Global Diversity and Local Consensus in Status Beliefs: The Role of Network Clustering and Resistance to Belief Change

ODD+D model description – V2 October2017

This document describes the agent-based model that we present in Grow, Flache and Wittek (2017), based on the Overview, Design, Details + Decisions (ODD+D) standard (Müller et al. 2013). Given that in our model interactions and individual decision making are tightly coupled, we combined the sections 'Individual decision making' and 'Interaction' of the ODD+D standard in the section 'Interactions and individual decision-making'.

We have implemented the model in NetLogo (Wilensky 1999); detailed information about using NetLogo can be obtained from http://ccl.northwestern.edu/netlogo/. Our model builds on and extends the model presented by Mark, Smith-Lovin, and Ridgeway (2009) and the NetLogo code makes it possible to add our extensions in a modular fashion. In our below description, we therefore explicitly indicate which technical aspects only pertain to the model of Mark et al. (2009), and which pertain only to our extensions. For consistency with Mark et al. (2009), we refer to agents as 'actors'.

Our description focuses on substantive parameters, variables, and sub-models. Parameters, variables, and sub-models that were necessary to implement the model in NetLogo code are only described in the model code itself. Many parts of this description are based on the description that we provide in Grow et al. (2017). However, here we provide only an abridged version of the theoretical and empirical research that underlies our work. We provide the full description in Grow et al. (2017).

I Overview

I.i Purpose

Formal models of status construction theory (SCT) suggest that beliefs about the relative social worth and competence of members of different social groups can emerge from face-to-face interactions in task-focused groups and eventually become consensual in large populations. Our model makes it possible to assess how two extensions of existing models, one at the macrolevel and one at the macrolevel, affect this outcome. First, our model incorporates the microlevel behavioral assumption of status construction theory that people can become resistant to belief change when a belief appears consensual in their local social environment. Second, it integrates the insight that the macrolevel social structure of face-to-face interactions in large populations often is a clustered network structure. We suggest that the combination of network clustering at the macrolevel and resistance to belief change at the microlevel can constrain the diffusion of status beliefs and generate persistent diversity in status beliefs. The model makes it possible to assess whether this implication follows logically from our theoretical argument.

I.ii Entities, state variables, and scales

The original model consists of a population of I actors. Each individual actor i is characterized by a social distinction N_i and a status belief S_i. The social distinction has the two states A and

B ($N_i \in \{A; B\}$), representing a salient social characteristic with two categories, such as gender with the categories male and female or race with the categories black and white. These states are fixed and visible to other actors. The status belief has three states: A, O, and B ($S_i \in \{A; O; B\}$). These states are flexible and can change over time, but they are not visible to other actors. When $S_i = A$ or $S_i = B$, actor i believes that those with the corresponding state on N_i are more competent than actors with the respective other state; when $S_i = O$, actor i does not believe that the members of the different categories differ in worth and competence.

In the original model, actors are not explicitly located in physical space, but in our extended version, they inhabit a plane of size $W \times W$. They also maintain undirected network ties with each other, so that a given pair i and j can either share a tie ($x_{ij} = 1$) or not ($x_{ij} = 0$). Furthermore, in the original model, actors have no memory, but in our extended model, they have a memory M_i that contains information about their most recent experiences with all members of the opposite social category with whom they have interacted so far.

Table 1 provides an overview of all state variables, together with additional model parameters that we introduce in Sect. 'II.iv Submodels' below.

I.iii Processes overview and scheduling

The modelling process consists of a setup phase and the main simulation phase that both consist of several sub-models. The setup phase consists of executing the following sub-models:

1. `do_make_world`: create the world that he actors inhabit
2. `do_make_actors`: create the actors and place them on the world's surface
3. `do_make_network`: create the interaction network among the actors, if required

Each sub-model is executed once in the order shown above and then the setup phase stops. The main simulation phase consists of an iterative process in which the following sub-models are executed repeatedly:

1. `do_select_interactants`: select two actors i and j for interaction
2. `do_interaction`: let i and j interact and determine whether a hierarchy emerges between them; create a temporary variable `supported_belief` that stores information about the outcome of i's and j's interaction
3. `do_memory_update`: if actors are endowed with a memory, use `supported_belief` to update i's and j's memories M_i and M_j
4. `do_belief_update`: give i and j the opportunity to update their status beliefs; if actors are not endowed with a memory, use the information in `supported_belief` for this, otherwise use M_i and M_j
5. `do_check_convergence`: check whether all actors are in a locally stable configuration, so that the simulation run has reached a stable equilibrium. If the run has not reached a stable equilibrium yet, go back to step 1. If a stable equilibrium has been reached:
    a. `do_calculate_outcome_measures`: calculate the outcome measures
    b. `stop`: terminate the simulation run

