How to Build the Best Macroscopic Description of Your Multi-Agent System?

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Abstract. The design and debugging of large-scale MAS require abstraction tools in order to work at a macroscopic level of description. Agent aggregation provides such abstractions by reducing the complexity of the microscopic description. Since it leads to an information loss, such a key process may be extremely harmful for the analysis if poorly executed. This paper presents measures inherited from information theory to evaluate abstractions and provide the experts with feedback regarding the quality of generated descriptions. Several evaluation techniques are applied to the spatial aggregation of an agent-based model of international relations. The information from on-line newspapers constitutes a complex microscopic description of agent states. Our approach is able to evaluate geographical abstractions used by the domain experts in order to provide efficient and meaningful macroscopic descriptions of the world global state.

Keywords: Large-scale multi-agent systems, agent aggregation, macroscopic description, information theory, geographical and news analysis.

1 Introduction

Because of their increasing size, complexity and concurrency, current multi-agent systems (MAS) can no longer be understood from a microscopic point of view. Design, debugging and optimization of such large-scale distributed applications need tools that proceed at a higher level, with insightful abstractions regarding the global system dynamics. Among abstraction techniques (dimension reduction, subsetting, segmentation, clustering, and so on [1]), this paper focuses on *data aggregation*. It consists in losing some information about the agent level to build simpler yet meaningful macroscopic descriptions. Such a process is not trivial for the data interpretation. In particular, unsound aggregations may lead to a critical misrepresentation of the MAS behavior. Hence, we have to determine what are the *good* abstractions and how to properly use them. At each stage of MAS development, aggregation processes should be carefully monitored and feedback should be provided regarding the quality of generated macroscopic descriptions.

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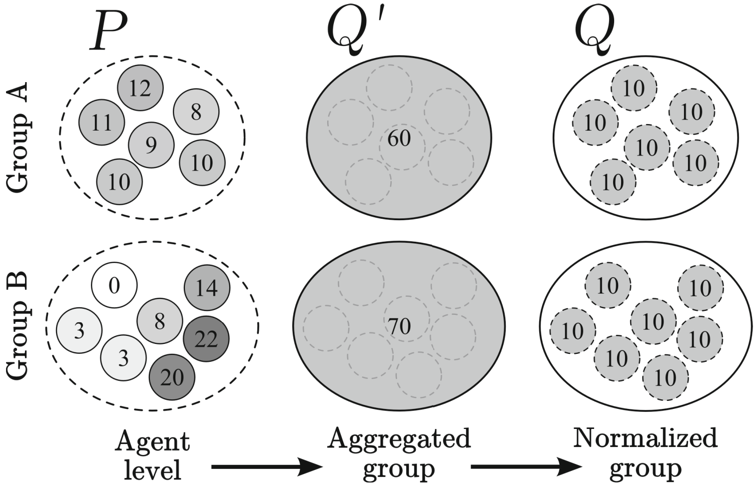


Fig. 1. Averaging the behavior of groups of agents may reduce the redundant information (group A) or it may lead to an unwanted information loss (group B)

A simple example can demonstrate how critical an aggregation can be. Fig. 1 shows two groups of agents that may be simplified by two abstract entities with an average behavior. Intuitively, group A constitutes a *good* abstraction since the induced global behavior is relatively similar to the microscopic one, unlike group B. Hence, aggregation of redundant information should be encouraged to reduce the description complexity (group A), but details regarding heterogeneous behaviors should be preserved in order to control the information loss (group B).

Very little work has been done in the MAS community to quantify such aggregation properties. The main contribution of this paper consists in introducing measures from information theory (Kullback-Leibler (KL) divergence [2] and Shannon entropy [3]) to clarify the notion of *good* aggregation. From these measures, we provide generic feedback techniques and an algorithm that builds multi-resolution descriptions out of hierarchically organized MAS. These techniques and algorithms are applied to the agent-based modeling of international relations: agents represent countries, and their behavior is extracted from online newspapers. Geographers exploit multi-level aggregates to build statistics regarding world areas. We show how these geographical abstractions should be used to better understand the system states and, with further research, its dynamics. This ambitious GEOMEDIA project is conducted in collaboration with experts from the CIST (*Collège International des Sciences du Territoire*, Paris).

