Temporal Vagueness, Coordination and Communication

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1 Introduction

How is it that people manage to communicate even when they implicitly disagree on the meaning of the terms they use? Take an innocent-sounding expression such as *tomorrow morning*. What counts as *morning*? There is a surprising amount of variation across different people.[1]

For Anna, morning starts 'when she gets up', and finishes 'when she has lunch'. For Bart (who verges on the pedantic), morning officially starts at 12:00 am and ends at 11:59 am. Yet another view, held by Cecile, is that morning starts sometime between 6:00 and 7:00 am, and ends sometime between 12:30 pm and 1:30 pm. Finally, Devendra (who regularly works into the small hours) believes that morning has barely started at 10:30 am and finishes around 3:30 pm. Nevertheless, if Anna says to Bart: *drop by my office tomorrow morning and we'll have a look at your proposal*, the chances are high that Anna and Bart will manage to meet (as long as they have no conflicting engagements).

In the kind of linguistic contexts we are concerned with in this paper, it seems plausible to treat *morning* as a grouping of time units at some level of granularity (e.g., seconds, minutes, quarter-hours), ordered in the usual way. According to this view, a sentence like *Let's meet tomorrow morning* is equivalent to *Let's meet at some point in tomorrow morning*. This allows us to claim, for example, that the moment 9:15 am belongs to the extension of *morning*, while 9:15 pm does not. It follows that *morning* is open to the Sorites paradox: if 9:15:00 am counts as morning, then so does 9:15:01 am (i.e., the moment that is one second later than 9:15:00 am). By tediously iterating through the process of adding one second at a time (or one millisecond, if preferred), we will ineluctably reach the unwanted conclusion that 9:15:00 pm counts as morning. If we take the Sorites paradox as criterial for vagueness, we can conclude that *morning* and its companion expressions, *afternoon*, *evening*, *day* and *night* are all vague.

In this paper, we do not take a position about the appropriate way to formally represent the fact that vague terms admit borderline cases — for example, that it may be indeterminate whether the time point 12:45 pm should be categorized as belonging to morning or afternoon. Instead, we address a different question, namely how does the semantic indeterminacy of vague temporal expressions affect task-based communication? Our approach is not empirical, in the sense of

[1] The variability in usage and interpretation of terms like *morning* and *evening* has been explored by Reiter et al. (2005) in the context of weather forecasts.

observing human verbal interaction. Instead, we will develop a simple computational model of communication between artificial agents, and investigate how a vague term functions in a specific collaborative task.

The approach we have adopted is inspired in large part by Parikh's (Parikh, 1994) observation that even though two speakers differ in the way they interpret a vague term like *blue*, if there is sufficient overlap in their interpretations, there will be positive utility in using the vague term. In his example, Ann requests Bob to fetch "a blue book on topology" from the book shelves in her study. The descriptive term contains enough information that even though they disagree on what counts as blue, the set of 'blue-for-Bob' books reduces his search space far enough to significantly increase his chances of finding the correct book relatively fast.

What we want to adopt from Parikh's scenario is the idea that the success of communication involving a vague term can be measured in terms of completing a task. In Parikh's case, the task is to identify a book; in our case, the task is for two agents to meet one another. Just as the term *blue* functions in Parikh's scenario to reduce the space within which the required book is located, we will assume that a term like *morning* reduces the temporal period within which the meeting will take place. More specifically, we assume there are two agents, say A_1 and A_2, who wish to meet up. Suppose A_1 says to A_2: *Let's meet up tomorrow morning. Drop by my office.* A_2 accepts the proposal. Both A_1 and A_2 have their own interpretation of what is meant by the phrase *morning*. For each of them, the interpretation is modelled as an interval, but these intervals do not need to coincide. Not surprisingly, we can observe that if the intervals overlap sufficiently, then the two agents will tend to be successful in meeting. However, we go beyond Parikh's scenario, and adopt the following hypothesis:

> *If individual agents modify their interpretation of the temporal term on the basis of observing each other's arrival times, over the course of successive interactions these interpretations will tend to converge within the community.*

We will use a simple multi-agent simulation in order to provide an explicit model of task based communication. In general, we believe this has a number of attractive aspects. For one thing, the simulation allows us to explore the consequences of setting various parameters in different ways, and to consider the interaction of these parameters that would be hard to achieve using a pencil-and-paper analysis. More broadly, we can study how resource-bounded decision making is affected by different choices of representation, with the goal of capturing some crucial aspects of human communication in context.

