Observation, Communication and Intelligence in Agent-Based Systems

Nader Chmait(✉), David L. Dowe, David G. Green, and Yuan-Fang Li

Faculty of Information Technology, Monash University, Clayton, Australia
{nader.chmait,david.dowe,david.green,yuanfang.li}@monash.edu

Abstract. The intelligence of multiagent systems is known to depend on the communication and observation abilities of its agents. However it is not clear which factor has the greater influence. By following an information-theoretical approach, this study quantifies and analyzes the impact of these two factors on the intelligence of multiagent systems. Using machine intelligence tests, we evaluate and compare the performance of collaborative agents across different communication and observation abilities of measurable entropies. Results show that the effectiveness of multiagent systems with low observation/perception abilities can be significantly improved by using high communication entropies within the agents in the system. We also identify circumstances where these assumptions fail, and analyze the dependency between the studied factors.

1 Introduction

The literature on multiagent systems has put forward many studies showing how factors such as *communication* [1,3,7,9] and *observation* [4,5,11] influence the performance of multiagent systems. However, it is ambiguous whether (a) augmenting the agents' observations to read/interpret the environment in which they operate, or rather (b) boosting communication between these agents, has higher influence on their performance, which is the main motivation behind this research. In fact, one of the fundamental characteristics of agent-based systems is their ability to observe/perceive and sense the environment [5,12]. Within a multiagent system setting, perhaps the main property of agents is their ability to interact and communicate [12, Sect.5].

The goal of this paper is to compare the above factors by measuring the influence that each has on the intelligence of cooperative agent-based systems. Moreover, we try to reveal the dependencies between one factor and another. To the best of our knowledge, no studies have applied formal intelligence tests for this purpose. In real-world multiagent applications, agents can have limited sensitivity of the environment (observations), thus relying on communication to improve their performance can be inevitable. Therefore, quantifying the influence of the rules of information aggregation on the effectiveness of such systems is likelyto have major implications by predicting the usefulness and expected performance of these systems over different settings.

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In this study we begin by introducing our approach to measuring the intelligence of groups of artificial agents in Sect. 2. We then describe our experiments (Sect. 4), the outcomes (Sect. 4) and conclude (Sect. 5) with a discussion of the implication of our findings on the current state of research.

2 Approach to Measuring Intelligence

Our approach is to use (machine) intelligence tests to evaluate a group of artificial agents collaborating in different settings. We adjust their communication and observation abilities over a series of controlled experiments in order to see whether the changes are reflected by their measured intelligence.

2.1 The Anytime Intelligence Test

To achieve our stated goal, we need to be able to *quantify* the performance of artificial agents. While many problems are relevant to agent-based systems, not every evaluation metric can be used as a formal (universal) intelligence test. We have chosen to use an extension of the Anytime Universal Intelligence Test [6] (anYnt) to quantify the performance of multiagent systems. The test is derived from formal and mathematical considerations [6, Sect.3] that build upon Legg and Hutter's definition of universal intelligence [8], and it can be used in practice to evaluate artificial agents in a dynamic setting [6, Sect.6.3] and [7]. We follow the agent-environment framework [8] where an environment is the world where agents can interact using a set of observations, actions and rewards. At each step of the test, the environment generates observations from the set of observations $\mathcal{O}$ and sends them to the agents. Agents performs actions from a limited set of actions $\mathcal{A}$ in response. Finally, the environment rewards back each agent from the set $\mathcal{R} \subseteq \mathbb{Q}$ based on the quality of its action. An iteration or step i of the test stands for one sequence of observation-action-reward.

2.2 Measuring Uncertainty and Information

We follow an information-theoretical approach building on the notion of *Shannon's entropy* [10] to measure the *uncertainty* $\mathrm{H}(\mu)$ in a given environment μ, as well as the amount of information in an observation o, or a communication range c. We define N to be the set of all possible states of an environment μ. At the beginning of a test (e.g anYnt), the entropy is maximal as there is complete uncertainty about the current state of μ from an agent's perspective. Therefore the probability $p(s_\mu)$ of a given state s_μ occurring follows a uniform distribution and is equal to $1/|N|$. Using $\log_2$ as a base for calculations, the uncertainty $\mathrm{H}(\mu)$ is calculated as follows: $\mathrm{H}(\mu) = -\sum_{s_\mu \in N} p(s_\mu) \log_2 p(s_\mu) = \log_2 |N|$ bits.

The amount of information an agent π is given about the environment can be calculated as the entropy H(o) of the observation o sent to π by the environment at one iteration of the test, which translates to the minimum number of bits used to describe o. Consequently, we expect from the theory that the more information given to an agent (or the larger its set of observation about the environment), the higher the probability that this agent will accurately reason about it by processing and interpreting the provided information. Furthermore, we denote by c the communication range of an agent π. The amount of information transmitted within c is calculated as the entropy H(c) which, using $\log_2$, refers to the minimal binary representation needed to describe the transmitted data over the range c.

2.3 Evaluating Different Agent Communication Modes

Given an anYnt testing environment μ with $|N|$ states, and a group of agents Π to be evaluated, each iteration or step i of the test is run as follows:

1. The environment μ sends an observation o to each agent $\pi \in \Pi$, where o is a description of: the state π currently occupies in μ, as well as a set of other neighbor (reachable) states of μ at iteration i.
2. Agents communicate by sharing their observations with other agents (using different communication strategies) within their communication range c.
3. Each agent takes an action based on its observation/communication details using its decision-making technique.
4. The environment rewards back each agent based on the quality of its action.