Section 2 presents the work related to the main concern of this article. Section 3 presents the agent-based model of the GEOMEDIA application. Section 4 introduces KL divergence to estimate *information loss* and section 5 Shannon entropy to estimate *complexity reduction*. Section 6 shows how these measures can be combined to identify *best* aggregations and to build multi-resolution representations. Section 7 concludes this paper and gives some perspectives.

2 Related Work

Aggregation can take place in every stage of a MAS development: from its design to its use. Even if abstraction techniques may differ, each stage should carefully take into consideration the quality of the aggregations. First, from a software perspective, this section shows that very few research efforts have been done to tackle this issue. (1) Most classical simulation platforms and monitoring systems do not even provide the user with abstraction tools; (2) some do handle the issue, but are still at an early stage of thought. Secondly, on a theoretical aspect, this section explains why classical techniques (*e.g.* data clustering, graph analysis) are not entirely satisfying to build consistent abstractions. In this regard, our approach should rather be compared to recent work in multi-level MAS [4] to which it may provide a formal and quantitative framework.

In a comprehensive survey of agent-based simulation platforms [5], Railsback *et al.* evaluate some of them by testing classical features of MAS modeling and analysis. Unfortunately, the abstraction problem is not tackled by this survey, thus indicating that such considerations are seldom if ever taken into account. Most platforms (Java Swarm, Repast, MASON, NetLogo and Objective-C Swarm) are limited to the microscopic simulation of agents. Railsback warns about the lack of "a complete tool for statistical output" in these platforms [5]. The provision of global views on the MAS macroscopic behavior thus constitutes an on-going research topic. Some tools for large-scale MAS monitoring address this issue by using aggregated data or visual abstractions to reduce the complexity of execution traces [6,7]. However, these abstractions are either limited to the simplification of agents internal behavior, and do not tackle multi-agent organizational patterns, or they do not provide feedback regarding the quality of such abstractions.

Some techniques from graph analysis and data clustering build groups of agents based on their microscopic properties [8,9,10]. Such considerations may meet ours from a theoretical point of view, but the approach presented in this paper supports a very different philosophy: *abstractions should be consistent with the macroscopic semantics of the system.* We claim that, to be meaningful, the aggregation process needs to rely on high-level concepts provided by the domain experts. Hence, our approach should rather be compared with research on multi-level agent-based models [4]. These works openly tackle the abstraction problem by designing MAS on several levels of organization according to expert definitions. Such approaches aim at reducing the computational cost of simulations by reducing the amount of detail. The measures and techniques presented in this paper may provide a formal and quantitative framework to support such a research effort.

To conclude, aggregation techniques should be more systematically implemented on MAS platforms in order to handle large-scale systems. They should combine consistent macroscopic semantics from the experts and feedback regarding the abstractions quality. For example, in this paper, abstractions used by geographers are evaluated according to their information content.

3 Agent-Based Modeling of International Relations

This section presents the GEOMEDIA agent-based model. It consists in the microscopic description of countries with agents and the macroscopic description of world areas with groups and organizations.

3.1 Microscopic Data: The Agent Level

Let A be a set of agents. It constitutes the MAS microscopic level. Visualization tools aim at displaying and explaining *variables* regarding these agents: their behavior and internal states, the events they are associated with, the messages they exchange, and so on. Given a variable v, the set of values $\{v(a)\}_{a \in A}$ forms the *microscopic description* of the system (illustrated by distribution P in Fig. 1).

In the GEOMEDIA project, we are interested in the analysis of world international relations. In that context, we make the assumption that citations or co-citations of countries, within news, are good indicators to represent and understand their relations. For example, we may assume that an often-cited country is likely to politically interact with the newspaper country. In our model, the microscopic level of agents is constituted of 168 countries. Information regarding their behavior has been extracted from 70 RSS feeds of English-language newspapers, from May 2011 to September 2012. The experiments in this paper focus on a very basic variable, `citations_nb`: the number of articles that name a country, and three newspapers: the Vancouver Sun (`feed_CAN`), the Daily Mail (`feed_GBR`), and the Philippine Daily Inquirer (`feed_PHL`).