Variable/ Parameter	Description	Type	Scale/Possible Values
		Original Model and Extended Model	
I	Number of actors	Model parameter	$0 < I < \infty$
h	Probability that hierarchies emerge spontaneously	Model parameter	$0 \leq h \leq 1$
a	Probability that actors acquire a status belief	Model parameter	$0 < a \leq 1$
l	Probability that actors lose a status belief	Model parameter	$0 < l \leq 1$
S_i	Status belief	Actor state variable	$A; O; B$
N_i	Nominal social distinction	Actor state variable	$A; B$
		Extended Model	
W	Spatial distance units	Model parameter	$0 < W < \infty$
k	Number of ties that each actor establishes	Model parameter	$\in \{1,2,\cdots,\lfloor .5(I-1)\rfloor\}$
y	Spatial distance parameter	Model parameter	$0 \leq y \leq \infty$
`consensus_-needed`	Threshold for belief acquisition	Auxiliary model parameter	.5, .7, .9
M_i	Memory	Actor state variable	See Sect. 'III.iv Submodels'
x_{ij}	Tie between actors i and j	Dyadic state variable	0;1

Table 1 Overview of state variables and model parameters

We explain the details of each of these sub-models in Sect. 'II.iv Submodels' below.

II Design concepts

II.i Theoretical and empirical background

SCT has described processes that might lead to status differentiation between social groups (Grow, Flache, and Wittek 2015; Mark et al. 2009; Ridgeway 2000; Ridgeway and Correll 2006). SCT focuses on interactions in small groups with a collective task focus (e.g., work teams, student learning groups, and neighborhood organizations) as building blocks of society. It holds that such groups can spontaneously develop hierarchies of influence and deference, in which some individuals are perceived as more respected and more competent than others. When such differentiation occurs consistently between members of different social categories, even if only by accident, individuals can come to believe that the social distinction is generally associated with differences in respect and competence. Once emerged, such beliefs can diffuse throughout the population, because people carry them into new interaction contexts, treat new interaction partners accordingly, and thereby create hierarchies that teach their beliefs to others (Ridgeway 2000). By that, beliefs about the relative social worth and competence of members of different social groups can emerge and become widely consensual in large populations

The modelling work by Mark et al. (2009) formalizes this prediction of SCT and shows that status beliefs have a strong tendency to emerge and to diffuse widely under minimal assumptions about the micro-process of hierarchy formation and belief diffusion. Yet, Mark et al.'s (2009) analysis did not incorporate a central assumption of SCT. Mark et al. (2009)

assumed that a single interactional experience with members of a different social category is sufficient for people to acquire a new status belief, or to lose an existing belief if a new experience contradicts it. By contrast, SCT holds that people consider multiple experiences, and that belief acquisition and maintenance depend on how consensual individuals perceive a given belief in their social environment (Ridgeway 2000; Ridgeway and Correll 2006). That is, while people might acquire a given belief from an experience they make in a local interaction context, they are unlikely to maintain this belief if it is not reinforced in subsequent interactions that make it appear consensual in their social environment. Once a given belief appears consensual, people can then become resistant to changing it, even in the light of occasionally disconfirming evidence (we refer to this also as *belief inertia*).

Furthermore, Mark et al. (2009) assumed complete and unstructured interaction networks in their actor populations, so that interactions between any two members of the population were equally likely at any point in time, regardless of the size of the population. In reality, people tend to interact only with a small subset of a large population, typically with others who are connected within the same local cluster of network ties (e.g., Davis 1970; Faust et al. 1999; Festinger, Schachter, and Back 1950; Granovetter 1973; Watts 1999; Wong, Pattison, and Robins 2006).

In Grow et al. (2017), we suggest that the predictions of SCT can change when belief inertia and network clustering are considered in models of SCT. The reason is that network clustering creates dense local interaction structures that can quickly diffuse any incidentally created belief among the members of local communities (or clusters). This results in a social reality that renders the belief highly consensual within a community. If belief acquisition and maintenance require some consensus in peoples' immediate social environment, the emergent local consensus can, in turn, ward off potential influence from less frequently occurring interactions with members of other communities in which different beliefs might have emerged. As a consequence, in different local regions of the network different status beliefs emerge and persist, without becoming consensual in the wider population. Yet, this can only happen if people are resistant to changing beliefs that appear consensual in their social environment. Network clustering in itself is not sufficient to prevent status beliefs to diffuse and become widely accepted in the larger population; it needs to be accompanied by the extension of the micro-process of status belief diffusion we propose.