2 Related Work

The kind of approach we explore in this paper has points of contact with a number of different threads in the literature.

As with Gärdenfors' framework of conceptual spaces (Gärdenfors, 2000; Warglien and Gärdenfors, 2007), we depart from the standard tenet of formal semantics that interpretation consists primarily of a static mapping from language to the world (or a model-theoretic counterpart thereof). For Gärdenfors, the shared meanings of expressions develop during language games — communicative interaction between language users — and involve mappings between conceptual representations that are constrained by the world. A so-called 'meeting of minds' occurs when the representations in the minds of the dialogue partners become sufficiently compatible. The simulation that we have developed can be viewed as such a language game, in which the representations of individual agents are brought to bear in, and are modified as a result of, communication about shared activities.

More computationally-oriented exploration of word meaning and multi-agent language games has been carried out by Steels and colleagues (Baillie and Steels, 2003; Steels and Vogt, 1997; Steels, 1998). Although such work has obvious points of contact with ours, there are a number of points of difference. First, we are not concerned with how new terms emerge as bearers of meaning, but rather with how pre-existing 'unstable' meanings come to stabilize as a result of interaction, and second, we are concerned with the relatively abstract domain of time, rather than directly perceptible phenomena. Feedback about the interpretation of terms is not acquired through explicit correction, as for example in (Baillie and Steels, 2003), but has to be inferred from whether proposals to meet are successfully consummated or not.

A third strand of relevant work involves ontology alignment (Euzenat and Shvaiko, 2007) in the context of multi-agent systems (Bailin and Truszkowski, 2003). Agents collaborating in a shared environment need to share an ontology (i.e., the conceptualization of a domain) in order to communicate with each other, but in an open system, different agents can in principle use quite heterogeneous ontologies. Wang and Gasser (2002) consider a scenario that, like ours, explicitly considers which instances fall within the extension of a concept, but do not consider cases where convergence in meaning contributes to successful collaboration a task. Somewhat closer to our approach in this respect is the work of McNeill et al. (2005), where agents are involved in jointly planning a task; plan failure triggers an attempt to diagnose mismatches in ontology; the agents use heuristics to repair their ontologies (in the sense of modifying the ontology signature), and then re-engage in the planning task. This cycle — communicate / diagnose failure / repair the ontology — is very similar to the kind of model that we are proposing.

3 Approach

As we have already indicated, our treatment of temporal expressions is highly simplified. For example, we ignore the element of context dependence in the application of temporal terms. For example, people who work together in an office will probably adopt a different view of what counts as morning than people who are up before dawn to milk the cows. Another contextual factor is the day of the week: for most Westerners, the temporal location of *morning* during the weekend diverges considerably from its location during the working week. We will abstract away from these factors, and only consider the case where the population of speakers adopts a shared context of use.

A second simplification is in our treatment of the expression *morning*. Given a specific day (say Monday 9th November 2009) and a specific speaker, say Anna, *morning* will denote a closed interval of time units.[2] For our purposes, it does not matter too much what level of granularity is chosen, but we will think of the intervals used by our agents as containing quarter-hour units; in other words, an interval with 12 elements would correspond to a period whose duration is three hours.

We will describe two families of experiments (referred to as Experiment 1 and Experiment 2 respectively), using a multi-agent simulator that was implemented in written in Python. The agents are modelled as processes in the SimPy Discrete Event Simulator.[3] Before discussing the specifics of the experiments, we will give more details of the agent coordination task.

Let $\mathcal{T}$ be a finite set of integers representing **time units**, and let $\mathcal{I}$ be a set of closed intervals over $\mathcal{T}$. Given a set Ag of agents, each $A_i \in Ag$ is assigned a **preferred interval** $\iota_i \in U$. ι_i is intended to be A_i's private interpretation of a temporal expression such as *morning*. Note that although the mapping from agents to intervals is a function, its inverse is not — that is, we let the cardinality of $\mathcal{I}$ be less than that of Ag. In our simulation, $\mathcal{I}$ is fixed as the set of intervals $\{[1, 10], [6, 15], [11, 20]\}$. Although the intervals are private to each agent, it is implicit in the model that the agents share the common time frame given by $\mathcal{T}$. For example, we might think of the three intervals in $\mathcal{I}$ as corresponding roughly to the time periods 7:00–9:30 am, 8:00–10:30 am and 9:30–12.00 am, respectively, where the time units 7:00 am, 7:15 am, ... have the same interpretation for all agents in Ag.

