A decentralized approach for establishing a shared communication vocabulary

Jurriaan van Diggelen, Robbert Jan Beun, Frank Dignum, Rogier M. van Eijk, John-Jules Meyer

Institute of Information and Computing Sciences
Utrecht University, the Netherlands
{jurriaan, rj, dignum, rogier, jj}@cs.uu.nl

Abstract. In this paper, we address the issue of communication between agents with heterogeneous ontologies. Our approach aims at providing the agents with a shared communication vocabulary. Instead of adopting a central service which carries out this task, we follow a decentralized approach, i.e. the task is performed collectively by every agent in the system. We describe four communication strategies which, when used by individual agents, give rise to a shared communication vocabulary on a global level. We evaluate these strategies using simulation techniques, which enables us to compare their performance according to specified criteria.

1 Introduction

A fundamental problem of communication in open multi agent systems is caused by the heterogeneity of the agent's knowledge sources, or more specifically of the underlying *ontologies*. Although ontologies are often advocated as a complete solution for knowledge sharing between agents, this is only true when all agents have knowledge about each others' ontology. The most straightforward way to establish this is to develop one common ontology which is used by all agents. However, this scenario is highly unlikely in open multi agent systems, like those on the internet, as it requires all involved system developers to reach consensus on which ontology to use. Moreover, a common ontology is disadvantageous for the problem solving capabilities of the agents as different tasks typically require different ontologies [3].

To deal with this problem, we deliberately diverge from the definition of an ontology as an explicit specification of a shared conceptualization [7]. We adopt private ontologies, which are not shared, and an intermediate ontology (or interlingua [13]) which is (partially) shared and not explicitly specified. The private ontology of an agent is used for storing and reasoning with *operational knowledge*, i.e. knowledge relevant to a particular problem or task at hand. The intermediate ontology is used for the communication of operational knowledge; we therefore refer to it as *communication vocabulary* (or cv). Communication proceeds by translating from the speaker's private ontology to the communication vocabulary which the hearer translates back again into its own private

ontology. The agent's operational knowledge base is dependent on the private ontology; it is *not* dependent on the communication vocabulary. The cv can therefore be treated as a *dynamic ontology* [8]. The agents' private ontologies, on the other hand, are *static*, i.e. they do not change over time.

Initially, the communication vocabulary is empty. To enable communication between agents, the cv is built. This raises the question: how is it built? Most approaches that deal with these issues use some centralized service which facilitates in publishing and making decisions about the the communication vocabulary. For example, the FIPA ontology agent [1] publishes information about ontologies and thereby facilitates communication by mediating between heterogeneous agents. Also, the Ontolingua server [6] is intended as a service to achieve consensus on a shared ontology in heterogeneous groups. However, these techniques are not straightforwardly applicable in systems which lack a clear organization. Consider, for example, the group of agents on the world wide web. If there would be one ontology agent that aligns every ontology in the system, it would be very difficult to make every agent accept its authority. Furthermore, this agent runs a high risk of getting overloaded. If, on the other hand, there would be a number of ontology agents on the web, communication problems would arise between agents that use different ontology agents.

In this paper, we try to overcome these problems by exploring ways to establish a communication vocabulary in a fully *decentralized* way. This means that, instead of making one agent pursue the goal of building a cv, we design *every* agent to pursue this common goal. This way, a shared cv emerges in the system due to the interactions of individual agents. We describe several communication strategies the agents can follow, and evaluate their quality according to specified criteria. One of these criteria is that the strategy should give rise to a cv which is limited in size, yet sufficiently expressive ([5]). Multiple terms with the same meaning (synonyms) are therefore not preferable; they increase the size of the cv, without adding anything to its expressivity.

Although this paper is primarily intended for the ontology integration community, we follow an approach which is related to research done in the language evolution community. Following Luc Steels [12], we assume that the meaning of a concept can be conveyed to another agent by pointing to shared instances. Furthermore, we also approach a language (or an ontology) as a complex adaptive system which can be studied by means of simulation [11, 9]. However, whereas most research on language evolution has an explanatory goal, our goals are purely constructive. Our primary aim is to provide a technique which can be used for ontology integration. Our work can thus be viewed as an *application* of language evolution to ontology integration.

