance" strategy to beat the "everyone passes in $N(m)$" strategy for every agent therefore increase with m.

4 Impatient Players

Here we show that if the discount factor δ is sufficiently close to 0, then every subgame perfect Nash equilibrium finalizes in a stable state with probability 1.

Unlike the case for patient agents, where the bound depends on the number of agents, our bound δ_{low} for impatient agents is constant. More concretely, $\delta_{low} = \frac{1}{10}$ suffices.

In order to prove this bound, we first need a few lemmas. For most of these lemmas the existence of a bound is relatively easy to see, but finding a precise number for the bound requires a lot of tedious calculations. We therefore do not prove the precise bound, and only give a qualitative argument for the existence of a bound.

Lemma 5. *Let N_0 be a network, and let m be the maximum increase of valuation brought about by any action of agent i, i.e., $m = \max\{val_i(N_1) - val_i(N_0) \mid N_0 \rightsquigarrow_i N_1\}$. Then for any strategy profile s, any s-timeline $\langle N_0, N_1, N_2, \dots \rangle$ and any $t \in \mathbb{N}$ we have $val(N_t) \leq val(N_0) + (m + 2t)t$.*

Proof. Consider the same action carried out in N_0 and N_k. This action will make some triads balanced, while making others unbalanced. Since N_0 and N_k differ in at most k edges, the number of triads made balanced when performing the action in N_k is at most k higher than in N_0, and the number of triads made unbalanced is at most k lower.

Turning a triad balanced increases valuation by 2, turning it unbalanced decreases it by 2. So in N_k the action yields at most $2k + 2k$ more valuation than in N_0, where it yields at most m. So the increase in valuation from N_k to N_{k+1} is at most $4k$. It follows that $val(N_t) \leq val(N_0) + \sum_{k=0}^{t-1}(m + 4k) \leq val(N_0) + m \cdot t + \frac{4t}{2} \cdot t = val(N_0) + (m + 2t)t$.

It follows that for sufficiently small δ, agents will not take any action that would cause a loss of valuation to them.

Lemma 6. *Let $\delta < \frac{1}{10}$ and s a Nash equilibrium. Then at every game (N, s), none of the agents take any action that changes the network unless that action increases their valuation.*

Proof. Taking an action that changes the network will incur the cost of change. An action that changes the network but does not increase the agent's valuation therefore causes a short term loss in utility for that agent. A sufficiently impatient agent will never take such an action.

Lemma 5 gives an upper bound on the long term benefit of taking a short term loss. Since this bound does not depend on n, the bound δ_{low} below which agents are sufficiently impatient does not depend on n either.

Finally, if some agent has a valuation increasing move available, then such a move will be taken by at least one agent.

Lemma 7. *Let $\delta < \frac{1}{10}$ and s a Nash equilibrium. Then in every subgame (N, s), if any agent has an available action that will increase its valuation, then at least one agent takes an action that increases its valuation.*

Proof. Any action that increases valuation increases it by at least two, so the increase in valuation outweighs the cost of change, resulting in a short term increase in utility.

Theorem 2. *Let $\delta_{low} = \frac{1}{10}$. Then for any discount factor $\delta < \delta_{low}$ and any subgame perfect Nash equilibrium s, the following holds:*

1. *every s-timeline that contains a stable network finalizes in that stable network;*
2. *for every N, the subgame (N, s) reaches a stable network with probability 1.*

Proof. The first part of the theorem follows from Lemma 6. The second part follows from Lemmas 6 and 7.

5 Discussion

Accuracy Balance theory predicts that social networks broadly tend towards balance, but that a fully balanced network is not always reached. This is also confirmed by empirical studies. The same general behavior is observed in balance games: rational agents will generally increase the amount of balance in the network, but under most circumstances a fully balanced outcome is not guaranteed.

Whether balance games accurately predict agents' behaviour on a more detailed level is not currently known, and remains an interesting question for further research.