Let c (the communication range an agent π) be the set of neighbor states over which π can transmit/receive data. We evaluate a cooperative group of local search agents using the three communication techniques briefly summarized below. A detailed description of the implementation of these agents and their communication techniques can be found in [2, Sect.4].

Stigmergy or Indirect Communication. Agents communicate by altering the environment so that it reflects their observations. At each iteration of the test, when an agent senses a reward as part of its observation o, it communicates with the other agents by inducing *fake-rewards* in its communication range c. The fake rewards reflect the real reward the agent has observed.

Direct Communication. At each iteration of the test, agents broadcast a copy of their observation o, to the other agents in their communication range c. Agents then select the action leading to the highest visible reward.

Imitation. In this setting - in addition to the evaluated agents - we introduce a smart agent that always takes the most rewarding action at each iteration of the test. The evaluated agents imitate the smart agent by mimicking its action when it is in their communication range c. The agents also share this action with the other agents located in their communication range c, if any exist.

In the context of the above settings, the observation entropy H(o) can be increased/decreased by adding/removing states to/from the set of neighbor states in o sent by the environment μ. Likewise, adding/removing states to/from the set of states belonging to the communication range c allows us to increase/decrease the communication entropy H(c) of the evaluated system.

3 Experiments

We have conducted a series of controlled experiments on a cooperative collective of agents Π over the anYnt test, using the test environment class implementation found in [2, Sect. 3.2], which is an extension of the spatial environment space described in [6, Sect.6.3]. Each experiment consisted of 200 iterations of *observation-communication-action-reward* sequences and the outcome from each experiment is an average score returning a per-agent measure of success of the collective of evaluated agents over a series of canonical tasks of different algorithmic complexities. The number of agents used was $|\Pi| = 20$ agents, evaluated over an environment space of $\mathrm{H}(\mu) = 11.28$ bits of uncertainty.

A description of our experiments can be stated as follows: we evaluate a group of agents Π over a series of (anYnt) intelligence tests and record the group's score $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ over a range of entropy values H(o) and H(c). The score $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ is a real number in $[-1.0, 1.0]$. Average results of Π (using the different communication modes described in Sect. 2.3) taken from 1000 repeated experiments are depicted in Fig. 1. Note that the coefficient of variation is less than 0.025 across our experiments. We denote by E the set of entropy values used in Fig. 1. These values are in the range $[0.04, 10.84]$ bits, and they correspond to $\log_2 n$, where n is the number of states in o or c, as appropriate. Moreover, Fig. 2 depicts the scores $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ from Fig. 1, plotted for fixed values of H(c) across increasing values of H(o) (left-side plots of Fig. 2) and vice versa (right-side plots of Fig. 2). We analyze and discuss these results in the following section.

4 Results and Discussion

Indirect Communication. Figures 1 and 2a show that the effectiveness of the agents in Π monotonically increases with the observation entropy of the agents H(o) until it converges around an H(o) of 10.8 bits. Increasing the (stigmergic) communication entropy H(c) between the agents also has an impact on their intelligence. However, the influence of H(c) on intelligence is rather more complicated, as it seems also to depend on the observation entropies H(o). For instance, for an H(o) of 0.04 bits, the best performance, $\max(\Upsilon(\mathrm{H_o}, \mathrm{H_c}))$, is reached when the coefficient $\alpha = \frac{\mathrm{H(c)}}{\mathrm{H(o)}} = 9$. For larger H(o) entropies, the best performances are reached at smaller α values until $\alpha \approx 1$ at an H(o) of 10.84 bits. The overall picture from Fig. 1 (indirect communication) shows that the performance drops as the entropy H(c) moves away from $\alpha \times \mathrm{H(o)}$. This non-monotonic variation of scores shows that increasing communication does not necessarily always lead to an increase in performance as presumed. To understand the influence of indirect communication on the scores of the collectives we have to analyze further the relationship between H(o) and H(c). Figure 3 is a whisker plot showing the variation in the scores across different entropy values $\mathrm{H(c)} \subseteq E$ for fixed entropies H(o), and vice versa. The figure also shows that - for indirect communication - H(c) is most significant when $\mathrm{H(o)} \in [0.3, 1.9]$ bits. For instance, using stigmergy to communicate very short observations (low H(o) entropies) does not have a

Observation entropies : **H**(o)

