Conviviality by Design

Patrice Caire [1] and Antonis Bikakis [2] and Vasileios Efthymiou [3]

Abstract. With the pervasive development of socio-technical systems, such as Facebook, Twitter and digital cities, modelling and reasoning on social settings has acquired great significance. Hence, an independent soft objective of system design is to facilitate interactions. Conviviality has been introduced as a social science concept for multiagent systems to highlight soft qualitative requirements like user friendliness of systems. Roughly, more opportunity to work with other people increases the conviviality. In this paper, the question we address is how to design systems to increase conviviality by design. To evaluate conviviality, we model agent interactions using dependence networks, and define measures that quantify interdependence over time. To illustrate our approach we use a gaming example. Though, our methods can be applied similarly to any type of agent systems, which involve human or artificial agents cooperating to achieve their goals.

1 Introduction

As software systems gain in complexity and become more and more intertwined with the human social environment, models that can express the social characteristics of complex systems are increasingly needed [13, 8, 16]. For example, people may live far apart, speak different languages and have never physically met, but still, they expect to interact electronically with each other as they do physically. Hence, an implicit soft objective of system design is often to facilitate interactions. Conviviality emerges, but we want to design systems that foster conviviality among people or devices [18].

So far, most systems let users find their own ways to cooperate without providing any help or support. In such cases, users have to coordinate their actions and cooperate in a distributed way. Without any support from the system, they are not able to evaluate their cooperation and therefore the conviviality of the system; consequently they also cannot find ways to increase it. Conviviality is more than mere cooperation; it gives agents the freedom to chose with whom to cooperate.

Our proposed approach follows an alternative direction. It is based on the intuition that, to be convivial, the system itself should provide its users with potential ways to cooperate. For example, the system may suggest to the employees of a company, possible ways of interaction that will improve their cooperation. The system may monitor the evolution of these interactions, evaluate the agents' cooperation, and update the suggestions it makes to increase conviviality. Our research question is the following:

[1] University of Luxembourg, email: patrice.caire@uni.lu
[2] UCL, United Kingdom, email: a.bikakis@ucl.ac.uk
[3] University of Luxembourg, email: vasileios.efthymiou@uni.lu

Research Question: How to, by design, increase conviviality in multiagent systems?

This breaks down into the following sub-questions:

(a) How to evaluate conviviality?
(b) How to measure conviviality over time?
(c) What are the assumptions and requirements for such measures?
(d) How to use the measures in MAS?

In agent systems, conviviality measures quantify interdependence in social relations, representing the degree to which the system facilitates social interactions. Roughly, more interdependence increases conviviality among groups of agents or coalitions, whereas larger coalitions may decrease the efficiency or stability of these involved coalitions. We are, therefore, interested in two main issues. The first one is to design multiagent systems so that they foster conviviality, while the second one is to evaluate conviviality. For the first issue we adopt the paradigm of dependence networks, based on the intuition that conviviality may be represented by the interdependence among the agents of the system. For evaluating conviviality over time, we build on the *static* measures originally introduced in [4]. We extend these measures by proposing new ones, that we call *temporal* case.

In this paper, we build on the notion of social dependence introduced by Castelfranchi [7]. Castelfranchi brings concepts like groups and collectives from social theory to agent theory to enrich agent theory and develop experimental, conceptual and theoretical new instruments for social sciences.

Moreover, we take as a starting point the notion of dependence graphs and dependence networks initially elaborated by Conte and Sichman [20], and Conte et al. [21], and further developed by these authors [20].

We build on the *Temporal Dependence Networks*, introduced in [5] to compare time sequences of different dependence networks. This time however, we model the potential evolutions of sequences within the same dependence network. We introduce three principles to define three new measures, and therefore compare conviviality in Temporal Dependence Networks in a macro- and micro-organizational scale.

The remainder of the paper is structured as follows: First, we introduce our motivating example, highlighting the main challenges. Then, we identify requirements for convivial system design measures. We introduce our temporal dependence networks measures and principles. Finally, we present some of the most related works and summarize this paper.