Taken together, we suggest that the processes that SCT describes not only lead to the emergence of widespread *consensus* in status beliefs, as suggested by Mark et al. (2009). They can also lead to the emergence of *persistent diversity* in status beliefs, if network clustering and belief inertia are considered jointly. The extended simulation model makes it possible to assess the logical consistency of this conclusion formally.

II.ii Interactions and individual decision-making

Actors engage in small-group interaction to reach collective goals (albeit goal achievement is not actually modelled). During these interactions, actors need to coordinate their work, and decide who of them might be worthier of respect and more competent at the task. Thus, hierarchies can emerge that put some actors in a status-advantaged (i.e., more influential) position, and other interactants in a status-disadvantaged (i.e., less influential) position.

The model focuses on the dyad as the smallest possible group and interaction partners can be selected in one of two ways (i.e., according to different conditions). In one condition, there is no network and actors are randomly paired with any other member of the actor population to engage in dyadic interaction. This interaction regime is the same as in Mark et al. (2009). In a second condition, there is a network and actors are randomly paired with one other actor from the set of actors with whom they maintain a tie. The introduction of this latter interaction regime is one of our extensions of the model by Mark et al. (2009).

II.iii Learning

Actors try to infer from their own interactions with members of the opposite social category which category is on average worthier of respect and more competent. For this, they rely on the status hierarchies that have formed during their interactions. In the original model, actors only consider their most recent interaction with somebody who differs from them in N_i. In the extended version, they remember all of their last interactions with those who differ from them in N_i.

If their past interaction(s) seem to support the belief that members of one category are worthier of respect and more competent than members of the other category, they can acquire a corresponding status belief. Yet, if they already hold a status belief, they might lose this belief if their experiences do not sufficiently support it anymore. Actors are only informed about their own status beliefs and experiences, there is thus no collective learning.

II.iv Individual sensing

Actors know about their own interactional experiences, which they use to form status beliefs. During interactions, actors sense their own category membership and that of their interaction partner, but they only sense their own status beliefs. They also sense who of them was in the low/high status position during their interaction. Sensing occurs implicitly and is local; it is not erroneous and there are no costs attached to it.

II.v Individual prediction

Actors use their own status beliefs to infer whether they are more or less worthy of respect and more or less competent than their interaction partner. This inference process is erroneous in the sense that there are no objective differences that would justify differences in respect or that would create competence differences between actors.

II.vi Collectives

There are no collectives.

II.vii Heterogeneity

There is no heterogeneity among actors apart from possible differences in their state variables and the ties they maintain with other actors.

II.viii Stochasticity

The following processes involve randomness: (1) actors are assigned the position on the world's surface at random; (2) ties between actors are established at random; (3) for each interaction two interactants are selected at random; (4) if two interactants both believe that they are (not) more/less respectable and competent than their interaction partner, their status positions are assigned randomly; (5) for actors whose experiences support a given belief, and who have not acquired this belief yet, there is a random chance that they will actually acquire this belief; (6) for actors who have already acquired a status belief, but whose experiences do not sufficiently support this belief anymore, there is random chance that they will lose this belief.

II.ix Observation

We use three measures to assess the extent to which status beliefs emerge and diffuse throughout the actor populations and how much this diffusion is correlated with the network structure in which actors are embedded (if there is a network).

The first two measures assess whether status beliefs emerge and how widely they diffuse. The first measure is the largest share (LS) of actors who either hold the belief $S_i = A$ or the belief $S_i = B$. We calculate this measure as

$$LS = \frac{\max(\#S_i = A, \#S_i = B)}{I}, \quad (1)$$

where $\#S_i = A$ and $\#S_i = B$ refer to the number of actors with the beliefs $S_i = A$ and $S_i = B$, respectively. LS ranges from 0 to 1. The closer it comes to 1, the more widely a single belief has become adopted by the actors; the closer it comes to 0, the fewer actors have acquired any status belief (i.e., the more actors hold the state $S_i = O$). Values in between indicate that diversity in status beliefs exists. The second measure builds on LS and assesses whether in a given run a belief has emerged and has been acquired by all actors, which is indicated by $LS = 1$. We refer to this as completed diffusion (CD), meaning that $CD = 1$ when $LS = 1$ and $CD = 0$ when $LS < 1$.