Indirect communication

Communication entropies : **H**(c)	0.04	0.11	0.22	0.36	0.54	0.76	1.01	1.30	1.62	1.99	2.38	2.82	3.29	3.79	4.33	4.91	5.53	6.18	6.86	7.58	8.34	9.14	9.97	10.84
10.84	0.0506	0.0693	0.0927	0.1120	0.1329	0.1517	0.1735	0.1998	0.2256	0.2545	0.2753	0.2903	0.3059	0.3277	0.3431	0.3615	0.3833	0.4076	0.4234	0.4328	0.4439	0.4470	0.4472	0.4470
9.97	0.0469	0.0646	0.0837	0.1078	0.1290	0.1502	0.1712	0.1978	0.2256	0.2667	0.2990	0.3179	0.3297	0.3422	0.3609	0.3778	0.3933	0.4140	0.4291	0.4385	0.4448	0.4475	0.4468	0.4473
9.14	0.0450	0.0657	0.0883	0.1008	0.1203	0.1434	0.1738	0.1950	0.2486	0.2907	0.3245	0.3419	0.3491	0.3652	0.3823	0.3930	0.4073	0.4213	0.4335	0.4398	0.4470	0.4472	0.4469	0.4465
8.34	0.0441	0.0618	0.0824	0.1022	0.1200	0.1409	0.1766	0.2188	0.2637	0.3064	0.3394	0.3588	0.3695	0.3779	0.3955	0.4059	0.4180	0.4273	0.4339	0.4458	0.4470	0.4459	0.4464	0.4468
7.58	0.0461	0.0702	0.0849	0.1046	0.1222	0.1497	0.1841	0.2333	0.2793	0.3249	0.3541	0.3707	0.3845	0.3945	0.4046	0.4131	0.4231	0.4311	0.4419	0.4450	0.4449	0.4466	0.4461	0.4471
6.86	0.0489	0.0677	0.0863	0.1056	0.1274	0.1584	0.2024	0.2542	0.3105	0.3445	0.3696	0.3828	0.3943	0.4005	0.4111	0.4202	0.4268	0.4389	0.4410	0.4448	0.4458	0.4465	0.4463	0.4467
6.18	0.0486	0.0671	0.0875	0.1076	0.1313	0.1676	0.2249	0.2817	0.3274	0.3575	0.3752	0.3897	0.4002	0.4079	0.4153	0.4229	0.4325	0.4383	0.4388	0.4409	0.4432	0.4438	0.4451	0.4468
5.53	0.0478	0.0720	0.0927	0.1139	0.1470	0.1853	0.2503	0.3062	0.3457	0.3669	0.3827	0.3969	0.4053	0.4119	0.4172	0.4284	0.4327	0.4318	0.4360	0.4362	0.4386	0.4404	0.4438	0.4467
4.91	0.0506	0.0721	0.0959	0.1199	0.1556	0.2088	0.2733	0.3255	0.3614	0.3770	0.3872	0.4016	0.4080	0.4141	0.4236	0.4295	0.4293	0.4306	0.4336	0.4353	0.4370	0.4408	0.4442	0.4468
4.33	0.0506	0.0701	0.0965	0.1268	0.1726	0.2388	0.3002	0.3446	0.3698	0.3875	0.3941	0.4053	0.4136	0.4202	0.4246	0.4255	0.4271	0.4294	0.4299	0.4300	0.4330	0.4395	0.4436	0.4471
3.79	0.0498	0.0745	0.1018	0.1413	0.1971	0.2685	0.3224	0.3579	0.3803	0.3893	0.3989	0.4073	0.4157	0.4187	0.4167	0.4197	0.4231	0.4227	0.4220	0.4249	0.4294	0.4373	0.4432	0.4469
3.29	0.0528	0.0741	0.1050	0.1534	0.2286	0.2955	0.3363	0.3670	0.3859	0.3960	0.4037	0.4103	0.4165	0.4138	0.4168	0.4179	0.4162	0.4171	0.4158	0.4182	0.4256	0.4344	0.4425	0.4470
2.82	0.0486	0.0790	0.1126	0.1686	0.2504	0.3151	0.3456	0.3732	0.3870	0.3982	0.4038	0.4132	0.4081	0.4109	0.4119	0.4135	0.4108	0.4071	0.4122	0.4128	0.4186	0.4308	0.4414	0.4464
2.38	0.0533	0.0809	0.1203	0.1881	0.2643	0.3216	0.3506	0.3770	0.3906	0.4011	0.4066	0.4046	0.4056	0.4054	0.4018	0.3999	0.4014	0.3987	0.4034	0.4102	0.4165	0.4279	0.4403	0.4463
1.99	0.0530	0.0836	0.1338	0.2069	0.2717	0.3202	0.3493	0.3731	0.3897	0.3976	0.3947	0.4017	0.4001	0.3958	0.3948	0.3917	0.3913	0.3956	0.3948	0.4023	0.4113	0.4285	0.4404	0.4465
1.62	0.0533	0.0898	0.1457	0.2127	0.2681	0.3125	0.3444	0.3705	0.3893	0.3902	0.3907	0.3919	0.3939	0.3867	0.3846	0.3856	0.3862	0.3843	0.3869	0.3990	0.4083	0.4269	0.4404	0.4461
1.30	0.0570	0.0929	0.1562	0.2140	0.2566	0.2991	0.3378	0.3690	0.3729	0.3830	0.3816	0.3879	0.3829	0.3784	0.3774	0.3800	0.3791	0.3811	0.3873	0.3899	0.4062	0.4238	0.4391	0.4469
1.01	0.0565	0.1033	0.1582	0.2100	0.2538	0.2894	0.3195	0.3447	0.3622	0.3741	0.3772	0.3811	0.3755	0.3741	0.3739	0.3752	0.3779	0.3805	0.3830	0.3926	0.4056	0.4247	0.4397	0.4468
0.76	0.0604	0.1051	0.1568	0.1969	0.2339	0.2635	0.2985	0.3269	0.3488	0.3615	0.3665	0.3693	0.3705	0.3718	0.3727	0.3745	0.3757	0.3811	0.3799	0.3886	0.4017	0.4243	0.4403	0.4467
0.54	0.0645	0.1002	0.1448	0.1849	0.2159	0.2478	0.2758	0.3061	0.3352	0.3500	0.3577	0.3635	0.3705	0.3736	0.3757	0.3771	0.3747	0.3794	0.3813	0.3890	0.4008	0.4220	0.4392	0.4468
0.36	0.0660	0.0956	0.1355	0.1637	0.1899	0.2197	0.2580	0.2882	0.3188	0.3381	0.3560	0.3650	0.3705	0.3741	0.3781	0.3798	0.3828	0.3873	0.3853	0.3899	0.4022	0.4216	0.4405	0.4467
0.22	0.0605	0.0917	0.1150	0.1514	0.1777	0.2061	0.2378	0.2714	0.3023	0.3317	0.3498	0.3643	0.3768	0.3797	0.3817	0.3877	0.3910	0.3916	0.3941	0.3958	0.4058	0.4231	0.4420	0.4472
0.11	0.0548	0.0779	0.0997	0.1313	0.1592	0.1893	0.2186	0.2520	0.2864	0.3165	0.3372	0.3630	0.3728	0.3845	0.3911	0.3952	0.4016	0.4032	0.4024	0.4090	0.4137	0.4274	0.4422	0.4469
0.04	0.0486	0.0676	0.0919	0.1146	0.1400	0.1715	0.2025	0.2317	0.2671	0.2987	0.3307	0.3542	0.3734	0.3890	0.3970	0.4031	0.4091	0.4116	0.4141	0.4194	0.4265	0.4305	0.4422	0.4464