2 Example Scenario

In order to demonstrate the requirements and challenges of conviviality among heterogeneous agents, we use an example scenario from the domain of social networks. This example allows us to compare different instances of a game and illustrate how the system may increase the conviviality by evaluating the games against a number of conviviality principles.

Consider a game in Facebook, in which different users form teams and cooperate in order to achieve a common goal. We assume the members of each team to be completely unknown to each other (they are not Facebook friends and they have no friends in common), and that the game allows only one-to-one interactions between team members. For the sake of simplicity, we also assume that each team must consist of the same number of players. The game consists in finding answers to questions involving information that is available in the public profiles of the team members. The game unfolds in three different phases, and for each phase there is one associated problem in the form of a question/answer to be solved.

For the first phase, the question ($Q1$) is: *"Which team member has the most in common with the others?"*. For example, in a five-member team *A: Alice, Bob, Carlo, Dimitra* and *Eve*, it could be that Eve has common interests with Alice in tennis, with Carlo in Spanish movies, and with Dimitra in ancient history. Alice and Dimitra have a common interest in climbing, and Bob and Carlo are both interested in football. For team A, the correct answer would be 'Eve".

The second phase question ($Q2$) is: *"Which country corresponds to both the picture uploaded by answer of Q1* (Eve) *and one (and one only) of the team members?"*. For our team A, the correct answer would be "Greece" based on the fact that Eve has uploaded a photo, which was taken in Athens, and Dimitra is the only team member that comes from Greece.

The last question ($Q3$) is: *"What is the place among the answers provided to Q2 that most team members prefer?* (Greece). The answer would be "Santorini", which is "liked" by Alice, Dimitra and Eve, while other places in Greece, such as Athens or Crete, are "liked" only by two of the team members.

The team that manages to solve the riddles faster than the other teams is the winner. Building on instances of the game, we analyze how the system may increase the conviviality of the game by evaluating it against proposed principles.

Winning such a game requires finding the proper ways to cooperate, and assessing the team's performance by evaluating conviviality. In brief, the challenges of this game are:

1. **Cooperation.** If one of the team members does not cooperate, this would probably mean that the team may not be able to answer a question, and consequently win the game. The challenge, here, is to enable and foster cooperation between the team players.
2. **Evaluation of conviviality.** This process will help the team assess its performance in each round of the game, and find ways to improve it. For example, if team A could not provide an answer to $Q1$, because there were not enough interactions between the team members, the team should be able to realise the reasons for their poor performance and find ways to improve it for the next rounds. The challenge, in this case, is to develop principled methods for measuring the conviviality among the team members.

3 Hypotheses and requirements

To represent agents' interdependencies we use dependence networks [9, 19, 2], differentiating static and temporal cases.

3.1 Static case

In this case, all interdependencies are modelled in a single "global" dependence network, as in [9, 19, 2]. We consider that the agents' goals and interdependencies have been identified using a goal-oriented method like Tropos [3], for instance. Abstracting from method-specific concepts (e.g. tasks and resources in Tropos), we define a dependence network as in [4]:

Definition 3.1 (Dependence network) *A dependence network (DN) is a tuple $\langle A, G, dep, \geq \rangle$ where: A is a set of agents, G is a set of goals, $dep : A \times A \rightarrow 2^G$ is a function that relates with each pair of agents, the sets of goals on which the first agent depends on the second, and $\geq$: $A \rightarrow 2^G \times 2^G$ is for each agent a total pre-order on sets of goals occurring in his dependencies: $G_1 >_{(a)} G_2$.*

To illustrate our definition, we consider that during the first phase of the game, only A and B interact to answer Q1; during phase 2, B and C interact as well as D and C; and during phase 3, B and E interact as well as D and E, and A and E. Figure 1 depicts a dependence network that captures this situation. The nodes A, B, C, D and E represent agents Alice, Bob, Carlo, Dimitra and Eve. The arrows indicate the goal dependencies (i.e. ask a question or reply to it). A number of coalitions are formed among the five agents, such as (A, E), (A, B, E) and (A, B, C, D, E).