In the next section, we present the communication protocol. Because the communication protocol is non-deterministic, a communication strategy is required to guide the agents in making the right choices. Section 3 presents four possible strategies. The strategies are compared in three simulation experiments which serve to evaluate how the strategies contribute to the agents' mutual understanding, what kind of cv the strategy gives rise to, and how well the strategy

performs in a sparsely connected network. We conclude in section 4 and give directions for future research.

2 Communication Protocol

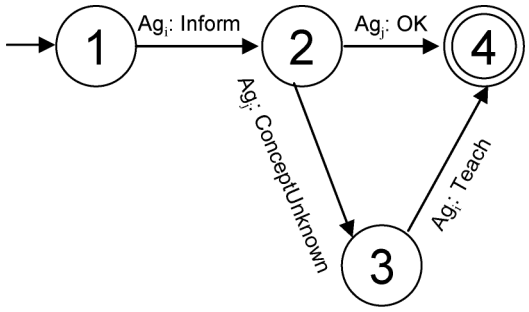

Fig. 1. Communication Protocol

The communication protocol in figure 1 defines the possible dialogues that may happen when an agent informs another agent about something. After Ag_i has sent its message to Ag_j, Ag_j may respond in two ways. When it knows the terms in the message, it translates the terms to its own ontology and responds "OK". When it doesn't know a term, it responds with "ConceptUnknown", which leaves no option for Ag_i but to *teach* the meaning of the term to Ag_j. For the purposes of this paper, it suffices to say that the teaching agent presents a number of examples of the term which enables the other agent to discover its definition in terms of its private ontology. For a more elaborate discussion on this teaching process, the reader is referred to [4]. After Ag_j has learned the meaning of the term, it translates the message to its own ontology after all, and the dialogue finishes.

We now discuss the inform action in further depth. In doing so, we distinguish the following agent components of agent Ag_i:

- ONT_i : The set of concept names defined in the agent's private ontology.
- AKB_i : The assertional knowledge base, consisting of statements of the form $x(a)$, where $x \in \text{ONT}_i$ and a is an element from the (shared) domain of discourse.
- VOC_i : The set of terms constituting the agent's knowledge of the communication vocabulary.
- DEF_i : $\{\langle x, y\rangle | x \in \text{VOC}_i \wedge y \in \text{ONT}_i\}$: A set of concept pairs, defining every concept in VOC_i as a concept in ONT_i. We write $\text{DEF}_i(x)$ to denote $y \in \text{ONT}_i$, where $\langle x, y\rangle \in \text{DEF}_i$. For the purposes of this paper, it suffices to

regard these definitions as *precise* mappings. For a discussion on approximate mappings, the reader is referred to [4].
- $\mathrm{SCR}_i : \mathrm{VOC}_i \rightarrow \mathbb{N}$ is a data structure which assigns a score to every term. This score is used by the agent's strategy.

We omit the subscripts of the components when it is clear to which agent the component belongs. The communicative abilities of the agents are specified as actions. During the execution of actions, messages are sent through the instruction send(Ag_j, $\langle \mathrm{SpeechActType}, p_1, .., p_n \rangle$), where Ag_j is the addressee of the message, the SpeechActType specifies what the message is about, and $p_1..p_n$ are parameters of the message. The effect of this instruction is that Ag_j is able to perform a Receive(Ag_i, $\langle \mathrm{SpeechActType}, x_1, .., x_n \rangle$) action, where Ag_i is the sender of the message and $x_1..x_n$ are instantiated to $p_1..p_n$. In the specification of actions we will adopt Ag_i as the sender and Ag_j as the receiver of messages. The Inform-action is specified as follows:

Action `SendInform`($\mathrm{Ag}_j, x(a)$)
where $x(a) \in AKB$
Candidates := $\{y' | \langle y', x \rangle \in \mathrm{DEF}\}$
y := `Select`(Candidates), *where* `Select` *is implemented in the agent's strategy*
Send(Ag_j, $\langle \mathrm{Inform}, y(a) \rangle$)

Action `ReceiveInform`
Receive(Ag_i,$\langle$ Inform,$x(a)\rangle$)
If x $\in$ VOC Then Add $y(a)$ to AKB, s.t. $\langle x, y \rangle \in$ DEF
Else Send(ConceptUnknown)
`UpdateScore`(Ag_i,x), *where* `UpdateScore` *is implemented in the agent's strategy*