Our third measure assesses a different implication of our main argument. We contend that if actors are embedded in a network structure and if this structure is clustered, those actors who are linked with each other should have a higher likelihood of holding the same state on S_i than actors who are not linked with each other. To assess how much having the same belief is associated with being connected or not, we adapted a network segregation measure developed by Moody (2001). Moody (2001) was interested in assessing how similarity and dissimilarity in race affects the formation of friendship ties between pupils in US school contexts. For this, he devised a segregation index that assessed whether pupils who belong to the same race are more likely to share a tie than pupils who belong to different races. In our case, we want to assess how the presence or absence of a tie between actors affects whether they held similar status beliefs. Hence, we adjusted Moody's (2001) measure so that it captures the degree to which actors who share a tie are more likely to hold the same belief than actors who do not share a tie. We calculated this measure of network belief segregation (NBS) as

$$NBS = log\left[\frac{\#(S_i = S_j | x_{ij} = 1)/\#x_{ij} = 1}{\#(S_i = S_j | x_{ij} = 0)/\#x_{ij} = 0}\right]. \quad (2)$$

In Eq. (3), the numerator focuses on the set of all pairs of actors who share a tie and measures the fraction of these pairs that hold the same state on S_i. The denominator focuses on the set of all pairs of actors who do not share a tie and indicates the fraction that hold the same state on S_i. NBS can take values between -∞ and ∞. A value of 0 is obtained if similarity in status beliefs is disassociated from the network structure. This can happen when there is population-wide consensus in status beliefs, but also when different beliefs exist and are randomly distributed across the network. Values larger than 0 indicate positive belief clustering in the network, so that actors who share a tie are more likely to hold the same state on S_i than actors who do not share a tie. Values smaller than 0 indicate negative belief clustering in the network, meaning that actors who share a tie are less likely to hold the same state on S_i than actors who do not share a tie. Evidently, NBS can only be calculated if actors are embedded in a network structure and we thus report this measure only for conditions in which networks were present.

Furthermore, we also assessed the time it took a given simulation run to reach a stable equilibrium. For computational efficiency, in the actual simulations we assessed convergence after every 20,000 dyadic interactions between actors (rather than after each such interaction). Hence, we measured the time to convergence (TTC) in the number of these assessment cycles. For example, a value of $TTC = 3$ indicates that a given run had reached a stable equilibrium after three assessment cycles, which corresponds to about 60,000 interactions among pairs of actors.

III Details

III.i Implementation details

The model has been implemented in NetLogo version 6.0.1 (Wilensky 1999), using the `Nw` (network) extension. The code can be obtained from https://www.openabm.org/model/5493.

III.ii Initialization

See Sect. 'III.iv Submodels' for details.

III.iii Input data

There are no input data.

III.iv Submodels

Setup phase

`do_make_world`

A square world of size $W \times W$ is created. We chose the size 5×5 spatial units.

`do_make_actors`

A number of $I = 500$ actors are created, of which 250 belong to category $N_i = A$ and 250 belong to $N_i = B$. These actors hold no status beliefs ($S_i = O$) and they are randomly placed on the surface of the world.

`do_make_network`

As indicated above, actors might be embedded in a network structure. If a network is required, it is generated as follows.

The network is binary, so that any two population members can either share a tie ($x_{ij} = 1$) or not ($x_{ij} = 0$). To establish the network, actors are selected one at a time (without replacement) to choose a number of k ($k \in \{1,2,\cdots,\lfloor .5(I-1)\rfloor\}$) other actors to whom they are not connected yet for establishing a tie. The likelihood that actor i will select actor j from the set of available alternatives depends on the Euclidian distances between their places of residence (d_{ij}), and is proportional to the value of the spatial distance function $f(y, d_{ij})$ over all alternatives. This function is defined as

$$f(y, d_{ij}) = \exp(-y[d_{ij}]), \qquad (1)$$

in which y ($0 \leq y \leq \infty$) governs the effect that spatial distance has on the probability that actor i selects actor j for establishing a tie. For a given level of k, when $y = 0$, the network has a random structure that is not associated with spatial distances between the actors and that does not show any clustering. Increasing y reduces the average distance that ties cover. This means that network clustering typically increases as y increases, because actors who live close to each other will increasingly be connected to the same set of other actors who also live close by. In our simulations, we set $k = 5$ and varied y, so that it could take the values 0 or 8.