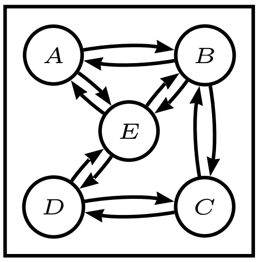


Figure 1. Example of a dependence network.

Based on [4], we make the following hypotheses:

H1 the cycles identified in a dependence network are considered as coalitions. These coalitions are used to evaluate conviviality in the network. Cycles are the smallest graph topology expressing interdependence, thereby conviviality, and are therefore considered atomic relations of interdependence. When referring to *cycles*, we are implicitly signifying *simple cycles*, i.e., where all nodes are distinct [10]; we also discard self-loops. When referring to conviviality, we always refer to potential interaction not actual interaction.

H2 conviviality in a dependence network is evaluated in a bounded domain, i.e., over a $[0, 1]$ interval. This allows the comparison of different systems in terms of conviviality.

H3 larger coalitions have more conviviality.

H4 the more coalitions in the dependence network, the higher the conviviality measure (ceteris paribus).

Our top goal is to maximize conviviality in the multiagent system. Some coalitions provide more opportunities for their participants to cooperate than others, being thereby more convivial. Our two sub-goals (or requirements) are thus:

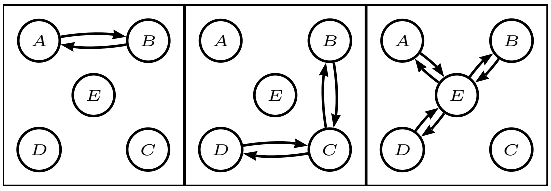
R1 maximize the size of the agent's coalitions, i.e. to maximize the number of agents involved in the coalitions,
R2 maximize the number of these coalitions.

3.2 Temporal Case

For more fine-grained exploration, the network can be divided up into sequences, and analysis performed on each sequence. This allows for local analysis of the network and is less computationally intensive. Definition 3.2 formalizes how dependence networks can be extended to capture the temporal evolution of dependencies between agents, inspired from [5].

Definition 3.2 (Temporal dependence network) *A temporal dependence network (TDN) is a tuple* $\langle A, G, T, dep\rangle$ *where: A is a set of agents, G is a set of goals, T is a set of natural numbers denoting the time units or sequence number,* $dep : T \times A \times A \to 2^G$ *is a function that relates with each triple of a sequence number, and two agents, the set of goals on which the first agent depends on the second.*

Returning to our example, the static view illustrated Figure 1 is now captured as a sequence in Figure 2. If we call the temporal dependence network TDN_k, TDN_k^j denotes the individual dependence network that corresponds to the j^{th} step. Note that $|A|$, the number of agents (5 in this case), remains constant over TDN_k. $|TDN_k|$ refers to the length of the temporal dependence network (3 in this case).



(a) TDN_k^1 (b) TDN_k^2 (c) TDN_k^3

Figure 2. Example of a temporal dependence network.

Building on the static case, our assumptions are:

H5 the more regularly the number of coalitions increases, the higher the conviviality measure (ceteris paribus); for example, in human society, allowing people to get to know each other progressively enables trust to build up. In cases, where agents need to quickly form a grand coalition without build up, and dissolve, the assumptions may differ.
H6 the more different agents take part in coalitions, the higher the conviviality (ceteris paribus); for example, by allowing all agents to participate in interactions.

Our two additional requirements are thus:

R3 maximize the regular increment of the number of coalitions,
R4 maximize the involvement of each individual agent in the coalitions.

4 Conviviality measures

In multiagent systems, conviviality has been evaluated by measuring the interdependencies among the agents [4]. In this section, we use the static conviviality measures presented in [4], that we call *static* case. We extend these measures by proposing new ones, that we call *temporal* case. The main challenge in defining conviviality measures over time is to make assumptions about the sequences. For example, when modelling the agents' interdependencies as a sequence of dependence networks, we could leave out one dependence network from a sequence, or introduce multiple copies of the same dependence network. How this affects the conviviality and its evaluation depends on the underlying assumptions.