On each run of a simulation, two agents A_i and A_j are selected at random. One of the agents is assigned the role of **proposer**, while the other takes on the role of **responder**; we'll refer to these as P and R respectively. P takes the lead in sending a "let's meet" message to R and chooses an arrival time arr_{P} from its period ι_{P}, while R chooses an arrival time arr_{R} from ι_{R}. One important feature of the model (which could however be relaxed) is that agents tend to pick an arrival time that falls somewhere in the middle of their preferred interval. This seems plausible when the proposed meeting time is some kind of approximation or vague interval. This feature is implemented by selecting A_i's arrival time (coerced to an integer) at random from a gaussian distribution whose mean is the median of ι_i, with standard deviation 1.

Every agent A_i can call a function $\delta : \mathcal{I} \mapsto \mathcal{T}$ such that $\delta(\iota_i) = dep_i$ is A_i's departure time. P and R are judged to **meet** if $[arr_{\mathsf{P}}, dep_{\mathsf{P}}] \cap [arr_{\mathsf{R}}, dep_{\mathsf{R}}] \neq \emptyset$.

[2] This approach is intended to be compatible with that proposed by Ohlbach (2000), who points out that a temporal expression such as *February* can be used to refer to a particular February; or to denote the set of all Februaries in the history of mankind; or, more generally, to refer to a function which given some year y returns the particular February of y.

[3] `http://simpy.sourceforge.net/`

We assume that on each run, P knows the arrival and departure time of R, even if they fail to meet. For simplicity, we take δ to be as follows for P:

$$\delta(\iota_{\mathsf{P}}) = \begin{cases} arr_{\mathsf{P}} + 1 & \text{if } (dep_{\mathsf{R}} < arr_{\mathsf{P}} \text{ or } arr_{\mathsf{R}} \in \iota_{\mathsf{P}}) \text{ and } (arr_{\mathsf{P}} + 1) \in \iota_{\mathsf{P}}, \\ \text{end of } \iota_{\mathsf{P}} & \text{otherwise} \end{cases} \tag{1}$$

In other words, P departs at time $t + 1$ if she knows that R has come and gone, or if R is already present at time t. Otherwise, P waits until the last point of ι_{P}. For simplicity, we do not treat the length of the meeting as a factor in determining costs or utility.

In principle, P incurs a waiting cost which is proportional to the length of the interval $[arr_{\mathsf{P}}, dep_{\mathsf{P}}]$,[4] and we will refer to this cost below. However, the cost is ignored in Experiment 1 and treated as a fixed value in Experiment 2.

It may be helpful to enumerate the four cases which determine whether or not a meeting occurs:

1. R arrives and departs before arr_{P}; the meeting fails with no waiting cost for P.
2. R has already arrived but not yet departed when P arrives; the meeting is accomplished with no waiting cost for P.
3. R arrives after arr_{P} but before dep_{P}; the meeting is accomplished with a waiting cost for P.
4. R arrives after dep_{P}; the meeting fails with a waiting cost for P.

These four options are shown graphically in Figure 1.

As mentioned before, each agent is assigned a preferred interval, which is intended to be a cognitive representation of a vague temporal expression. Since there is only one such expression in use in the community, we do not need to explicitly label it. The preferred interval, therefore, is a key aspect of each agent's mental state. Agents have no access to the mental states of others, and only observe their behaviour in arriving and departing at particular times. Each agent keeps a record of the other's arrival behaviour. More precisely, each agent A_i maintains a list $L(A_j)$ of observed arrival times for each other agent A_j, and the list is updated on any run in which A_i plays the P role and A_j plays the R role. Given $L(A_j)$, A_i can estimate the mean arrival time of A_j up to the current run in the simulation. We refer to this estimated mean as $\mu(\iota_j)$.

In order to provide a more concrete impression of the way the simulation works, in Figure 2 we have included a small extract from one simulation log file.

4 Experiment 1

4.1 Alignment

In the first set of experiments, we allow the proposer to update its preferred interval in the light of its experience so far. After each encounter, P attempts to

[4] We assume that the cost is zero if $dep_{\mathsf{P}} = arr_{\mathsf{P}} + 1$.