We assume that initially, for all Ag_i the set $\mathrm{VOC}_i = \mathrm{ONT}_i$, and $\mathrm{DEF}_i = \{\langle x, x \rangle | x \in \mathrm{VOC}_i\}$. This means that the agents start communication by using their private concept names. The SendInform action therefore always sends a message because there is always a way to translate a concept in ONT to a term in VOC. The ReceiveInform action does not always translate a received term to the private ontology because there is not always a translation available in DEF. In these cases, the agent responds with "ConceptUnknown" after which the unknown term will be taught to him. When Ag_i teaches a term x to Ag_j, Ag_j adds the term to VOC_j, adds the definition of the term to DEF_j and sets $\mathrm{SCR}_j(x)$ to 0. For this reason, an agent soon ends up having multiple ways to translate a concept in ONT to a term in VOC: one possible translation is its private concept name (a translation which is available due to the initialization of VOC), other translations are terms it has learned from other agents. All possible translations are listed in the set "Candidates" in the `SendInform`-action. Although all terms in the Candidate-set are allowed translations, the agents follow a strategy to select the *best* candidate. An agent Ag_i bases its decision on the score of the term, given by SCR_i. The agents may update the score of a term each time they receive a message with that term from other agents, i.e. in the `UpdateScore`

action which is performed at the end of the `ReceiveInform` action. Different implementations of `Select` and `UpdateScore` give rise to different communication strategies. This is the topic of the next section, but first we present an example to illustrate the need for a communication strategy.

Example
Consider an English, French and a Dutch agent (Ag_1, Ag_2, Ag_3 respectively), which all have an ontology consisting of one concept which they use to represent cheese. The agents' components are as follows:

	ONT_i	VOC_i	DEF_i
$i = 1$	{Cheese}	{Cheese}	$\{\langle \text{Cheese}, \text{Cheese}\rangle\}$
$i = 2$	{Fromage}	{Fromage}	$\{\langle \text{Fromage}, \text{Fromage}\rangle\}$
$i = 3$	{Kaas}	{Kaas}	$\{\langle \text{Kaas}, \text{Kaas}\rangle\}$

Consider the following conversation in which Ag_1 wishes to inform Ag_2 that object a is cheese :

1 Ag_1 sends to Ag_2: Inform(Cheese(a))
2 Ag_2 sends to Ag_1: ConceptUnknown
3 Ag_1 teaches Cheese to Ag_2
4 Ag_2 adds Cheese to VOC_2 and adds $\langle \text{Cheese}, \text{Fromage}\rangle$ to DEF_2. Because it now knows the definition of Cheese, it can understand the received Inform message and adds Fromage(a) to AKB_2.

Suppose Ag_1 also informs Ag_3 about the fact that object a is Cheese. This results in a similar dialogue in which Ag_1 also teaches Ag_3 the meaning of Cheese. Now, the agents' components are as follows:

	ONT_i	VOC_i	DEF_i
$i = 1$	{Cheese}	{Cheese}	$\{\langle \text{Cheese}, \text{Cheese}\rangle\}$
$i = 2$	{Fromage}	{Fromage, Cheese}	$\{\langle \text{Fromage}, \text{Fromage}\rangle, \langle \text{Cheese}, \text{Fromage}\rangle\}$
$i = 3$	{Kaas}	{Kaas, Cheese}	$\{\langle \text{Kaas}, \text{Kaas}\rangle, \langle \text{Cheese}, \text{Kaas}\rangle\}$

Now, suppose that Ag_2 wishes to inform Ag_3 about the fact that object b is Fromage. There are two possible dialogues because Ag_2 knows two terms which mean Fromage. The dialogues are:

5a Ag_2 sends to Ag_3: Inform(Fromage(a))
6a Ag_3 sends to Ag_2: ConceptUnknown
7a Ag_2 teaches Fromage to Ag_3
8a Ag_3 now knows the definition of Fromage, and adds Kaas(a) to AKB_3.

or

5b Ag_2 sends to Ag_3: Inform(Cheese(a))
6b Ag_3 sends to Ag_2: OK. Because Ag_3 knows the definition of Cheese, it can immediately translate the term and add Kaas(a) to AKB_3

Both dialogues are allowed by the communication protocol. However, we prefer the second dialogue, which leads to an immediate understanding of the message. This illustrates the issues surrounding the implementation of the agent's communication strategy.