4.1 Static Case

The basic idea for the conviviality measures introduced in [4], is the following. Since the atomic structure reflecting conviviality is a pair of reciprocating agents, the conviviality measures should also be based on the pairing relations in the dependence networks. Hence, for each pair of agents, the number of cycles that contains this pair is counted. Furthermore, the measures introduced in [4] were normalized to be in $[0, 1]$ in order to allow the sensible comparison of any two dependence networks in terms of conviviality. Equation 1 is the general formula to express the pairwise conviviality measure $conv(DN)$ of a dependence network.

$$conv(DN) = \frac{\sum coal(a, b)}{\Omega}, \quad (1)$$

where $\mathrm{coal}(a, b)$ for any distinct $a, b \in A$ is the number of cycles that contain both a and b in DN and Ω is the maximum the sum in the numerator can get, over a dependence network of the same set of goals and the same number of agents but with all possible dependencies.

To compare the conviviality of each of the three steps in TDN_k of Figure 2, using the measure of Equation 1, we would just have to count the pairs of agents that belong to cycles, since the denominator Ω is the same for all three steps. In TDN_k^1 there are two pairs participating in a cycle: $(A, B), (B, A)$, in TDN_k^2, four pairs of agents: $(B, C), (C, B), (C, D), (D, C)$ and in TDN_k^3 six pairs: $(A, E), (E, A), (B, E), (E, B), (D, E), (E, D)$. This makes the third step more convivial than the first two.

4.2 Temporal Case

Conviviality in Temporal Dependence Network can be measured on at least two separate scales: the micro organizational and the macro-organizational scales. Measurements at the macro-organizational scale focus on the evaluation and comparison of the conviviality measures of each step in the sequence of dependence networks, whereas micro-organizational measurement reflects topological aspects within each dependence network. We consider three measurement principles:

Principle 1 (Dominance) *A temporal dependence network has more conviviality than another one if, ceteris paribus, each individual dependence network of the former has more conviviality than the corresponding (same sequence number) individual dependence network of the latter. This is a combination of R1 and R2 from the single transition case.*

Principle 2 (Volatility) *A temporal dependence network has more conviviality than another one if, ceteris paribus, the conviviality measures of all individual dependence networks in the former shows less volatility than in the latter.*

Principle 3 ((Micro-organizational) Entropy) *A temporal dependence network has higher conviviality than another one if, ceteris paribus, the dependence topology in the former shows more variations than in the latter, i.e., if the agents have the opportunity to interact in a greater variety of coalitions.*

For instance, when we state our Principle 1, *Dominance*, we compare conviviality measures of each step in the sequence of dependence networks, thus a measure at the macro-organizational is done. The same holds when we say that the conviviality measures should be equally distributed (Principle 2, *Volatility*). In contrast, to be able to compare the entropy within two sequences of temporal dependence networks, and evaluate the R.4, i.e., maximize the involvement of each individual agent in the coalitions, we need to study the temporal dependence network at a micro-organizational scale.

4.2.1 Macro-organizational scale

To illustrate our *Dominance* Principle, we return to our running example. Consider two instances of the game: l and k. The same five players, Alice, Bob, Carlo, Dimitra and Eve, are trying to improve their conviviality. Indeed, in game l they considered that they did poorly. They play a second game k and compare their performance with the first one. Figure 3 illustrates the *Dominance* Principle with these two games.

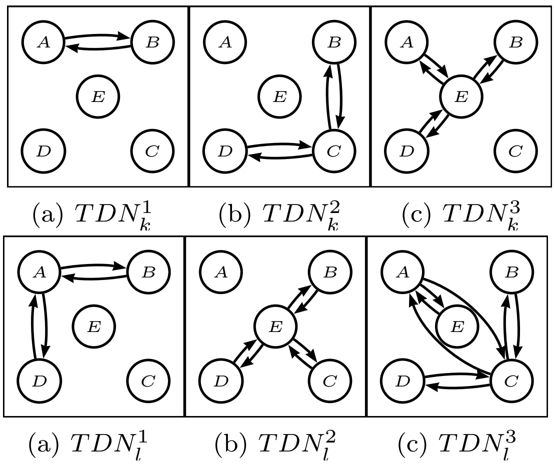


Figure 3. Illustration of Dominance.