3.2 Macroscopic Data: Groups and Organizations

A *group* $G \subset A$ is subset of agents that are members of a consistent organizational pattern. It can be interpreted as an *abstract agent* that sums up the behavior of its underlying agents. Hence, groups satisfy a recursive definition: a group is either an agent or a set of groups. Variables are defined on groups according to an aggregation operator: sum, mean, median, extrema, and so on [1]. In our case, since we work with *extensive* variables (*i.e.* variables that are proportional to the aggregate size), $v(G)$ is the *sum* of the values of the underlying agents: $v(G) = \sum_{a \in G} v(a)$ (see Q' in Fig. 1).

We define an *organization* O as a set of groups that constitutes a *partition* of the agent set A. Thus, in the scope of this paper, each agent is always a member of one and only one group. The set of group values $\{v(G)\}_{G \in O}$ composes a *macroscopic description* of the system wrt an organization. It simplifies the variable distribution, from the detailed microscopic description (P in Fig. 1) to an aggregated one (Q'). When comparing both descriptions, an assumption is made regarding the underlying distribution of the aggregated values (*e.g.* uniform, geometric or Gaussian distribution). In our case, we consider that each agent has the same weight within the aggregate. It is thus underlined that aggregated values are *uniformly distributed* over the agents (from Q' to Q). Consequently, as illustrated in Fig. 1, some groups are more suitable than others for the analysis. For example, using group A seems relevant since P is close to Q, unlike group B. Hence, organizations should be carefully chosen to provide accurate high-level abstractions. In particular, they should only aggregate homogeneous and redundant distributions. The next section presents a measure to quantify such a property.

Groups and organizations can be derived from semantical aspects of the agent space. In a geographical context, social, political, and economic organizations of the world are often used. However, in this paper, we focus on *topological* organizations, in order to be consistent with geographical maps of the world. Groups thus aggregate nearby territories. In the following experiments, we consider two hierarchical organizations of world countries, namely `WUTS` [11] and `UNEP` [12]. They define multi-level nested groups used by geographers to build global statistics about world areas, from the microscopic level of agents to the full aggregation (see [11] for a detailed presentation of these multi-scale organizations).

4 KL Divergence as a Measure of Organization Quality

Among classical similarity measures, Kullback-Leibler (KL) divergence [2] is of high interest because of its interpretation in terms of information content. This section shows how it can be exploited to provide feedback regarding the quality of groups and organizations.

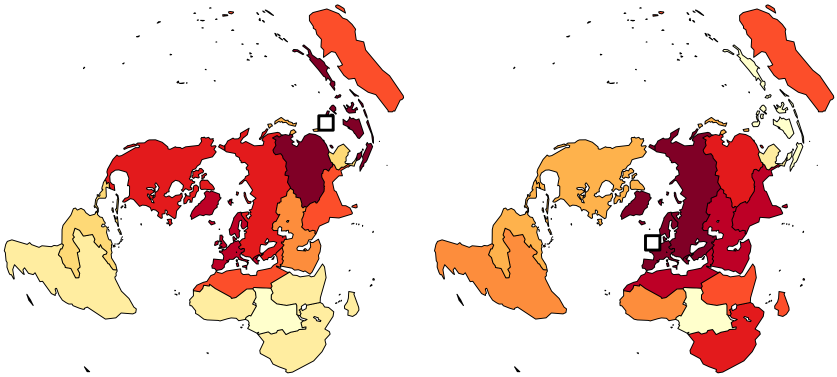
4.1 Kullback-Leibler Divergence

KL divergence measures the number of bits of information that one loses by using an approximated distribution Q to encode the citations of countries, instead of using the detailed source distribution P. In other words, KL divergence estimates the information that is lost by the aggregation process. As we assume that aggregated values are uniformly distributed among underlying agents, a group whose internal distribution is very homogeneous (group A) will have a low divergence (*i.e.* a low information loss), and conversely (group B).