3 Strategies

Description of strategies

The decision to be solved by the agent's strategy involves choosing a term among the possible candidates when sending an inform message. We assume that `Select` always returns the term with the highest score. The differences between the strategies lie in the way the scores are updated after a message is received. Strategy s1 only attributes a score to its private concept name. Therefore, in systems with agents that use strategy s1 (s1-systems), every agent holds on to its own private concept names when it comes to speaking. To understand other agents, they learn each other's concept names. This strategy is analogous to ontology alignment ([10]): every agent has a mapping to every other agent's ontology. Strategy s2 attributes a score of 1 to the most recently received term; all other terms with the same definition are attributed a score of 0. In s2-systems, an agent chooses the candidate term it has most recently received from another agent. Strategy s3 increases the score of a term each time a message with that term is received. This way, the agents in a s3-system choose the candidate term which they have most frequently received. Strategy s4 is similar to s3 but also takes into account *which* agents have used the term. The score of a term is increased more when an agent with many acquaintances uses the term than when an agent with few acquaintances uses the term. We assume that the number of acquaintances of an agent can be known by the agents. In systems where every agent has an equal amount of acquaintances, s4 gives rise to the same behavior as s3. We therefore only discuss s4 in section 3.3, where we consider networks in which the agent's number of acquaintances differ. The four communication strategies are specified in figure 2.

Description of experiments

We evaluate the performance of these strategies using simulation experiments. To obtain a clear picture of the properties we are interested in, in the experiments, we abstract away from as many irrelevant aspects as possible. This way, the agents only exchange one meaning (but may use different terms to do so). An experiment consists of t steps at which randomly a speaker and a receiver is selected from the set of connected agents. The agents follow the communication protocol as described in the previous section. Because the agents only exchange one meaning, for every agent Ag_i, the elements in the set VOC_i all have the same definition in DEF_i. Therefore, all elements in VOC_i are allowed candidates when Ag_i sends a message. We distinguish between the terms that are understood by an agent (the *understandable terms*), and those that are spoken by an agent (the *spoken terms*). The understandable terms of Ag_i are those in the set VOC_i. The spoken terms are those that are selected from VOC_i by the agent's strategy. Using s1 and s2, there is only one spoken term per agent, because there is only one term with a highest score. s3 and s4 may give rise to several terms with an equal highest score, amongst which the the strategy randomly chooses one. In

// *The Select action is the same in every strategy*
// *Select returns the concept from Candidates with the highest score*
// *If several concepts have an equal highest score, it randomly picks one from them*
Action `Select`(Candidates)
Randomly choose y from $\{y' | y' \in$ Candidates and
for all $z \in$ Candidates: SCR$(z) \leq$ SCR$(y')\}$
return y

Strategy s1:
// *Always speak your own concept name.*
The scores of the agent's private concept names is kept equal on 1.
// *The score of every other term therefore remains 0.*
Action `UpdateScore`(Ag_i, x)
For all $y \in$ VOC $\cap$ ONT Do SCR$(y) := 1$

Strategy s2:
// *Speak the term which most recently another agent used*
Action `UpdateScore`(Ag_i, x)
SCR(x) := 1
For all $y \neq x$ with DEF$(y) =$ DEF(x) Do SCR$(y) := 0$

Strategy s3:
// *Speak the most frequently used term*
Action `UpdateScore`(Ag_i, x)
SCR$(x) :=$ SCR(x) +1

Strategy s4:
// *Speak the most frequently used term weighted by the user's number of acquaintances*
// *The number of acquaintances of Ag_i is denoted by k(Ag)*
Action `UpdateScore`(Ag_i, x)
SCR$(x) :=$ SCR(x) + k(Ag_i)

Fig. 2. Implementations of different strategies

these cases we say that there are several spoken terms, i.e. those with the highest score. The model-components are summarized below:

- A multi agent system is a network of agents, where:
  - n is the number of agents.
  - $\mathrm{AG} = \{\mathrm{Ag}_1..\mathrm{Ag}_n\}$ is the set of agents
  - $\mathrm{CAG} \subseteq \mathrm{AG} \times \mathrm{AG}$ is the set of pairs of *connected agents*, i.e. those that can communicate with each other. We assume that the graph $\langle \mathrm{AG}, \mathrm{CAG} \rangle$ is *connected*.
- UT_i is the set of understandable terms of Ag_i. This is equal to VOC_i
- $\mathrm{ST}_i \subseteq \mathrm{UT}_i$ is the set of Spoken terms of Ag_i. ST_i is equal to the set of terms with a maximum score.

We evaluate the communication strategies using the following criteria:

- How many steps does it take before every agent understands each other?
- How many different terms are used in the system?
- How does the strategy perform in sparsely connected networks?

These criteria are described in the following sections.

3.1 Understandings rate

We define that agent Ag_i understandable for agent Ag_j when every spoken term of Ag_i is understandable for Ag_j, i.e. $\mathrm{ST}_i \subseteq \mathrm{UT}_j$. We define the understandings rate to be the number of connected agent pairs that are understandable to each other (without having to teach each other new concepts) divided by the total number of connected agents. This is formalized as follows (we use # to refer to the number of elements in a set)

Definition 1. $UR = \frac{\#\{\langle Ag_i, Ag_j \rangle | \langle Ag_i, Ag_j \rangle \in CAG \wedge ST_i \subseteq UT_j\}}{\#CAG}$

All communication strategies eventually result in an understandings rate of 1, a situation which we call *common understanding*. This is because the communication protocol prescribes that in case a of an unknown term, the term is taught to the ignorant agent. However, the strategies differ in the number of steps it takes before common understanding is achieved. Following strategy 1, common understanding is achieved only after *every* pair of connected agents have communicated with each other. Given that at each time step a random pair of communicating agents is selected, probability theory predicts that the expected number of steps before UR = 1 is given by:

$E(X) = q \sum_{r=1}^{q} \frac{1}{r}$
where
- X is the number of steps it requires to reach common understanding.
- $q = \#\mathrm{CAG}$

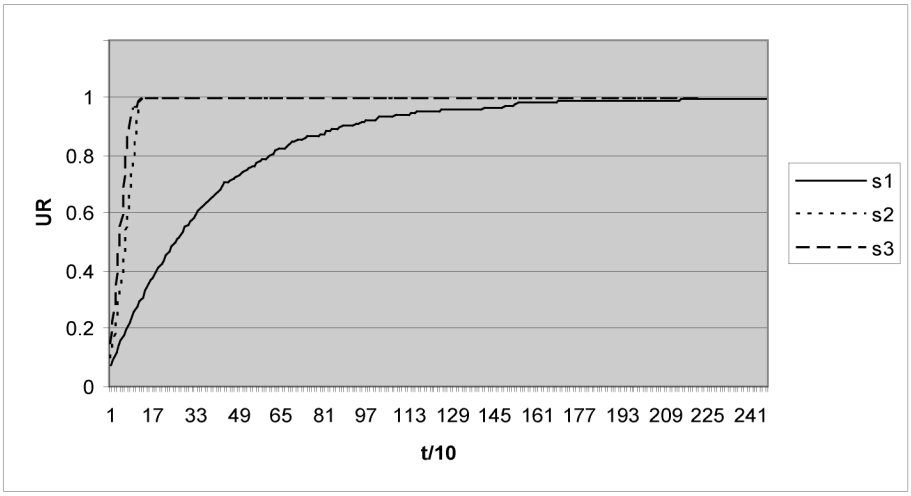

Fig. 3. Strategy performance w.r.t. understandings rate

Consider an agent system where n=20 and CAG = AG × AG, i.e. every agent speaks to every other agent. In this system, the formula above predicts that common understanding is reached after approximately 2400 turns. This prediction is confirmed by the experimental results shown in figure 3. The experiment also reveals that s2 and s3 require much fewer steps than s1 to reach common understanding. We argue that this is because s2 and s3 incites the agents also to speak each other's terms which gives rise to groups of agents that speak the same term. Therefore, two agents from the same group that never communicated before, are able to understand each other nevertheless. This explains the fast increase of UR in s2- and s3-systems.