The first game l, represented by the temporal dependence network TDN_l has more conviviality than the second, represented by TDN_k. In each corresponding phase of the game, there are more interactions among the agents in game l than in game k. For example, in phase 1, three agents from game l interact, namely A, D and B, to form two coalitions, whereas in the same phase, only two agents from game k interact, namely A and B, to form a single coalition.

We now introduce our fine-grained conviviality measures for temporal dependence networks. Let TDN_1 and TDN_2 be two temporal dependence networks.

Let $|TDN_1|$ and $|TDN_2|$ be the length of these temporal dependence networks, i.e., the number of steps in the sequences. Let $|A_1|$ and $|A_2|$ be the number of agents in TDN_1 and TDN_2 respectively. We recall that $|A_1|$ and $|A_2|$ are constant over the individual dependence networks Let TDN_i^j denote the j-th individual dependence network of the temporal dependence networks TDN_i.

Definition 4.1 (Dominance, formally) *Let* $|TDN_1| = |TDN_2|$. *If* $\forall TDN_1^j$ $conv(TDN_1^j) \geq conv(TDN_2^j)$, *then* $conv(TDN_1) \geq conv(TDN_2)$.

For each instance of TDN_l in Figure 3, the corresponding instance of TDN_k, containing the same agents and goals, has less cycles. This makes TDN_l overally more convivial.

Similarly as in the static case represented Figure 1, we can assume, for our example, that each cycle consists of the same two goals reciprocation in any given individual dependence network. For instance, illustrated Figure 3, in TDN_k^2, C depends on B and reciprocally, to ask and answer question, similarly C depends on D and reciprocally. This reflects the fact that the game is turn based, and all players have similar goals at a given phase of the game (i.e., in a given individual dependence network step). Then, there are a total of 2 goals in each individual dependence network of our examples (Figure 3 to Figure 5). The following are then constant over all the computation section for each individual dependence network:

- $Agents = \{A, B, C, D, E\}$,
- $Goals = \{$"ask a question", "reply to a question"$\}$,
- $\Omega = 6320$.

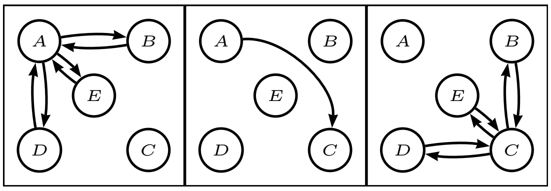
The conviviality computation of each individual dependence network step displayed on Figure 3 is presented in Table 1. For instance, the conviviality of TDN_k is explained in Paragraph 4.1. We see that the computed conviviality for each individual dependence network is higher in TDN_l than in TDN_k. In each phase of the game, the players have more interactions.As a conclusion and per *Dominance* Principle, TDN_l has more conviviality than TDN_k.

Table 1. Computations for TDN_k and TDN_l.

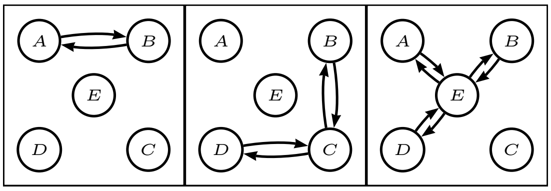
Phase 1	Phase 2	Phase 3
$conv(TDN_k^1) = \frac{2}{\Omega}$	$conv(TDN_k^2) = \frac{4}{\Omega}$	$conv(TDN_k^3) = \frac{6}{\Omega}$
$conv(TDN_l^1) = \frac{4}{\Omega}$	$conv(TDN_l^2) = \frac{6}{\Omega}$	$conv(TDN_l^3) = \frac{8}{\Omega}$

We illustrate our second Principle *Volatility*, corresponding to our Requirement R3, by comparing a previous instance of the game, namely k with a new one m, in which agents have had the same number of interactions to answer Q1 in phase 1 and Q3 in phase 3, but no reciprocal interaction to address Q2 in phase two. Figure 4 illustrates this case. The temporal dependence network TDN_k has more conviviality than TDN_m. In game k, players change their interactions more gradually over the three phases, whereas changes in game m are more erratic, going from many interactions in phase 1 to no interaction in phase 2, to many interactions again in phase 3.