From the KL formula [2], we define *divergence* (or information *loss*) of a group G as follows (more details can be found in [13]):

$$\mathrm{loss}(G) = \sum_{a \in G} \frac{v(a)}{v(A)} \times \log_2 \left(\frac{v(a)}{v(G)} \times |G| \right) \tag{1}$$

where $|G|$ is the size of the group (*i.e.* the number of aggregated agents), $v(G)$ is the sum of the aggregated values and $v(A)$ is the sum of all values (*i.e.* the total number of citations). KL divergence is expressed in bits/citation (or b/c). It verifies the *sum property* [14], meaning that the divergence of disjoint groups is the sum of their divergences. Therefore, for an organization O, we have: $\mathrm{loss}(O) = \sum_{G \in O} \mathrm{loss}(G)$.



(a) `feed_PHL` (Philippines) (b) `feed_GBR` (UK)

Fig. 2. Spatial variations of KL divergence for groups of the `WUTS_3` organization (the darker, the higher). Newspaper locations are indicated by white squares.

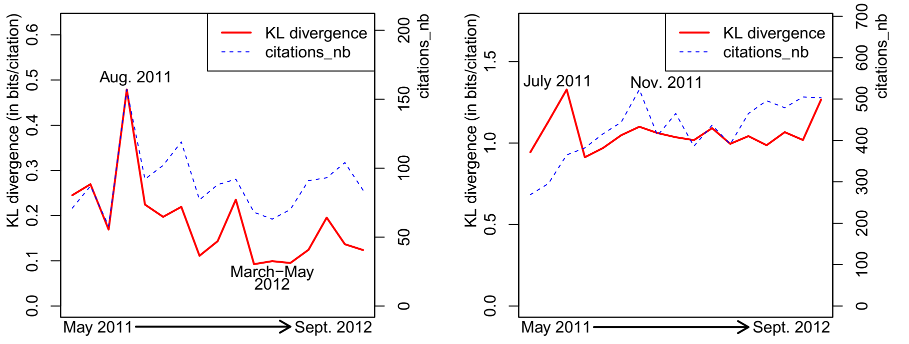
4.2 Groups Quality Is Correlated with the Source of Information

This first experiment aims at showing an essential feature of abstractions: their quality depends on the context of the analysis. Fig. 2 presents the KL divergence of groups from the `WUTS_3` mesoscopic organization, for two newspapers. The darker a group is, the less homogeneous its internal distribution is.

For the investigated dataset, we notice that groups *in which* newspapers are located have high information loss, as for groups that are located *close to* the newspaper (*e.g.* the `Eastern Asia` group in Fig. 2(a)) or that contain agents that are culturally or politically *related to* the newspaper country (*e.g.* `Southern Africa` in Fig. 2(b)). This can be explained by the fact that, for a newspaper, close or related agents may have very divergent behaviors, whereas distant agents are more or less the same. We do not aim at proving that such an hypothesis is universally verified, but at showing that groups should be chosen with respect to the dataset. In our case, this is partly correlated with the source of information. As a consequence, if an analyst uses distributed probes to observe a MAS, she does not want to use only a single abstraction pattern to summarize the information. This is consistent with the *subjectivist* account of emergence, according to which emergent phenomena strongly rely on the observation process [15].

4.3 Groups Quality Varies with Time

Fig. 3 presents the variation of KL divergence and `citations_nb` for two groups of countries on a monthly basis. Fig. 3(a) shows that a group can have a poor quality on specific time periods (*e.g.* August 2011) and high quality on others (*e.g.* from March to May 2012). Abstractions should then be chosen wrt the analyzed time period. Fig. 3(b) shows that the divergence variation is not strictly correlated to the `citations_nb` variation (*e.g.* July 2011 and Nov. 2011). Henceforth, citations number may not be a sufficient criterion for group evaluation.