Besides the speed of increase in UR , another important issue is the *size* of the communication vocabulary. s1 gives rise to a communication vocabulary of size n, i.e. every agent's private concept name eventually becomes part of the communication vocabulary. Besides the fact that this is the main cause for s1's slow increase in UR, another disadvantage is that newcomers in the system would have to learn a large number of terms to be able to understand everyone. It is therefore desirable that the total number of different terms which are spoken by the agents is as small as possible. This aspect is studied in the following section.

3.2 Number of terms

We refer to the number of terms that are used in the system with NT which is defined as follows:

Definition 2. $NT = \#\bigcup_i ST_i$

Obviously, in an s1-system the NT remains equal on n. For s2, it holds that, eventually, the NT becomes 1 in which case we say that the communication vocabulary has *converged*.

Property 1. In every s2-system: $\lim_{t\to\infty} P(\text{NT=1 after t steps}) = 1$

Proof: In every s2-system, the probability that NT becomes 1 after n steps is greater than 0 (recall that n is the number of agents). This happens when n times a speaker is selected with SC = x, and every agent with $SC \neq x$ is selected at least one time as a hearer. Furthermore, each "trial" (the execution of n steps) is independent of the other trials: the failure of one trial to result in NT= 1, does not systematically influence the probability that the next trial results in NT =1. Therefore, by the definition of chance, as the number of steps approaches infinity, the probability that NT=1 approaches 1.

□

Although the property described above is a nice theoretical result, in practice we are interested in the speed at which NT decreases. To obtain statistical significance, in the next experiment we use n=1000. Again, we set the structure as a fully connected network, i.e. CAG = AG × AG. Figure 4 shows the decrease of NT in this experiment. The results of this experiment show that the s2-system

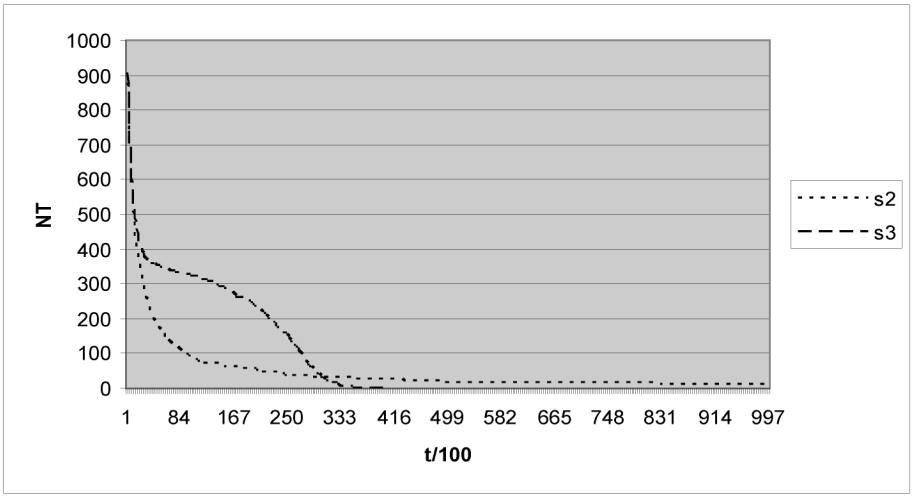

Fig. 4. Strategy performance w.r.t. number of terms

gives rise to a great decrease of NT at first, but does not lead to a fully converged cv. After 100000 steps, there were still 9 different terms in use, and it would have taken a very long time before the cv would have converged. S3, on the

other hand, performs relatively poorly at first, but gives rise to a converged cv after approximately 35000 steps. By that time, every agent spoke 35 times on average, which is not a bad result given the large size of the system.

The reason why the cv does not converge within reasonable time in an s2-system, is that in these systems NT decreases only by coincidence. At the end, the probability becomes very small that one of the terms "dies out", because each term is used by many agents. Agents that follow s3, keep an approximation up to date of which terms are most frequently used. Because every agent uses the term which they believe to be most frequently used, NT not only decreases by coincidence, but is guided by the beliefs of the agents.

Because s3 gives rise to a stable and converged cv, s3 is preferable over s2. In the next section we discuss the strategy's performance in other network structures.