Pareto optimality for low δ and subgame perfect Nash Equilibria for high δ Our results are "asymmetric", in the sense that δ_{high} is related to optimality while δ_{low} is related to equilibria. We conjecture that this asymmetry is fundamental: we think that for arbitrarily high $\delta < 1$ there remain equilibria that do not finalize in balanced networks and that for arbitrarily low $\delta > 0$ there remain Pareto optimal strategy profiles that do not finalize in stable networks. Unfortunately, the strategy space for balance games is very large and hard to describe. So while we have reasons to believe that there are no lower bound for optimality and upper bound for equilibria, we have not yet managed to find the counterexamples that prove this to be the case.

Cost of Change Changing a relation takes some amount of effort, so it should be associated with some cost $c > 0$. Furthermore, agents seem willing to incur this cost in order to make their relations more balanced. This suggests that the increase in valuation caused by the increase in balance is higher than the cost of change, so $c < 2$. We therefore consider values of c outside the interval $(0, 2)$ to be implausible. Still, for the sake of completeness we explain how out results change for any $c \in [0, \infty)$.

The bound δ_{high} is not qualitatively affected by the cost of change: for every $c \in [0, \infty)$, there is still a bound δ_{high} above which every optimal solution finalizes in balance with probability 1 and δ_{high} approaches 1 as n approaches infinity.

For any $c \in (0, 2)$, the bound δ_{low} is also qualitatively unaffected. The exact value of the bound may change, but a bound δ_{low} still exists and $\lim_{n\to\infty} \delta_{low} > 0$.

The first statement of Theorem 2 still applies: every equilibrium timeline that contains a stable network finalizes in that network. But the second part of Theorem 2 does not hold for $c \in (2, \infty)$. If $c > 2$ and δ is sufficiently low then some timelines finalize before reaching a stable network.

This leaves the two cases $c = 0$ and $c = 2$. If $c = 0$, then no bound δ_{low} exists: for every $\delta \in (0, 1)$ there are equilibria where agents move out of a locally optimal stable state and eventually reach a globally optimal balanced state. Finally, for $c = 2$, there is a bound δ_{low}, but in that case we do not know whether $\lim_{n \to \infty} \delta_{low} = 0$.

Complete graphs We assumed all edges to be either positive or negative, unlike some works on social balance we do not consider neutral relations. This is because for networks with neutral edges we do not consider there to be sufficient data to accurately determine the agents' preferences.

6 Conclusion

In this paper we viewed structural balance of a social network as a result of its agents playing a *balance game*. When the agents are patient, their Pareto optimal strategies result in a *balanced* network as the game proceeds. When, on the other hand, the agents are impatient, their subgame perfect Nash equilibrium strategies result in a *stable* network. By a framework accommodating both the concepts of balance and stability, our work bridged the classical literature on social balance [3] and its recent development using a logical approach [17].

There is still work that remains to be done. In particular, while we have shown that bounds δ_{high} and δ_{low} exist, we have not yet found tight bounds. Furthermore, as mentioned in Section 5, we conjecture that an equilibrium for patient agents may not finalize in balance and that an optimal profile for impatient agents may not finalize in balance. A proof (or, for that matter, a disproof) of these conjectures would be interesting. It would also be good to know more about the behaviour of agents that are neither as patient as to guarantee balance nor so impatient to guarantee stability.

Additionally, there are a number of further questions related to generalizations of the balance game. The balance game could, for example, be generalized to different kinds of networks. These include incomplete networks (were agents i and j may be neither friends nor foes), weighted networks (where some friendships/enmities are stronger than others) and directed networks (where i's relation towards j may be different from j's relation towards i).

It should also be interesting to allow different kinds of agents. Some agents might be more patient than others, or have a higher tolerance for unbalance. The framework of Boolean games [14,10] seems to be appropriate for modelling the diversity of agents in their goals.

Another way to increase diversity is in the strategies of agents. By going further to formalizing the dynamics of balance games in the framework of temporal logic, in particular, alternating-time temporal logic [1,2], we can get a better characterization of the time evolution and the flexibility of modeling agent's strategies in a formal and unified manner. We leave, however, all these for future work.

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