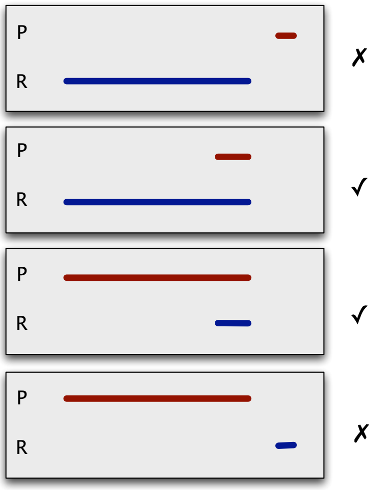

Fig. 1: Meeting Outcomes

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activating agent-2 at 156
agent-2 proposed the following period and arrival time:
[12, 13, 14, 15, 16, 17, 18, 19, 20, 21] / 15
agent-3 is using following period:
[2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
Outcome of this meeting:  not-met
agent-2 present: [15]
agent-3 present: [5, 6, 7, 8, 9, 10, 11]
agent-2 waited 0 mins
agent-2's cur reward: -2
agent-2's cumulative reward over 35 proposals: 26
successes to date: 26.000
proposals to date: 35.000
success ratio: 0.743
reward ratio: 0.371
```

Fig. 2: Extract of a Simulation Log

align with P. It does so by adjusting ι_{P} so that the median (mid-point) of ι_{P} approaches $\mu(\iota_{\mathsf{R}})$; that is, if t is the new target median and *len* returns the length of an interval, then the adjusted interval is simply $[t - len(\iota_i)/2, t + len(\iota_i)/2]$. Let's refer to the median of interval ι_{P} as $md(\iota_{\mathsf{P}})$ and let ι'_{P} be the new interval of P after alignment has taken place. Then we try to meet the following constraint after each run (where $|x|$ is the absolute value of x):

$$|\mu(\iota_{\mathsf{R}}) - md(\iota_{\mathsf{P}})'| < |\mu(\iota_{\mathsf{R}}) - md(\iota_{\mathsf{P}})| \tag{2}$$

In Experiment 1, we implemented the following update, where $\lambda \in [0, 1]$ is a scaling factor that we called the **learning rate**:

$$md(\iota_{\mathsf{P}})' = md(\iota_{\mathsf{P}}) + \lambda(\mu(\iota_{\mathsf{R}}) - md(\iota_{\mathsf{P}})) \tag{3}$$

4.2 Results

In analysing the results of Experiment 1, we focus on two dimensions for measuring the outcome: **interval overlap** and **proposal success ratio**. Given a proposer P and responder R, we use the following definitions:

Definition 1 *The **overlap between intervals** ι_P, ι_R (where $\|x\|$ is the cardinality of x) is:*

$$\frac{\|\iota_P \cap \iota_R\|}{\|\iota_P \cup \iota_R\|}$$

i.e., the cardinality of time points in the intersection of ι_P and ι_R divided by the cardinality of time points in the union of ι_P and ι_R.

According to Definition 1, a value of 1.0 indicates complete overlap while 0 indicates no overlap.[5]

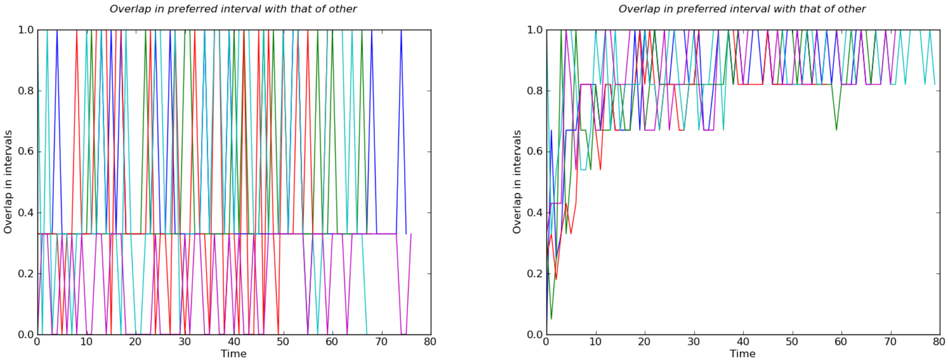
Definition 2 *The **success ratio** for an agent is the quotient*

$$\frac{\textit{\# of successful meetings}}{\textit{\# of proposals}}$$

Figures 3 and 4 show results for a population of five agents with 350 runs. We illustrate two cases for each of the measures, one where there is no learning, and one where the learning factor λ is set at 0.3. In these graphs, the outcomes for each agent are plotted separately. In Figure 3(b), we see that after about 40 runs, the overlap between intervals oscillates between 0.8 and 1.0.

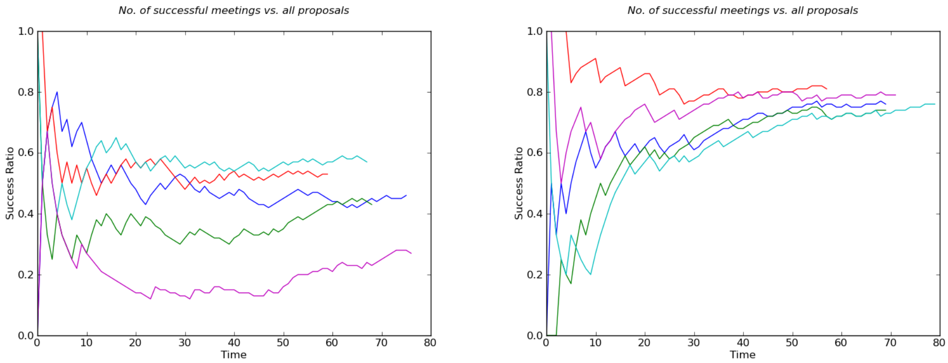
Table 1 illustrates the intervals that are associated with each agent at the end of one complete simulation, after alignment has taken place. It can be observed that some of the intervals are left-shifted beyond the earliest point in $\mathcal{I}$. We will return to this issue later.