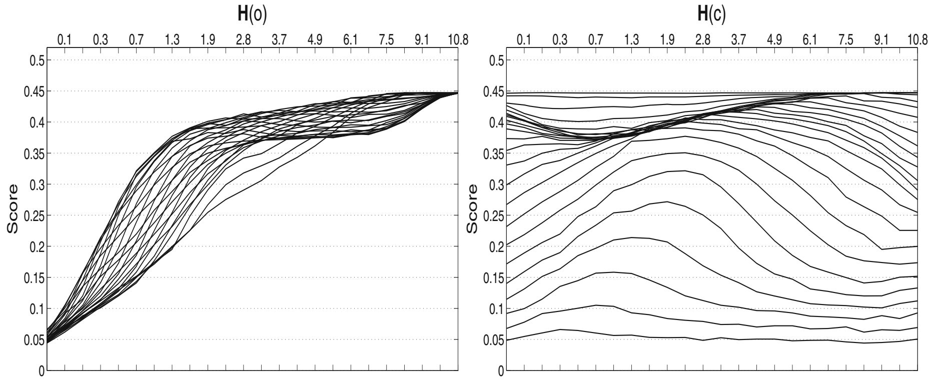
Direct communication

Communication entropies : **H**(c)	0.04	0.11	0.22	0.36	0.54	0.76	1.01	1.30	1.62	1.99	2.38	2.82	3.29	3.79	4.33	4.91	5.53	6.18	6.86	7.58	8.34	9.14	9.97	10.84
10.84	0.3487	0.3843	0.4119	0.4271	0.4352	0.4424	0.4443	0.4454	0.4469	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470
9.97	0.3487	0.3843	0.4119	0.4271	0.4352	0.4424	0.4443	0.4454	0.4469	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470
9.14	0.3487	0.3843	0.4119	0.4271	0.4352	0.4424	0.4443	0.4454	0.4469	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470
8.34	0.3487	0.3843	0.4119	0.4271	0.4352	0.4424	0.4443	0.4454	0.4469	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470
7.58	0.3487	0.3843	0.4119	0.4271	0.4352	0.4424	0.4443	0.4454	0.4469	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470
6.86	0.3487	0.3843	0.4119	0.4271	0.4352	0.4424	0.4443	0.4454	0.4469	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470	0.4470
6.18	0.3449	0.3799	0.4057	0.4208	0.4282	0.4364	0.4385	0.4400	0.4418	0.4416	0.4420	0.4429	0.4432	0.4440	0.4444	0.4447	0.4455	0.4462	0.4469	0.4469	0.4470	0.4469	0.4469	0.4470
5.53	0.3377	0.3698	0.3947	0.4120	0.4205	0.4290	0.4316	0.4326	0.4353	0.4356	0.4359	0.4378	0.4391	0.4403	0.4415	0.4422	0.4435	0.4452	0.4463	0.4465	0.4469	0.4470	0.4469	0.4469
4.91	0.3294	0.3588	0.3888	0.4028	0.4111	0.4191	0.4217	0.4241	0.4253	0.4277	0.4308	0.4321	0.4333	0.4367	0.4377	0.4398	0.4417	0.4437	0.4455	0.4464	0.4472	0.4470	0.4469	0.4468
4.33	0.3153	0.3557	0.3767	0.3901	0.4016	0.4079	0.4115	0.4156	0.4167	0.4193	0.4222	0.4269	0.4280	0.4311	0.4352	0.4365	0.4401	0.4418	0.4449	0.4461	0.4470	0.4469	0.4468	0.4468
3.79	0.3069	0.3415	0.3633	0.3801	0.3890	0.3976	0.4016	0.4046	0.4080	0.4125	0.4153	0.4183	0.4219	0.4264	0.4295	0.4350	0.4380	0.4407	0.4436	0.4460	0.4471	0.4471	0.4469	0.4471
3.29	0.3002	0.3349	0.3544	0.3709	0.3760	0.3844	0.3912	0.3942	0.3985	0.4023	0.4068	0.4100	0.4179	0.4216	0.4276	0.4326	0.4360	0.4407	0.4431	0.4458	0.4467	0.4470	0.4469	0.4471
2.82	0.2826	0.3124	0.3395	0.3561	0.3614	0.3732	0.3780	0.3822	0.3873	0.3944	0.3979	0.4047	0.4103	0.4163	0.4229	0.4306	0.4342	0.4390	0.4430	0.4458	0.4470	0.4470	0.4467	0.4469
2.38	0.2713	0.3035	0.3237	0.3433	0.3503	0.3590	0.3651	0.3716	0.3741	0.3829	0.3906	0.3965	0.4030	0.4113	0.4174	0.4259	0.4315	0.4383	0.4422	0.4454	0.4466	0.4475	0.4468	0.4468
1.99	0.2624	0.2916	0.3074	0.3278	0.3395	0.3483	0.3535	0.3588	0.3656	0.3713	0.3827	0.3898	0.3989	0.4032	0.4136	0.4241	0.4309	0.4375	0.4420	0.4454	0.4469	0.4472	0.4470	0.4468
1.62	0.2444	0.2764	0.2979	0.3130	0.3273	0.3341	0.3413	0.3507	0.3547	0.3640	0.3756	0.3830	0.3918	0.4025	0.4108	0.4212	0.4288	0.4358	0.4413	0.4444	0.4468	0.4471	0.4467	0.4468
1.30	0.2303	0.2669	0.2875	0.3060	0.3114	0.3237	0.3316	0.3365	0.3466	0.3548	0.3652	0.3765	0.3830	0.3951	0.4072	0.4140	0.4263	0.4357	0.4410	0.4451	0.4474	0.4472	0.4468	0.4468
1.01	0.2201	0.2494	0.2714	0.2913	0.2981	0.3104	0.3202	0.3285	0.3365	0.3434	0.3561	0.3671	0.3789	0.3905	0.4033	0.4158	0.4231	0.4338	0.4397	0.4442	0.4468	0.4475	0.4466	0.4469
0.76	0.2100	0.2408	0.2586	0.2780	0.2876	0.2969	0.3071	0.3184	0.3225	0.3362	0.3468	0.3627	0.3735	0.3849	0.3994	0.4098	0.4211	0.4311	0.4397	0.4445	0.4468	0.4475	0.4468	0.4470
0.54	0.1959	0.2220	0.2405	0.2616	0.2734	0.2800	0.2955	0.3037	0.3124	0.3251	0.3390	0.3536	0.3663	0.3825	0.3967	0.4108	0.4211	0.4304	0.4385	0.4447	0.4469	0.4476	0.4471	0.4467
0.36	0.1750	0.2062	0.2265	0.2386	0.2591	0.2728	0.2820	0.2909	0.3023	0.3170	0.3298	0.3484	0.3627	0.3768	0.3910	0.4050	0.4189	0.4283	0.4382	0.4432	0.4469	0.4477	0.4468	0.4469
0.22	0.1536	0.1798	0.2008	0.2240	0.2412	0.2551	0.2689	0.2824	0.2952	0.3089	0.3214	0.3379	0.3517	0.3732	0.3878	0.4045	0.4176	0.4267	0.4372	0.4428	0.4470	0.4473	0.4469	0.4466
0.11	0.1245	0.1577	0.1780	0.1981	0.2143	0.2311	0.2505	0.2646	0.2784	0.2950	0.3129	0.3314	0.3507	0.3665	0.3844	0.4005	0.4141	0.4290	0.4373	0.4434	0.4471	0.4476	0.4464	0.4470
0.04	0.0879	0.1194	0.1405	0.1642	0.1803	0.2043	0.2236	0.2455	0.2636	0.2847	0.3026	0.3240	0.3427	0.3635	0.3782	0.3971	0.4133	0.4273	0.4367	0.4435	0.4470	0.4478	0.4469	0.4463