(a) `W. Asia & N. Africa` group (b) `Europe & N. Asia` group

Fig. 3. Time variation of the KL Divergence and the citations number for two groups of agents (for `feed_GBR`)

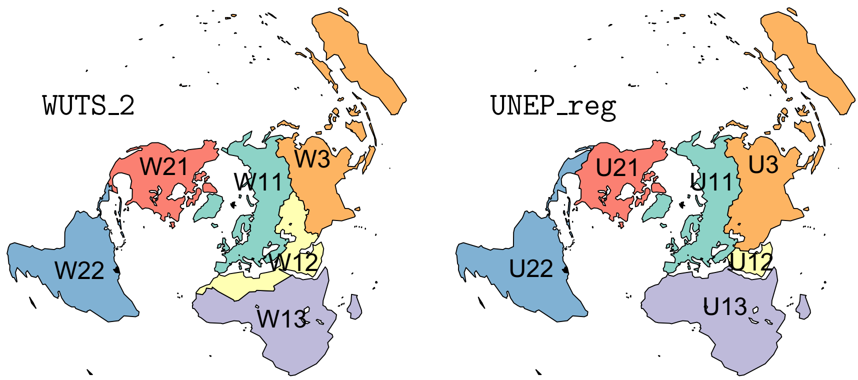


Fig. 4. Two organizations of the agents space in six similar (but not equivalent) groups: locations of the `N. African` agents, the `W. Asian` agents and the `Mexico` agent differ

4.4 Comparing Two Similar Organizations

The purpose of this third experiment is to compare two mesoscopic agent organizations: `WUTS_2` and `UNEP_reg` (see Fig. 4). First, a global comparison can decide which organization is the *best* according to KL divergence. The induced information loss is compared with the total quantity of information contained in the microscopic description, given by the Shannon entropy [3], to give the percentage of lost information.

	`feed_CAN`	`feed_GBR`	`feed_PHL`
`WUTS_2`	1.80 b/c (62.1%)	1.46 b/c (26.4%)	2.07 b/c (51.0%)
`UNEP_reg`	1.57 b/c (54.1%)	1.51 b/c (27.3%)	2.26 b/c (55.7%)

It appears that, both for `feed_GBR` and `feed_PHL`, divergence is slightly lower for `WUTS_2` than for `UNEP_reg`. Hence, if one should choose between these two organizations, `WUTS_2` should be preferred. However, for `feed_CAN`, `UNEP_reg` is better. Once again, abstractions should be chosen wrt the source of information.

One can perform a more subtle analysis in order to determine the groups *best* shapes. For example, we notice in Fig. 4 that $\texttt{U22} = \texttt{W22} \cup \texttt{Mexico}$ and $\texttt{W21} = \texttt{U21} \cup \texttt{Mexico}$. Hence, one may ask: what is the best location of the `Mexico` agent? Should it be aggregated with the `Northern America` group (`W21`/`U21`) or with the `Latin America` one (`W22`/`U22`)? For `feed_GBR`, we have:

$$\text{loss}(\texttt{W21}) + \text{loss}(\texttt{W22}) = 0.048 \text{ b/c } < 0.055 \text{ b/c } = \text{loss}(\texttt{U21}) + \text{loss}(\texttt{U22})$$

Thus, the citations number of the `Mexico` agent is closer to those of the `Northern America` agents. `Mexico` should be grouped accordingly. This technique allows to evaluate and choose the shape of abstractions used by the experts.

5 Complexity Reduction of Organizations

The information content cannot be increased by the aggregation process. Hence, for any pair of disjoint groups, we have: $\text{loss}(G_1 \cup G_2) \geq \text{loss}(G_1) + \text{loss}(G_2)$. This means that, if we only rely on KL divergence, the more detailed is always the better. Hence, we need a measure that also expresses what one *gains* with the aggregation. To do so, this section presents two measures of *complexity reduction*. They estimate the information quantity that one saves by encoding a group G rather than its underlying agents: $\text{gain}(G) = \left(\sum_{a \in G} Q(a)\right) - Q(G)$, where Q estimates the quantity of information needed to represent an agent or a group.

5.1 Number of Encoded Values

One way of measuring information quantities consists in estimating the number of bits needed to encode the values of a given description. We suppose that it is constant for each agent or group: $Q(a) = Q(G) = q$, where q depends on the data type of the encoded values. Hence, for a group, we have: $\text{gain}(G) = (|G| - 1) \times q$. It is a basic complexity measure, but it fits well with classical visualizations (as for the maps of this paper) since the number of displayed values defines the granularity of the visualization.