3.3 Network structure

In the previous sections, we have evaluated the strategies in fully connected agent networks. In this section we discuss the strategy's performance in a more sparsely connected network. In doing so, we adopt some terminology from graph theory. We assume that the network is a non-directed graph, i.e. $\langle x, y\rangle \in \text{CAG} \rightarrow \langle y, x\rangle \in \text{CAG}$. We call the number of acquaintances of an agent, the *degree* of an agent, denoted by k:

Definition 3. $k(Ag_i) = \#\{Ag_j | \langle Ag_i, Ag_j\rangle \in CAG\}$

Many networks, amongst which the world-wide-web, are structured as a *scale-free network* [2]. Networks of this type are characterized by a large number of nodes with a relatively small k. A few nodes, however, are stars in the network and have a relatively high degree. Stated more precisely, the degree distribution follows a power law: $P(k) \sim k^{-\gamma}$, where $P(k)$ denotes the probability that a node has k edges.

The next experiment describes the results of s3 and s4 in a scale-free network, with n=1000, an average k of 3.11, and a maximum k of 50.

Although s3 gave rise to a converged communication vocabulary in fully connected networks within reasonable time, the NT does not go below 140 in the experiment described above. This happens because most agents have a low degree and are not capable to form a realistic approximation of which terms are most frequently used. To overcome this problem, s4 using agents take into account the degree of the speaking agent when they update their scores. Agents with a high degree have a more realistic approximation of the most frequently used sign, and are therefore taken more seriously than agents with a low degree. This explains why s4 performs better than s3 in this experiment, although it still does not give rise to a fully converged communication vocabulary.

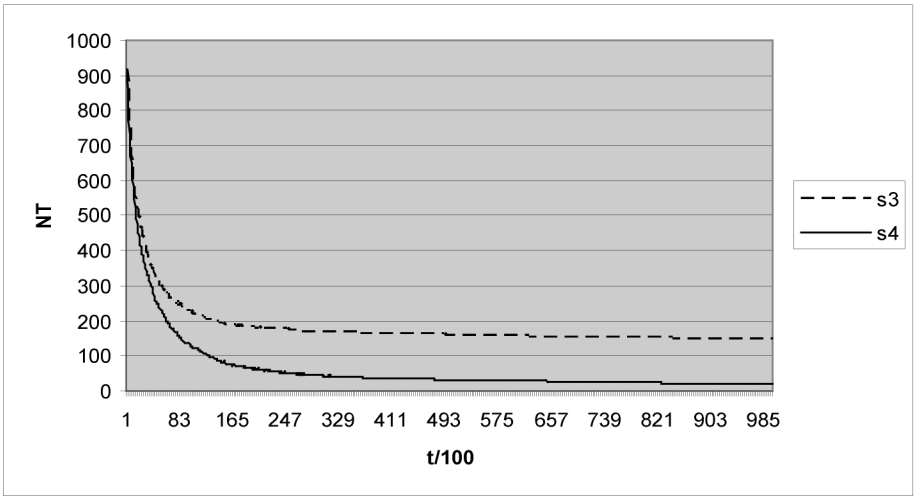

Fig. 5. Strategy performance w.r.t. NT in a scale-free network

4 Conclusion and future research

In this paper, we have described four strategies which, when used by individual agents, give rise to a shared communication vocabulary on a global level. While evaluating these strategies, the following issues were demonstrated. Firstly, a strategy which incites the agents to adopt each others' concept names for speaking (such as s2 and s3) has considerable advantages over a strategy in which every agent holds on to its own concept names for speaking (such as s1 or ontology alignment). Secondly, the strategy of adopting the most frequently used concept name (s3) is usable in a network with a simple interaction pattern, i.e. when everyone speaks to everyone with equal probability. Thirdly, it was demonstrated that in a scale-free network, the performance of the strategy of adopting the most frequently used concept name is improved when the agents' number of acquaintances is taken into account (as is done in strategy s4).

We continue this line of research by testing the strategies in networks with more complicated interaction patterns and by exploring adjustments which could lead to better performance in those environments. Furthermore, we intend to explore combinations between these communication strategies and centralized services for ontology integration as mentioned in the introduction of this paper.

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