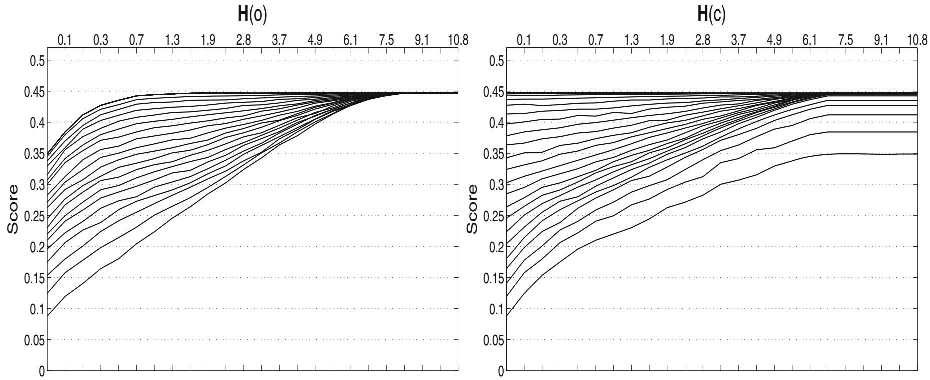
Imitation

Communication entropies : **H**(c)	0.04	0.11	0.22	0.36	0.54	0.76	1.01	1.30	1.62	1.99	2.38	2.82	3.29	3.79	4.33	4.91	5.53	6.18	6.86	7.58	8.34	9.14	9.97	10.84
10.84	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978
9.97	0.7977	0.7977	0.7977	0.7978	0.7977	0.7978	0.7978	0.7978	0.7978	0.7977	0.7978	0.7978	0.7977	0.7977	0.7977	0.7977	0.7978	0.7977	0.7978	0.7978	0.7977	0.7977	0.7978	0.7978
9.14	0.7976	0.7976	0.7976	0.7977	0.7976	0.7977	0.7977	0.7976	0.7976	0.7977	0.7978	0.7977	0.7977	0.7977	0.7977	0.7977	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978	0.7978
8.34	0.7975	0.7975	0.7975	0.7976	0.7976	0.7976	0.7975	0.7976	0.7976	0.7976	0.7976	0.7976	0.7977	0.7977	0.7977	0.7976	0.7977	0.7978	0.7978	0.7978	0.7978	0.7977	0.7979	0.7978
7.58	0.7977	0.7975	0.7977	0.7975	0.7977	0.7974	0.7976	0.7976	0.7976	0.7975	0.7975	0.7977	0.7976	0.7977	0.7978	0.7978	0.7978	0.7979	0.7977	0.7979	0.7980	0.7978	0.7978	0.7978
6.86	0.7973	0.7976	0.7975	0.7974	0.7973	0.7973	0.7976	0.7975	0.7977	0.7976	0.7975	0.7976	0.7973	0.7976	0.7974	0.7978	0.7979	0.7979	0.7979	0.7980	0.7979	0.7979	0.7978	0.7979
6.18	0.7973	0.7971	0.7973	0.7969	0.7972	0.7971	0.7976	0.7973	0.7973	0.7974	0.7971	0.7973	0.7972	0.7976	0.7976	0.7976	0.7976	0.7976	0.7977	0.7980	0.7981	0.7978	0.7979	0.7979
5.53	0.7973	0.7972	0.7971	0.7976	0.7973	0.7971	0.7974	0.7974	0.7974	0.7975	0.7972	0.7975	0.7974	0.7972	0.7972	0.7979	0.7975	0.7979	0.7979	0.7976	0.7978	0.7978	0.7978	0.7979
4.91	0.7966	0.7964	0.7966	0.7966	0.7965	0.7968	0.7970	0.7972	0.7966	0.7970	0.7969	0.7967	0.7970	0.7975	0.7974	0.7974	0.7974	0.7978	0.7979	0.7976	0.7980	0.7978	0.7978	0.7979
4.33	0.7958	0.7961	0.7960	0.7960	0.7960	0.7962	0.7964	0.7964	0.7966	0.7968	0.7968	0.7968	0.7974	0.7975	0.7969	0.7978	0.7977	0.7977	0.7983	0.7981	0.7980	0.7982	0.7981	0.7981
3.79	0.7950	0.7956	0.7953	0.7956	0.7954	0.7955	0.7958	0.7955	0.7958	0.7963	0.7967	0.7960	0.7959	0.7972	0.7967	0.7970	0.7969	0.7970	0.7973	0.7976	0.7979	0.7982	0.7977	0.7979
3.29	0.7937	0.7952	0.7945	0.7947	0.7951	0.7938	0.7947	0.7949	0.7949	0.7957	0.7952	0.7949	0.7955	0.7966	0.7960	0.7962	0.7968	0.7972	0.7971	0.7979	0.7981	0.7979	0.7979	0.7979