5.2 Shannon Entropy

The number of encoded values *only* depends on the groups partitioning. In contrast, Shannon entropy *also* depends on the variable distribution. It is a classical complexity measure that is consistent with KL divergence: it can be defined as *the divergence from the uniform distribution* [2]. Briefly, entropy evaluates the information quantity needed to encode *each citation* (and not only the citations number for *each agent*). Based on Shannon's formula [3], we define the *entropy reduction* (or *gain*, in bits/citation) of a group G as follows:

$$\text{gain}(G) = \left(\frac{v(G)}{v(A)} \log_2\left(\frac{v(G)}{v(A)}\right)\right) - \sum_{a \in G}\left(\frac{v(a)}{v(A)} \log_2\left(\frac{v(a)}{v(A)}\right)\right) \quad (2)$$

The choice of either one of these complexity measures depends on the performed analysis. *Shannon entropy* should rather be used for the visualization of individuated citations, whereas *the number of values* is more consistent with the visualization of aggregated values. In any case, techniques presented in this paper are meant to be generic. They can be used with any complexity measure as long as it fits with some algebraic properties (see [13] for more details).

6 Multi-resolution Organizations of MAS

As a conclusion to the previous sections, finding a *good* organization relies on two aspects: the *gain* and the *loss* induced by the aggregation of agents into an average behavior. Choosing an organization thus consists in finding a compromise between a complexity reduction and an information loss.

6.1 Parametrized Information Criterion

A *parametrized Information Criterion* can express the trade-off between complexity reduction and information loss for a given group G:

$$\mathrm{pIC}(G) = p \times \mathrm{gain}(G) - (1 - p) \times \mathrm{loss}(G) \tag{3}$$

where $p \in [0, 1]$ is a parameter used to balance the trade-off. For $p = 0$, maximizing the pIC is equivalent to minimizing the loss: the user wants to be as precise as possible (microscopic level). For $p = 1$, she wants to be as simple as possible (full aggregation). When p varies from 0 to 1, a whole class of nested organizations arises. The analyst has to choose the ones that fulfill her requirements: between the expected amount of details and the computational resources available for the analysis.

Fig. 5 presents such a two-dimensional evaluation of the groups of the `WUTS_3` organization. By comparing KL divergence and entropy reduction, one can easily

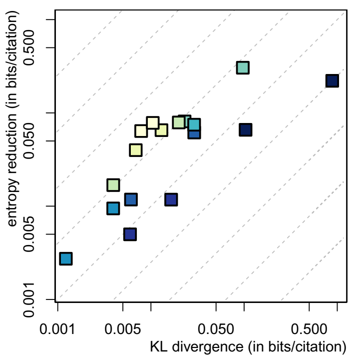


Fig. 5. Comparison of KL divergence and entropy reduction (on logarithmic scales) for groups of `WUTS_3` (for `feed_PHL`)

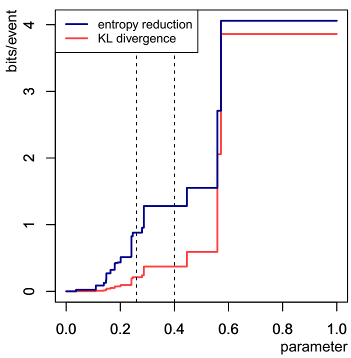


Fig. 6. Variation of the KL divergence and the entropy reduction of best organizations as p varies from 0 to 1

spot groups that have a good gain/loss ratio. The closer a group is to the top-left corner (light squares), the more its complexity reduction compensates its information loss, whereas bottom-right groups have a poor gain/loss ratio and should not be aggregated (dark squares).

6.2 Organizations within a Hierarchy

Given a value of p, *best* organizations are those that maximize the information criterion. Clustering techniques, using *gain* and *loss* measures as distances, could find such optimal partitions. However, results may have very little meaning for the MAS analysis since agents would be aggregated regardless of their location within the system. In contrast, we assume that, in most spatial MAS, there is a correlation between topology and behavior. Hence, we propose that organizations should fit with topological constraints. In other agent-based applications, such constraints can be derived from *semantic* properties of the system (and not necessarily *topological* properties).