During the network generation process, it is possible that by chance at least one actor is not connected to somebody who differs from him/her in N_i. Given that in the model interactions with members of a different category are the only source of status beliefs, we have implemented a routine in NetLogo that ensures that one tie of each actor who does not have at least one network neighbor who differs from him/her in N_i is 're-wired' to another actor who differs from him/her in N_i (see NetLogo code for details).

It is also possible that a network consists of two or more components that are not connected to each other. In this case, beliefs can by definition not diffuse throughout the entire population and we implemented a routine in NetLogo that ensures that if there is more than one component, single members of each component will be connected, so that in the end there is only one component (see NetLogo code for details).

Main simulation phase

`do_select_interactants`

Two actors i and j are randomly selected to be interaction partners. Technically, actor i is selected first from the set of all actors. Actor j is then selected in one of two ways. If there is no network, j is selected from the set of all other population members. When there is a network, j is selected from the set of actors with whom i maintains ties.

Technically, it is not necessary to model interactions between actors who belong to the same social category ($N_i = N_j$), because such interactions cannot affect actors' status beliefs (see details below). Hence, to speed-up the simulation process, in NetLogo j is selected from the set of actors who belong to a different social category than i ($N_i \neq N_j$) (either from the entire population if there is no network, or from the subset of the population to which i is connected if there is network).

	$N_j = B$ $S_j = A$	$N_j = B$ $S_j = O$	$N_j = B$ $S_j = B$
$N_i = A$ $S_i = A$	(1) $\Pr(R_i > R_j) = 1$	(2) $\Pr(R_i > R_j) = 1$	(3) $\Pr(R_i = R_j) = 1 - h$ $\Pr(R_i > R_j) = .5h$ $\Pr(R_i < R_j) = .5h$
$N_i = A$ $S_i = O$	(4) $\Pr(R_i > R_j) = 1$	(5) $\Pr(R_i = R_j) = 1 - h$ $\Pr(R_i > R_j) = .5h$ $\Pr(R_i < R_j) = .5h$	(6) $\Pr(R_i < R_j) = 1$
$N_i = A$ $S_i = B$	(7) $\Pr(R_i = R_j) = 1 - h$ $\Pr(R_i > R_j) = .5h$ $\Pr(R_i < R_j) = .5h$	(8) $\Pr(R_i < R_j) = 1$	(9) $\Pr(R_i < R_j) = 1$

Table 2 Possible combinations of status beliefs (S_i) and outcomes of interactions in dyads whose members belong to different social categories ($N_i \neq N_j$)

Note: R_i and R_i represent the relative status rank that the actors have attained during their interaction. For example, if $R_i > R_j$, actor i was in the status advantaged position and actor j was in the status disadvantaged position. If $R_i = R_j$, no hierarchy has emerged.

`do_interaction`

During any interaction, a hierarchy can emerge that puts one actor (say i) in a status-advantaged (i.e., more influential) position, and the other actor (say j) in a status-disadvantaged (i.e., less influential) position. When the actors belong to the same social category, so that they share the same state on N_i, there is nothing that might favor either of the two actors to take the advantaged position. Still, in the model a hierarchy can emerge spontaneously with probability h ($0 \leq h \leq 1$). If this happens, both actors are equally likely to take the status advantaged or the status disadvantaged position. Yet, as indicated above, for computational efficiency such interactions are not considered in the actual simulation process.

The situation is more complex when the actors belong to different categories, especially when one of the interaction partners believes that members of one category are more worthy and competent than members of the other category. Table 2 illustrates how S_i and S_j can combine in dyads whose members differ in N_i. It also shows the probabilities with which different types of status hierarchies can emerge. Consider first situations in which either i or j holds a status belief, whereas the respective other actor holds no belief, or in which both actors hold the same belief (cells 1, 2, 4, 6, 8, and 9 in Table 2). In these cases, at least one actor is assumed to be more respectable and competent than the other by at least one member of the dyad, whereas the other member of the dyad holds at least no contrary belief. The model assumes that an opposition-free belief affects the interactions between the actors, so that it is certain that a hierarchy emerges in which the actor who is advantaged by the belief will take the higher-status position. Consider next situations in which i and j hold no or opposing beliefs (cells 3, 5, and 7 in Table 2). In these cases, i's and j's beliefs do not unambiguously imply who is more respectable and competent and therefore should take the higher-status position. Yet, the model assumes that nevertheless a hierarchy might emerge between them with probability h. If this happens, both actors are equally likely to take the status advantaged position.