2.82	0.7916	0.7913	0.7915	0.7931	0.7916	0.7922	0.7925	0.7934	0.7922	0.7944	0.7929	0.7943	0.7938	0.7955	0.7953	0.7954	0.7962	0.7962	0.7973	0.7970	0.7988	0.7976	0.7975	0.7976
2.38	0.7851	0.7834	0.7821	0.7846	0.7833	0.7856	0.7859	0.7849	0.7837	0.7852	0.7871	0.7895	0.7900	0.7900	0.7914	0.7937	0.7932	0.7948	0.7968	0.7971	0.7983	0.7976	0.7972	0.7975
1.99	0.7610	0.7593	0.7615	0.7633	0.7619	0.7593	0.7587	0.7654	0.7641	0.7618	0.7702	0.7655	0.7721	0.7737	0.7793	0.7815	0.7882	0.7918	0.7950	0.7958	0.7972	0.7977	0.7968	0.7970
1.62	0.7127	0.7040	0.7115	0.7101	0.7045	0.7092	0.7086	0.7039	0.7062	0.7140	0.7183	0.7253	0.7337	0.7497	0.7555	0.7615	0.7754	0.7809	0.7895	0.7913	0.7958	0.7961	0.7953	0.7952
1.30	0.6097	0.6166	0.6097	0.6138	0.6055	0.6237	0.6146	0.6345	0.6267	0.6436	0.6527	0.6614	0.6854	0.7006	0.7162	0.7322	0.7526	0.7692	0.7812	0.7874	0.7930	0.7925	0.7917	0.7921
1.01	0.5052	0.5024	0.5071	0.5055	0.5126	0.5064	0.5218	0.5310	0.5573	0.5743	0.5996	0.6151	0.6418	0.6680	0.6911	0.7166	0.7427	0.7603	0.7730	0.7844	0.7891	0.7912	0.7902	0.7898
0.76	0.4050	0.4179	0.4161	0.4078	0.4130	0.4397	0.4653	0.4780	0.5062	0.5369	0.5583	0.5941	0.6191	0.6506	0.6790	0.7054	0.7311	0.7566	0.7704	0.7792	0.7867	0.7874	0.7867	0.7867
0.54	0.3244	0.3319	0.3414	0.3232	0.3570	0.3796	0.4192	0.4419	0.4697	0.5038	0.5380	0.5718	0.6015	0.6442	0.6649	0.6982	0.7248	0.7471	0.7634	0.7771	0.7829	0.7837	0.7818	0.7815
0.36	0.2465	0.2639	0.2783	0.2940	0.3215	0.3555	0.3781	0.4181	0.4469	0.4841	0.5207	0.5547	0.5910	0.6277	0.6591	0.6891	0.7136	0.7397	0.7580	0.7699	0.7783	0.7774	0.7772	0.7771
0.22	0.1997	0.2101	0.2366	0.2667	0.2938	0.3299	0.3571	0.3970	0.4341	0.4675	0.5009	0.5394	0.5784	0.6125	0.6492	0.6783	0.7058	0.7336	0.7499	0.7657	0.7713	0.7726	0.7722	0.7725
0.11	0.1589	0.1932	0.2122	0.2377	0.2735	0.3148	0.3483	0.3819	0.4159	0.4624	0.4988	0.5302	0.5725	0.6052	0.6417	0.6744	0.7008	0.7270	0.7463	0.7599	0.7662	0.7676	0.7668	0.7671
0.04	0.1319	0.1672	0.2036	0.2318	0.2640	0.3031	0.3337	0.3740	0.4166	0.4458	0.4883	0.5272	0.5632	0.5998	0.6343	0.6666	0.6975	0.7198	0.7419	0.7544	0.7615	0.7625	0.7615	0.7620