[5] This is known as the Jaccard index of similarity. We have also experimented with a related measure, Dice's coefficient, which yields comparable results.



(a) $\lambda = 0$ (b) $\lambda = 0.3$

Fig. 3: Overlap in Intervals



(a) $\lambda = 0$ (b) $\lambda = 0.3$

Fig. 4: Proposal Success Ratio

agent-0: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
agent-1: [-1, 0, 1, 2, 3, 4, 5, 6, 7, 8]
agent-2: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
agent-3: [-1, 0, 1, 2, 3, 4, 5, 6, 7, 8]
agent-4: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

Table 1: Aligned Intervals after 350 runs, $\lambda = 0.3$

4.3 Discussion

As shown in Figure 4(a), when the discrepancy in preferred intervals is allowed to persist throughout the simulation, success in meeting tends to diminish over successive runs for all the agents. By contrast, Figure 4(b) shows gradual improvement to a mean success rate of around 0.8 when learning takes place. In addition, a positive value for λ enables the agent population to reach a relatively stable alignment of intervals. Despite this, complete convergence is not reached. One way of interpreting this result is to say that the chosen temporal unit is still vague, at the population level, but less so before alignment occurred. That is, if we regard the shared concept as the union of the concepts of the constituent individuals, then we have a *range* of possible boundaries to the concept, along the lines of the egg-yolk theory (Gotts and Cohn, 1996) or vague granular partitions (Bittner and Smith, 2001a,b).

One major disadvantage of the framework used in Experiment 1 is that we have, so to speak, 'hard wired' the goal of alignment into our agents. It could be argued that this has some plausibility; for example, there is considerable empirical evidence that human speakers do align to each other at numerous levels of cognitive representation in dialogue, ranging from phonetics up to the levels of semantic representation and the internal 'situation model' (Pickering and Garrod, 2004). Nevertheless, the process captured in our simulation corresponds more closely to alignment *across* successive dialogues, rather than within a dialogue, which considerably weakens the analogy. Is it possible instead to devise a more principled approach which allows agents to discover the advantages of alignment by themselves?

5 Experiment 2

5.1 Reinforcement Learning

In the second family of experiments, we adopt a simple form of reinforcement learning (Sutton and Barto, 1998) to replace the alignment strategy of Experiment 1.

To simplify exposition, let's suppose initially that we have a pool of two agents, with a fixed assignment of roles. Each run t of the simulation contains a representation of a state s_t, on the basis of which P selects an action a_t. On the next run, P receives a numerical reward r_{t+1} and finds itself in state s_{t+1}; the reward is used to calculate the utility of action a in state s_t. P maintains a mapping from states to probabilities of selecting each possible action. This mapping is called a *policy*, and is updated in the light of rewards received in states up to and including the current one.