In this subsection, we consider hierarchically organized MAS. A *hierarchy* H is a set of nested groups, defined from the microscopic level (each agent is a group) to the whole MAS (only one group). The number of possible multi-resolution organizations within such a hierarchy *exponentially* depends on the number of levels. For `UNEP` (3 levels) and `WUTS` (5 levels), we respectively have 1.3×10^6 and 3.8×10^{12} possible organizations. Finding the best one can thus be computationally expensive. Algorithm 1 below finds topologically-consistent organizations that maximize our information criterion. Its complexity *linearly* depends on the number of groups in the hierarchy (respectively 196 and 231 groups) by doing a classical linear search within the branches of the hierarchy. Indeed, according to the *sum property* [14] of our information-theoretic measures (see subsection 4.1), each branch can be independently evaluated.

This algorithm has been executed on the `WUTS` hierarchy for the `feed_PHL` newspaper. As we increase the gain/loss parameter p, complexity decreases and divergence increases (see Fig. 6). For $p = 0$, all agents are displayed (see Fig. 7).

Algorithm 1. linearly finds best organizations within a hierarchy

Require: A hierarchy H and a trade-off parameter p in $[0, 1]$.
Ensure: An organization made of groups in H that maximizes the pIC.

function FINDBESTORGANIZATION(H, p)
    if H contains only one group G **then** **return** $\{G\}$
    $G \leftarrow$ biggest group of H
    bestOrganization $\leftarrow \emptyset$
    for each direct subhierarchy S of H **do**
        $aux \leftarrow$ FINDBESTORGANIZATION(S, p)
        $bestOrganization \leftarrow$ UNION($bestOrganization, aux$)
    if pIC of $\{G\} > pIC$ of $bestOrganization$ **then return** $\{G\}$
    else return $bestOrganization$
end function

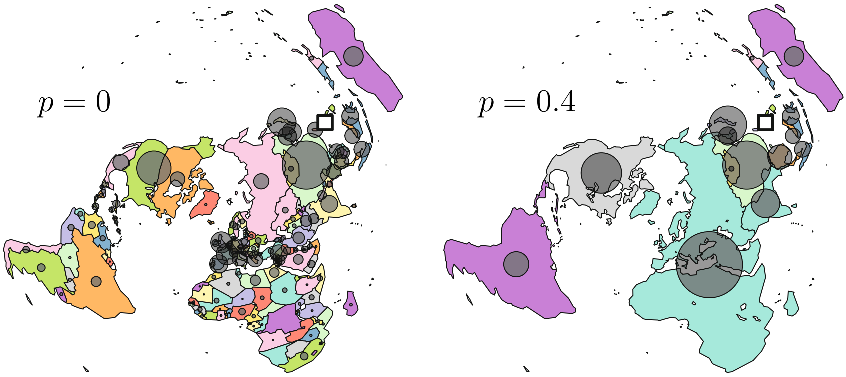


Fig. 7. Two multi-resolution organizations within the `WUTS` hierarchy, generated from Algorithm 1, for different values of the trade-off parameter p

This map is hard to read because too much information is displayed (*e.g.* in Western Europe). The map on the right presents the best organization generated by the algorithm for $p = 0.4$. Some groups are aggregated (*e.g* `Latin America` and `S. Africa`). They correspond to the groups in Fig. 2(a) that have a very low KL divergence. Other groups, that have a high information loss wrt their complexity reduction, are kept detailed. As p increases, higher-level groups are displayed, thus reducing the map complexity while saving the more information. This technique leads to multi-resolution maps that fit the variable distribution. For $p > 0.56$, only the total number of citations is displayed (full aggregation).

7 Conclusion and Perspectives

The design and debugging of complex MAS need abstraction tools to work at a higher level of description. However, such tools have to be built and exploited with the greatest precaution in order to preserve useful information regarding the system behavior and to guarantee that generated descriptions are not misleading. To that extent, this paper focuses on aggregation techniques for large-scale MAS and gives clues to estimate their quality in term of information content. They are applied to the geographical aggregation of international relations through the point of view of on-line newspapers. We show that, by combining information theoretic measures, one can give interesting feedback regarding geographical abstractions and build multi-resolution maps of the world that adapt the visualization complexity to the effective information content.

Future work will apply these techniques to other dimensions of the analysis: *e.g.* for temporal aggregation, thematic aggregation, multi-dimensional aggregation [16]. Besides this work, we are currently exploiting these techniques for performance visualization of large-scale distributed systems [17]. This kind of application shows that our techniques can be scaled up to 1 million agents.