We use the notion of standard deviation σ, which reflects the volatility in a set of measures. A low standard deviation indicates that data points tend to be very close to the mean, whereas high standard deviation indicates that the data is



(a) TDN_m^1 (b) TDN_m^2 (c) TDN_m^3



(a) TDN_k^1 (b) TDN_k^2 (c) TDN_k^3

Figure 4. Illustration of Volatility.

spread out over a large range of values. We note $\sigma(TDN_i)$ the standard deviation over the individual dependence networks belonging to the temporal dependence network TDN_i. We also need to fix the conviviality mean of TDN_1 and TDN_2, respectively noted $\mu(TDN_1)$ and $\mu(TDN_2)$.

Definition 4.2 (Volatility, formally) *Let* $|TDN_1| = |TDN_2|$, *and* $\mu(TDN_1) = \mu(TDN_2)$. *If* $\sigma(TDN_1) < \sigma(TDN_2)$, *then* $conv(TDN_1) > conv(TDN_2)$.

Even if the two temporal dependence networks of Figure 4 have the same mean value for conviviality, $\frac{4}{\Omega}$, the standard variation of TDN_k is less than the standard variation of TDN_m. This means that the conviviality of TDN_k changes more gradually and therefore TDN_k is more convivial. The intuition for this principle is that volatility and dependency are two conflicting notions.

To evaluate the conviviality of the temporal dependence networks depicted Fig. 4, we first compute conviviality for each individual dependence network step, presented Table 2.

Table 2. Computations for TDN_m and TDN_k, Fig. 4.

Phase 1	Phase 2	Phase 3
$TDN_m^1 = \frac{6}{\Omega}$	$TDN_m^2 = 0$	$TDN_m^3 = \frac{6}{\Omega}$
$TDN_k^1 = \frac{2}{\Omega}$	$TDN_k^2 = \frac{4}{\Omega}$	$TDN_k^3 = \frac{6}{\Omega}$

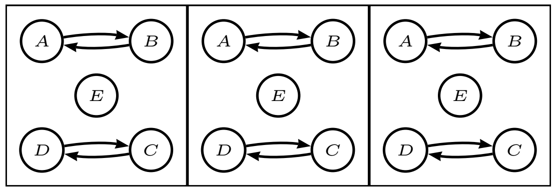
Table 3 presents the means and the standard distribution, showing that TDN_k is more convivial than TDN_m, as $\sigma(TDN_m) > \sigma(TDN_k)$.

Table 3. Means and standard distribution.

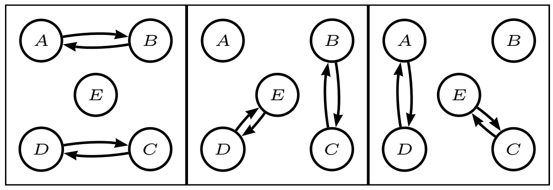
	Game m	Game k
Means	$\mu(TDN_m) = \frac{4}{\Omega}$	$\mu(TDN_k) = \frac{4}{\Omega}$
St. dist.	$\sigma(TDN_m) = \sqrt{\frac{8}{\Omega^2}}$	$\sigma(TDN_k) = \sqrt{\frac{8}{3\times\Omega^2}}$

4.2.2 Micro-Organizational Scale

Figure 5 illustrates *Entropy*: TDN_i is more convivial than TDN_j. In game i, players change partners more often, allowing all players to interact, whereas in game j the same players interact with each other and one player is never involved.



(a) TDN_j^1 (b) TDN_j^2 (c) TDN_j^3



(a) TDN_i^1 (b) TDN_i^2 (c) TDN_i^3

Figure 5. Illustration of Entropy.

Let δ_T be the number of different coalitions over all steps in the sequences of the temporal dependence network T.