We represent a state as a triple of variables $\langle$*alignment*, *met*, *wait*$\rangle$. Taking the two simpler cases first, *met* is boolean-valued, and *wait* takes a non-negative integer as value. *alignment* takes as value one of five possible labels, each of which serves as a bin for a range of integers, corresponding to the difference σ between the median $md(\iota_{\mathsf{P}})$ of P's preferred interval and estimated mean $\mu(\iota_{\mathsf{R}})$ of R's arrival times. The correspondence between labels and the value of σ are shown in Table 2. For example, *alignment* would be assigned the value *other_v_early* just in case $md(\iota_{\mathsf{P}}) - \mu(\iota_{\mathsf{R}}) > 6$.

bin labels	**range of σ**
other_v_early	$\sigma > 6$
other_early	$6 \geq \sigma > 1$
aligned	$1 \geq \sigma > -2$
other_late	$-2 \geq \sigma > -7$
other_v_late	$\sigma \leq -7$

Table 2: Values of the *alignment* variable

The set $\mathcal{A}$ of possible actions for P are analogous to the set of possible alignments:

$$\mathcal{A} = \{\textit{shift\_far\_earlier}, \textit{shift\_earlier}, \textit{no\_op}, \textit{shift\_later}, \textit{shift\_far\_later}\}$$

Each action is a mapping from intervals to intervals. The actions *shift_far_earlier* and *shift_far_later* move their input five units earlier or later, respectively, while *shift_earlier* and *shift_later* only move their inputs one unit earlier or later. *no_op* just returns its input unchanged. The actions are defined so that intervals cannot be shifted beyond a stipulated lower and upper boundary (taken to be 1 and 21 in the current model). This constraint is realistic to the extent that, for example, the start point of *morning* would not normally occur before 12.00 am. However, the way that we have implemented these constraints could definitely be improved (for example by definining a probability distribution over possible start times).

Note that despite the potential fit between actions and alignments, any association between the two has to be learned by the agents, rather than being stipulated in the model.

The reward received by an agent depends on the values of the variables *met* and *wait*, and is allocated according to the matrix in Table 3.

	$wait = 0$	$wait > 0$
met = True	2	1
met = False	-2	-3

Table 3: Reward Matrix

In order to choose an action, the agent estimates the relative values of all members of $\mathcal{A}$. The estimated value of action a on the t^{th} run is written $\mathcal{Q}_t(a)$, and we define this to be the average of the rewards received by the time the action was selected. That is, if a has been selected k times by the time of run t, giving rise to rewards $r_1, r_2, \ldots, r_k$, then its value is estimated to be

$$\mathcal{Q}_t(a) = \frac{1}{k}\sum_{i=1}^{k} r_i \tag{4}$$

When $k = 0$, we take $\mathcal{Q}_t(a) = 0$. $\mathcal{Q}_t(a)$ is re-computed on each run of the simulation.