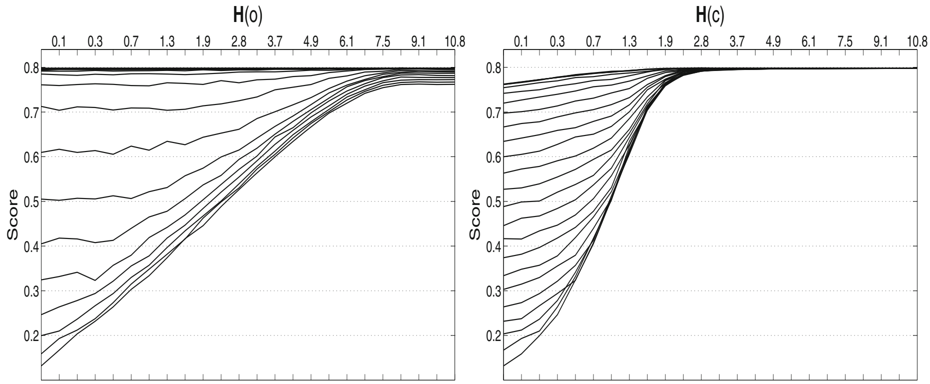
Fig. 1. Test scores $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ for different values of H(o) and H(c) (in bits), for the same collective of agents using the communication modes described in Sect. 2.3. The gray color-map intensities reflect how high the score values $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ are, where higher intensities mean larger scores (higher values are black and lower values are white). We consider the small variations in the scores along the fourth decimal place as experimental error.



(a) Variation in scores for collective Π using indirect communication.



(b) Variation in scores for collective Π using direct communication.



(c) Variation in scores for collective Π using imitation.

Fig. 2. Variation in the scores (from Fig. 1) of collective Π using different communication strategies. The scores are plotted for fixed values of H(c) across increasing values of H(o) (left-side plots of Fig. 2), as well as for fixed values of H(o) across increasing values of H(c) (right-side plots of Fig. 2).

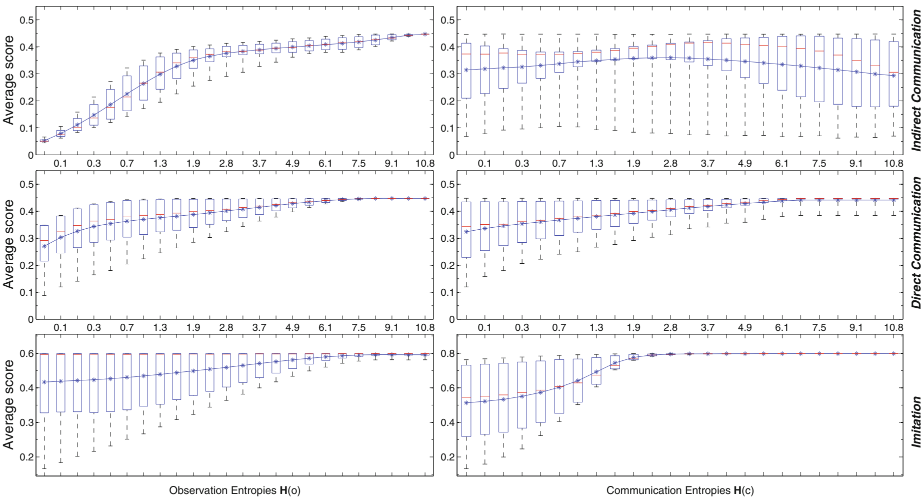


Fig. 3. Whisker plot showing the variation in test scores across different entropy values H(c) for fixed entropies H(o) (left-side), and vice versa (right-side). The central mark (in red) is the median while the edges of the box represent the 25^{th} and 75^{th} percentiles of the scores and the whiskers extend to the most extreme score values. The blue line-plot shows the average scores at each of the intermediate entropy values.

large influence on performance possibly because the observations do not carry much information. Likewise, using stigmergy within collectives of agents with extended observation abilities (high H(o) entropies) has no significant effect on performance, as the uncertainty in the environment is already reduced as a result of the agents' observations. However, communication using stigmergy was fairly effective in less extreme cases. To make our observation more concrete, we define below the communication-over-observation coefficient of success ϕ.

Definition 1. *Let* $S = \{(x, y) \in E \times E \mid x > y\}$*. The communication-over-observation coefficient of success is:* $\phi = (\sum_S \inf(\Upsilon(x, y), \Upsilon(y, x)) \div |S|)$*, where* $\inf(a, b)$ *is a function that returns* 1 if $a < b$*, or zero otherwise.*

For this mode of communication, the coefficient $\phi = 11/276 = 0.0399$. Knowing that the test scores are of the form $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$, the value of ϕ suggests that, for this communication mode, it is much more effective to increase the observation entropies of the agents as opposed to increasing their communication entropies[1]. More importantly, the dependency of communication H(c) on observation H(o) is made explicit here. For instance, using H(c) values inferior to H(o) is rarely more rewarding than in the reciprocal case.

Direct Communication. While increasing observation entropies still leads to a significant increase in performance, the influence of direct communication is much more significant than in Fig. 2a. We can observe a clear pattern in

[1] Recall that we are experimenting for the entropy values E, using a number of agents $|\Pi| = 20$, over an environment of uncertainty $\mathrm{H}(\mu) = 11.28$ bits.