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References

1. Elmqvist, N., Fekete, J.: Hierarchical Aggregation for Information Visualization: Overview, Techniques, and Design Guidelines. IEEE Transactions on Visualization and Computer Graphics 16(3), 439–454 (2010)
2. Kullback, S., Leibler, R.: On Information and Sufficiency. Annals of Mathematical Statistics 22(1), 79–86 (1951)
3. Shannon, C.: A mathematical theory of communication. Bell System Technical Journal 27, 379–423, 623–656 (1948)
4. Gil-Quijano, J., Louail, T., Hutzler, G.: From Biological to Urban Cells: Lessons from Three Multilevel Agent-Based Models. In: Desai, N., Liu, A., Winikoff, M. (eds.) PRIMA 2010. LNCS (LNAI), vol. 7057, pp. 620–635. Springer, Heidelberg (2012)
5. Railsback, S.F., Lytinen, S.L., Jackson, S.K.: Agent-based Simulation Platforms: Review and Development Recommendations. Simulation 82, 609–623 (2006)
6. Búrdalo, L., Terrasa, A., Julián, V., García-Fornes, A.: A Tracing System Architecture for Self-adaptive Multiagent Systems. In: Demazeau, Y., Dignum, F., Corchado, J.M., Pérez, J.B. (eds.) Advances in PAAMS. AISC, vol. 70, pp. 205–210. Springer, Heidelberg (2010)
7. Tonn, J., Kaiser, S.: ASGARD – A Graphical Monitoring Tool for Distributed Agent Infrastructures. In: Demazeau, Y., Dignum, F., Corchado, J.M., Pérez, J.B. (eds.) Advances in PAAMS. AISC, vol. 70, pp. 163–173. Springer, Heidelberg (2010)
8. Sharpanskykh, A., Treur, J.: Group Abstraction for Large-Scale Agent-Based Social Diffusion Models with Unaffected Agents. In: Kinny, D., Hsu, J.Y.-j., Governatori, G., Ghose, A.K. (eds.) PRIMA 2011. LNCS (LNAI), vol. 7047, pp. 129–142. Springer, Heidelberg (2011)
9. Peng, W., Grushin, A., Manikonda, V., Krueger, W., Carlos, P., Santos, M.: Graph-Based Methods for the Analysis of Large-Scale Multiagent Systems. In: AAMAS 2009, pp. 545–552 (2009)
10. Iravani, P.: Multi-level network analysis of multi-agent systems. In: Iocchi, L., Matsubara, H., Weitzenfeld, A., Zhou, C. (eds.) RoboCup 2008. LNCS (LNAI), vol. 5399, pp. 495–506. Springer, Heidelberg (2009)
11. Grasland, C., Didelon, C.: Europe in the World – Final Report. ESPON Project 3.4.1, vol. 1 (2007)
12. United Nations Environment Programme: Global Environmental Outlook: environment for development, Nairobi, vol. 4 (2007)
13. Lamarche-Perrin, R., Vincent, J.M., Demazeau, Y.: Informational Measures of Aggregation for Complex Systems Analysis. Technical Report RR-LIG-026, Laboratoire d'Informatique de Grenoble, France (2012)
14. Csiszár, I.: Axiomatic Characterizations of Information Measures. Entropy 10(3), 261–273 (2008)

15. Deguet, J., Demazeau, Y., Magnin, L.: Element about the Emergence Issue: A Survey of Emergence Definitions. ComPlexUs 3, 24–31 (2006)
16. Lamarche-Perrin, R., Demazeau, Y., Vincent, J.M.: The Best-partitions Problem: How to Build Meaningful Aggregations? Technical report, Laboratoire d'Informatique de Grenoble, France (forthcoming, 2013)
17. Lamarche-Perrin, R., Schnorr, L.M., Vincent, J.M., Demazeau, Y.: Evaluating Trace Aggregation Through Entropy Measures for Optimal Performance Visualization of Large Distributed Systems. Technical report, Laboratoire d'Informatique de Grenoble, France, RR-LIG-037 (2012)