The simplest strategy for action selection is the greedy method: choose an action which has the highest estimated value. However, it turns out to be advantageous to behave greedily most of the time while occasionally — with small probability ϵ — selecting at random some other action. We take $\epsilon = 0.1$ initially, and let it decrease over successive runs, so that the action space is sampled more broadly at the beginning of the simulation. This is termed an **ϵ-decreasing** strategy.

5.2 Results

In Experiment 1, we only required agents to update their preferred interval with respect to the the observed behaviour of their most recent partner. For example, we might have agent A_1 moving ι_i earlier after interacting with A_2 and moving it later on a successive turn after interacting with A_3. In practise, this did not appear to be too stringent a condition. However, in Experiment 2 we allow agents to align not to the pattern of their individual partners, but rather to the mean behaviour of all their partners. We shall refer to these two conditions as ALIGN_TO_GROUP = *False* vs. ALIGN_TO_GROUP = *True*, respectively.

Figures 5(a), (b) show the **average reward ratios** achieved over 2000 runs. For individual agents, the reward ratio is defined as follows, where K is set to be the maximum possible reward in a state, i.e. $K = 2$:

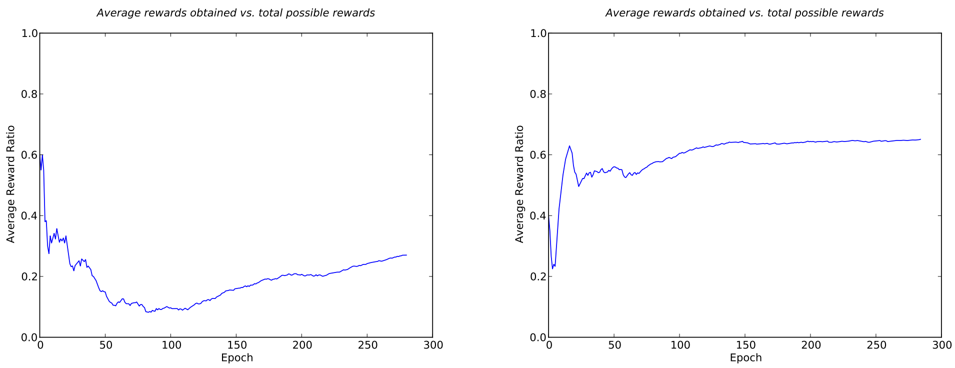
Definition 3 *The* ***reward ratio*** *for an agent is the quotient*

$$\frac{\textit{sum of rewards received}}{\#\ \textit{of proposals} \times K}$$

The average reward ratio is obtained as the mean of the reward ratio taken over the whole population. It remains low throughout the simulation under condition ALIGN_TO_GROUP = *False*, but reaches a point above 0.6 when ALIGN_TO_GROUP = *True*. Examination of the figures for individual agents, shown in Figures 6(a), (b), suggests a tendency for sub-populations to emerge, some of which are more successful than others.

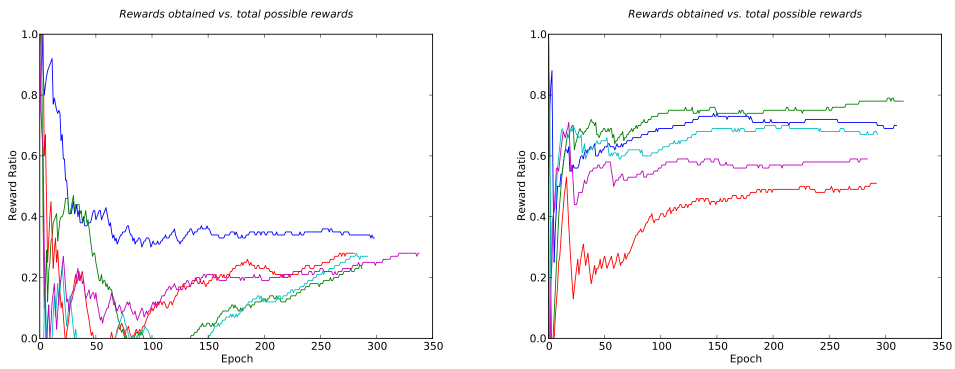
Figures 7(a), (b) suggest that a reasonably stable alignment of intervals only emerges under condition ALIGN_TO_GROUP = *True*.

Finally, Figure 8 shows the extent to which proposals by agents lead to successful meetings.



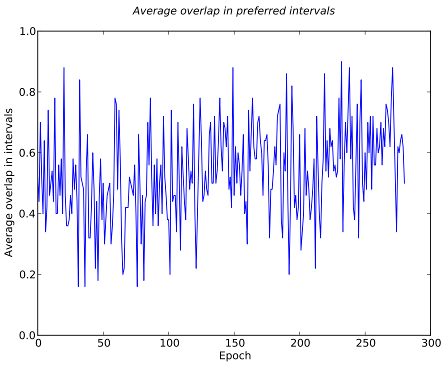
(a) ALIGN_TO_GROUP = *False* (b) ALIGN_TO_GROUP = *True*

Fig. 5: Average Reward Ratio

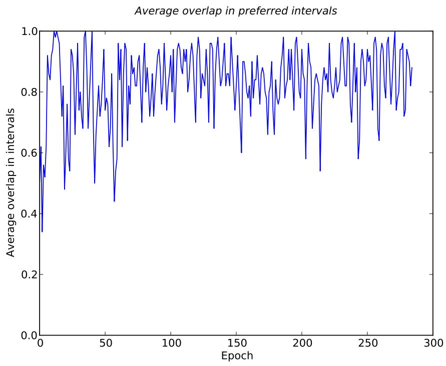


(a) ALIGN_TO_GROUP = *False* (b) ALIGN_TO_GROUP = *True*

Fig. 6: Individual Reward Ratio

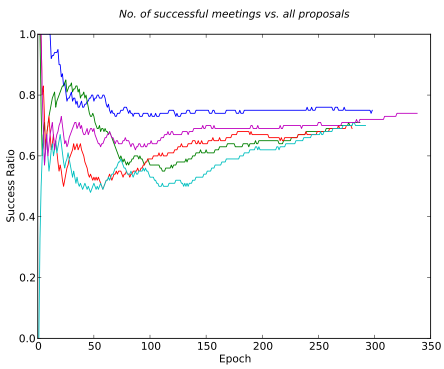


(a) ALIGN_TO_GROUP = *False*

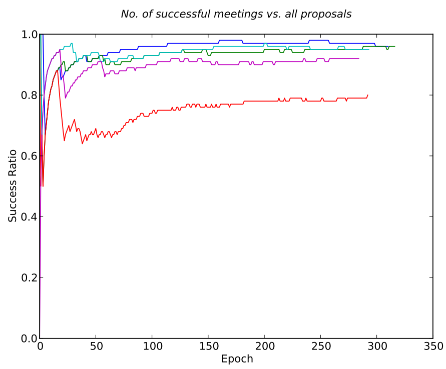


(b) ALIGN_TO_GROUP = *True*

Fig. 7: Average Overlap in Intervals



(a) ALIGN_TO_GROUP = *False*



(b) ALIGN_TO_GROUP = *True*

Fig. 8: Success Ratios

5.3 Discussion

In general, the framework using reinforcement learning yields alignment results that are comparable with those achieved with the 'hard wired alignment' approach only under the condition the ALIGN_TO_GROUP = *True*. Moreover, the number of runs required is roughly an order of magnitude greater than we saw for Experiment 1. On the other hand, other simulations we have run, not reported here, show that very rapid convergence under both conditions can be achieved if the agents are given a bias to prefer one of the actions (say *move_far_earlier*) at the outset of the simulation.