Fig. 2b showing higher performances for higher communication entropies for a fixed H(o). Nevertheless, in this setting using very low H(o) entropies does not ensure optimal performances for Π. However, re-compensating these short-sighted agents with high H(c) entropies can lead to a system up to four times better in performance, which also indicates the very low-dependency of H(c) on the value of H(o). On the other hand, for fairly high observation entropies, augmenting communication between the agents is at least as effective as mounting their observations, and can sometimes be even more effective as shown in Fig. 3. In this setting the coefficient $\phi = 272/276 = 0.9855$, meaning that augmenting the communication entropies within the system will highly likely lead to a more intelligent system. Consequently, communication is effective here even when the observation entropies are slim, again suggesting a low dependency on H(o).

Imitation. Figure 2c highlights the significance of communication in agent collectives relying on imitation. In this setting, $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ is mainly controlled by how much entropy is exchanged through communication between the agents. For agents with very-low observations, the scores can be improved up to six times higher (e.g. from 0.1319 to 0.7978 in Fig. 2c) by increasing their communication entropies. Figure 3 shows that, in this setting, increasing communication significantly influences performance, while the impact of observation is not as important. We can also see that tuning the observation entropies has a negligible effect when $\mathrm{H(c)} > 2.3$ bits as opposed to changing the communication entropies. We must point out that the effect of imitation is significant regardless of the type/intelligence of the agent that is being imitated. For instance, imitation will result in either positive or negative shift in performance, depending on the intelligence of the imitated agent. In this setting the coefficient $\phi = 274/276 = 0.9928$, leading to a similar and even stronger conclusion than in the case of direct communication.

Furthermore, we have plotted in Fig. 4 the gradient difference $\nabla\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ of the scores $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$, in the H(c) and H(o) directions across the entropy values E. For instance, each line in Fig. 4 depicts the gradient shift over multiple entropy values calculated according to Eq. (1) below:

$$\nabla\Upsilon(\mathrm{H_o}, \mathrm{H_c}) \leftarrow \left|\frac{\partial\Upsilon(\mathrm{H_o}, \mathrm{H_c})}{\partial\mathrm{H(c)}}\right| - \left|\frac{\partial\Upsilon(\mathrm{H_o}, \mathrm{H_c})}{\partial\mathrm{H(o)}}\right| \tag{1}$$

The outcome from (1) highlights the entropies where (in a environment of uncertainty $\mathrm{H}(\mu) = 11.28$ bits, and $|\Pi| = 20$) communication has the highest influence on the effectiveness $\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ of Π when compared to the influence of observation. We observe that indirect communication has highest impact across entropies of $[0.3, 1.9]$ bits. Direct communication is most significant within entropies of $[0.1, 1.9]$ bits, while imitation has the highest influence over entropy values in the range $[0.7, 4.9]$ bits[1].

Environment Space. Experimenting over environments with different uncertainties $\mathrm{H}(\mu)$ lead to similar conclusions as above. However, the scores converged

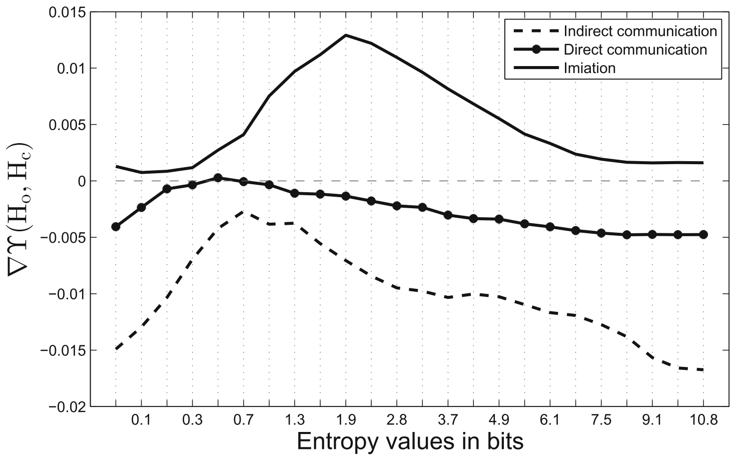


Fig. 4. Average difference in gradient $\nabla\Upsilon(\mathrm{H_o}, \mathrm{H_c})$ in H(c) and H(o) directions over a set of entropy values E

faster in environments of lower uncertainty and the gap in performance was less significant than in environments of high uncertainty.

Number of Agents. Testing with different number of agents also influenced the performance of the evaluated collectives. The influence of communication on the scores was stronger in many cases where a larger number of agents was used.

5 Conclusion

This paper follows an information-theoretical approach to quantify and analyze the effectiveness of a collaborative group of artificial agents across different communication settings. Using formal intelligence tests from the literature of artificial general intelligence, we measure the influence of two factors inherent to multiagent systems: the observation and communication abilities of agents, on the overall intelligence of the evaluated system.

Agents collaborating using three different communication strategies are evaluated over a series of intelligence tests, and their scores are recorded. We highlight the different configurations where the effectiveness of artificial agent-based systems is significantly influenced by communication and observation. We also show that dull systems with low observation or perception abilities can be recompensated for, and significantly improved, by increasing the communication entropies between the agents, thus leading to smarter systems. Moreover, we identify circumstances where the increase in communication does not monotonically improve performance. We also analyze the dependency between communication and observation and its impact on the overall performance.

The outcome from our experiments can have many theoretical and practical implications on agent-based systems as they allow us to predict the effectiveness and the expected performance of these systems over different (communication or collaboration) settings. We are aware that using different implementations or extensions of the studied communication strategies would possibly lead to a variation in the scores. However, the same approach can still be used to understand the rules of information aggregation within a multiagent setting, and the influence of these rules on the effectiveness of the evaluated system.

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