In our simulations, we considered the values .25, .5, and .75 for h.

`do_memory_update`

In the original model presented by Mark et al. (2009), actors have no memory and they simply update their status beliefs based on the outcome of their last interaction with somebody who differs from them in N_i. In our extension of the model, actors are endowed with a memory M_i, that contains information about their most recent experiences with all members of the opposite category with whom they have interacted so far. For example, imagine that actor i belongs to category A and has interacted with the actors j, o, and p, who belong to category B. Imagine further that i's last interactions with j and o supported the belief B, whereas the last inaction with p did not support any belief. Hence, M_i is filled with three elements, so that $M_i = \{B; B; O\}$. These experiences are sorted by the interaction-dyad to which they pertain, so that the first element refers to i's last interaction with j, the second to the last interaction with o, and the third to the last interaction with p. This implies that the number of elements in M_i increases if i interacts with somebody with whom he/she has never interacted before. Existing experiences remain unaffected if i interacts with somebody new, but they can be updated by new experiences with past interaction partners (e.g., the third element in the above example might change if i interacts again with p).

Note that if there is a network, the maximal length of actors' memory is determined by the number of actors who differ from them in N_i and with whom they shared a tie. If there is no network, actors' memory can contain as many elements as there were other actors who differ from them in N_i in the population, given that they can potentially interact with each of them.

`do_belief_update`

In the original model, actors consider their last experience with somebody who differs from them in N_i in the following way. First, if at the beginning of an interaction actor i holds no belief ($S_i = O$), but experiences a hierarchy in which a member of category A or B attains the higher-status position, i will acquire a corresponding status belief with probability a ($0 < a \leq 1$). If no hierarchy emerges, the actor will not acquire any belief. Second, if at the beginning of an interaction actor i holds a belief ($S_i = A$ or $S_i = B$) but makes an experience that contradicts this belief (e.g., no hierarchy emerges, or a member of the category that i believes to be less respected and competent manages to attain the high-status position), the actor loses his/her current belief with probably l ($0 < l \leq 1$). Third, if an actor makes an experience that is congruent with its current state on S_i, S_i remains unchanged.

In the extended model, actors also update their status beliefs after each interaction with somebody who differs from them in N_i. Yet, during this update, they use the information in M_i to determine which belief appears most consensual in their environment. If they currently hold no belief ($S_i = O$), they acquire the belief $S_i = A$ or $S_i = B$ with probability a when either A or B accounts for more than 50% of their experiences (or 70%, or 90%, depending on the value of the auxiliary parameter `consensus_needed`). If they currently hold a belief ($S_i = A$ or $S_i = B$), but their experiences in support of this belief do not account for the majority of all their experiences in M_i anymore, they lose this belief with probability l. For example, when $M_i = \{B; B; B; A\}$, the belief $S_i = B$ appears most consensual from i's point of view. Hence, if the actor currently holds no status belief, he/she will acquire this belief with probability a. By contrast, if $M_i = \{B; B; O; A\}$, the belief $S_i = B$ would not appear sufficiently consensual and i would lose this belief with probability l, if he/she currently held it. Thus, as in the original model, actors do not directly communicate their beliefs to each other. Instead, actors are influenced by the degree of consensus that exists in their network neighborhood via the interactional experiences with their network neighbors, because every experience results not only from a given actor's own beliefs but from the combination of the beliefs of both partners involved in the constituting interaction.

Note that if actors have so far interacted with only one other actor who differs from them in N_i, their memory will contain exactly one element. Hence, in line with the assumptions of SCT, interactional experiences in a given local context might induce a status belief, but for this belief to be maintained, subsequent interactions need to support it. Once an actor has made many congruent experiences, a single disconfirming experience is not enough to undermine an existing belief. Note also that, as in the original model, actors who currently hold a status belief that is not sufficiently supported anymore always need to transition though $S_i = O$ before they can acquire a new belief.

`do_check_convergence`

The model checks whether the run is in a stable equilibrium according to the principles described in the online supplement that accompanies Grow et al. (2017).

`do_calculate_outcome_measures`

The outcome measures are calculated as desripbed in Sect. 'II.ix Observation' above. Note that CD is not calculated by NetLogo, but needs to be calculated after a simulation run has been completed, based on the value of LS. The value of TTC can be inferred from the number of simulation steps (i.e., 'ticks') that have been conducted.

`stop`

The simulation run is stopped and outcomes are recorded.

IV References

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