6 Conclusions

The central goal of this paper has to been situate the interpretation of a vague temporal expression in the framework of task-oriented communication. This gives us leverage in modelling the utility of such an expression for acheiving coordinated action, more specifically for pairs of agents to arrange meetings between themselves. We have shown that, given certain assumptions, the utility of a temporal expression increases in line with interpretive alignment. That is, when the proposer's extension for the term overlaps more greatly with that of the responder, then the term is more effective in circumscribing the range of possible meeting times. This in turn increases the likelihood that two agents will successfully meet. If the agents adopt reinforcement learning, then over numerous interactions, they will tend to converge on more tightly aligned sets of interpretations, leading to a stable pattern of successful meeting proposals. However, as we pointed out earlier, our current model only achieves this convergence if agents align to the group average arrival time, rather than successively attempting to align to the average of their immediate partner.

Despite the fact that increased alignment correlates with increased utility, the way we have modelled multiagent simulation rarely if ever leads to complete alignment. This adds support for the contention that vague terms provide robustness to communication — they work 'well enough' in the absence of complete agreement on boundaries. In order to explore this point more fully, let's return to the details of Experiment 2. Figure 8(b) indicates that one of the five agents (namely `agent-1`) is less successful than all the others — achieving a score of 0.8 against an average of .95 for the other four. Inspection of the simulation log shows that `agent-1` has ended up with a preferred interval that diverges markedly from the rest of the members of the agent pool; see Table 4. Regardless of the reasons why `agent-1` has arrived at a sub-optimal policy, there is one striking fact: since there is enough overlap in extension, meetings will be successful sufficiently often that the policy persists. In other words, the residual divergence between preferred intervals across the population does not seriously impede the agents in achieving their goal of meeting.

Clearly there are many ways in which the model we have developed could be extended and improved. The most obvious question is what consequences ensue when agents have a choice not just of how to modify their interpretations

agent-0: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
agent-1: [7, 8, 9, 10, 11, 12, 13, 14, 15, 16]
agent-2: [3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
agent-3: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
agent-4: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

Table 4: Aligned Intervals after 2,000 runs, using Reinforcement Learning

of terms, but also a choice of using more or less precise terms. We intend to address this issue in future work.

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