Definition 4.3 (Entropy, formally) *Let* $|TDN_1| = |TDN_2|$, *and* $\mu(TDN_1) = \mu(TDN_2)$, *and* $\sigma(TDN_1) = \sigma(TDN_2)$. *If* $\delta_1 > \delta_2$, *then* $coal(TDN_1) > coal(TDN_2)$.

In Figure 5, none of the two temporal dependence networks TDN_j and TDN_i is dominant or less volatile. However, in TDN_j the same coalitions exist throughout the game, whereas in TDN_i, different coalitions are formed and consequently more players have the ability to participate, contribute and benefit. Therefore, TDN_i is more convivial.

Table 4. Entropy, Fig. 5.

$\mu(TDN_j) = \frac{4}{\Omega}$	$\sigma(TDN_j) = 0$	$\delta_{TDN_j} = 2$
$\mu(TDN_i) = \frac{4}{\Omega}$	$\sigma(TDN_i) = 0$	$\delta_{TDN_i} = 6$

Remark: this principle may lead to unexpected results since only the number of coalitions is taken into account (and not their length). If we limit ourself to coalitions of length 2, the above is sufficient. A further study is needed to understand the impact of this principle on coalitions with random lengths.

4.2.3 Discussion

In this section we define conviviality measures that satisfy the four requirements we distinguish and the three principles for our conviviality measures, and illustrate them with our running example. Our measures build up to allow the agents to compare their performances and increase their conviviality. Our first measures allow agents to compare their conviviality at each step of the game. However, these measures do not reflect the distribution of conviviality over the whole sequence, which is what our second measures provide. On the other hand, these second measures do not provide any insight on which agents cooperate to ensure individual agents' participation, which is addressed by our third measure.

5 Related research

In this paper, we use the notion of social dependence introduced by Castelfranchi [7]. Moreover, we build on the notion of dependence graphs and dependence networks, elaborated by Conte and Sichman [20], and Conte et al. [21], in order to model and measure conviviality.

By contrast, we use a more abstract representation of dependence networks, i.e., abstracting notions such as tasks, actions or plans. In this sense our approach also builds to Sauro's abstractions in [15], Boella et al. [2].Dependence based coalition formation is analyzed by Sichman [19], while other approaches are developed in [17, 11, 1].

Differently from Grossi and Turrini [12], our approach does not bring together coalitional theory and dependence theory in the study of social cooperation within multiagent systems. Moreover, our approach differs as it does not hinge on agreements. Finally, similarly to works such as in Johnson and Bradshaw et al. "coactive" design [14], we emphasize agents' interdependence as a critical feature of multiagent systems. Addtionally, the authors focus on the design of systems involving joint interaction among human-agent systems .

6 Summary

In agents systems, conviviality measures quantify interdependence in social dependence relations, representing the degree to which the system facilitates social interactions. In this paper, we distinguish static from temporal measures. In the static case, roughly, more interdependence increases conviviality among groups of agents, i.e., coalitions, whereas larger coalitions may decrease the efficiency or stability of these involved coalitions. In the temporal case, we consider sequences of dependence networks over time.

We distinguish four requirements to maximize conviviality in a multiagent system: 1) maximize the size of the agent's coalitions; 2) maximize the number of these coalitions; 3) maximize the regular increment of the number of coalitions; and 4) maximize the involvement of each individual agent in the coalitions. Furthermore, we distinguish three principles to guide our definition of conviviality measures: **dominance**, **volatility**, and **entropy**. Finally, we define conviviality measures that can be used to test our requirements following our three principles, and illustrate them with a gaming example.

A topic of further work is to define measures of temporal dependence networks for other interpretation of the temporal sequence, and to define conviviality measures for dynamic normative dependence networks. The difference between the two, is that in the latter, a normative system mechanism is used to change conviviality by changing social dependencies, for example by creating new obligations, hiding power relations and social structures. This has been used to define conviviality masks [6], and thus the measures of dynamic dependence networks will lead to measures of conviviality masks. However, we expect that the proposed measures do not apply in a straightforward way, but that new measures will be needed to capture further views of conviviality.

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