Modelling Multi-Issue Bargaining Dialogues: Data Collection, Annotation Design and Corpus

Volha Petukhova[1], Christopher Stevens[2], Harmen de Weerd[2], Niels Taatgen[2], Fokie Cnossen[2], Andrei Malchanau[1]

[1]Saarland University, Spoken Language Systems, Saarbrücken, Germany

[2]University of Groningen, Department of Artificial Intelligence, The Netherlands

[1]{v.petukhova,andrei.malchanau}@lsv.uni-saarland.de;

[2]{c.a.stevens,h.a.de.weerd,n.a.taatgen,f.cnossen}@rug.nl

Abstract

The paper describes experimental dialogue data collection activities, as well semantically annotated corpus creation undertaken within EU-funded METALOGUE project. The project aims to develop a dialogue system with flexible dialogue management to enable systems adaptive, reactive, interactive and proactive dialogue behaviour in setting goals, choosing appropriate strategies and monitoring numerous parallel interpretation and management processes. To achieve these goals negotiation (or more precisely multi-issue bargaining) scenario has been considered as the specific setting and application domain. The dialogue corpus forms the basis for the design of task and interaction models of participants negotiation behaviour, and subsequently for dialogue system development which would be capable to replace one of the negotiators. The METALOGUE corpus will be released to the community for research purposes.

Keywords: negotiation corpus collection, dialogue act annotation, ISO 24617-2 dialogue act annotation scheme extension, dialogue modelling

1. Introduction

Recently, we have been witnessing the steady increasing demand for human-computer systems and interfaces of various complexity. The current research efforts in human-computer system design diverge more and more from traditional paradigms to modelling of two-party task-oriented systems like information-seeking dialogues. The research community is currently targeting more flexible, adaptable, open-domain dialogue systems driven by modelling natural human multimodal behaviour. Advances are also being made in modelling and managing multi-party interactions, e.g. for meetings or multi-player games. Existing approaches developed for two-party dialogue have undergone certain changes. For instance, it has been acknowledged that assumptions that conversational agents act fully rationally and cooperatively do not hold in many conversational settings, see e.g. (Traum et al., 2008) and (Asher and Quinley, 2011). This is particularly true in competitive games, debates, and negotiations where participants do not have fully aligned preferences and do not adopt shared intentions or goals. In this paper we focus on modelling negotiations, more precisely multi-issue bargaining dialogues.

Much good work has been done on simple, well-structured negotiations - interactions among a few parties with fixed interests and alternatives, see (Georgila and Traum, 2011); (Efstathiou and Lemon, 2015) and (DeVault et al., 2015). In many real-life negotiations, parties negotiate over not one but multiple issues. Moreover, negotiators bargaining over one or multiple issues today may, and in real life most certainly will, come back to the negotiation table. So, there may be delays in making complete agreements, and previously reached agreements can be cancelled. In this paper we discuss multi-issue repetitive bargaining interactions collection and analysis as important steps towards computational modelling of such conversations. The paper is structured as follows. Section 2 discusses the application task domain, specifying participants roles and goals, and possible interactive phenomena to be encountered. Section 3 presents the designed scenario, interfaces and data collection procedure. In Section 4 we specify the annotation design in detail by describing the type of annotations performed and annotation scheme used proposing possible extension of those. We also provide various corpus statistics, examples and a corpus overview in terms of type of data, annotations performed and formats used. Section 5 presents initial task and interaction control models built/learned using the annotated data. Section 6 concludes the reported work by summarizing corpus collection, data annotation activities, finding derived from initial models, and outlines future research.

2. Task Domain

In a negotiation situation two or more parties have interests in reaching one or several possible agreements, but their preferences over these agreements are not completely identical (Raiffa et al., 2002). Thus, negotiators may have partially competitive and partially cooperative goals. In multi-issue bargaining, parties usually have the possibility to simultaneously bargain over several goods and attributes, and to search for integrative potential (interest-based bargaining or win-win bargaining), see Fisher and Ury, 1981. The latter is often the case in political negotiations where parties try to make trade-offs across issues in order for both sides to be satisfied with the outcome. In multi-issue bargaining, parties can give up more on one issue, but can receive in exchange for a larger share on another. They can delay making a complete agreements on the first discussed issue, e.g. postpone making an agreement or make a partial agreement, until the agreement on the second one is secured. They can commit to an agreement on some issues, but they also may exit agreements during the same interaction or later in a new negotiation round. They also may

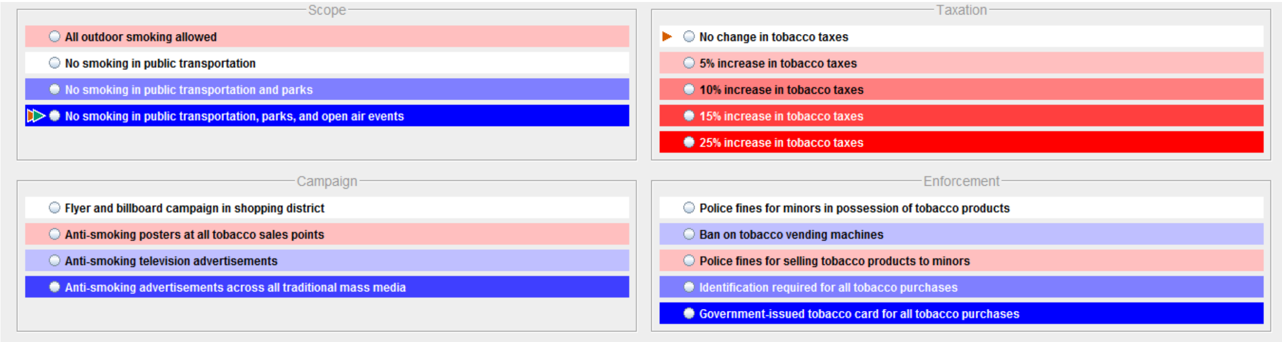

Figure 1: Example of values of issues presented to participants as a colour.

revise their past offers, accept or decline any standing offer, make counter-offers, etc. Thus, there is always a latent risk that bargaining may breakdown. It has been observed that the agenda (order in which the issues are negotiated) might influence on the overall outcome (Younghwan and Serrano, 2004).

All this allows bargainers to have a wide array of strategies. Moreover, preferences may be adapted and depend at the history of offers in the ongoing process (Inderst, 2000). The negotiators perform actions that are within the existing structure of the negotiation and actions that shape that structure in a way that is more favourable for the negotiator. This suggests that for adequate modelling we need to take into account that there are several types of actions that negotiators may perform: (1) actual negotiation/bargaining moves; (2) communicative actions to control the interaction, including (3) negotiation structuring acts. In general, in order to develop a dialogue system based on adequate modelling of human natural dialogue behaviour and good understanding of relevant phenomena, to predict interlocutors actions, a common procedure is, first, to collect and analyse the human-human data. In the next section we propose a method and scenario for multi-issue bargaining data collection.

3. Scenario and Data Collection

The specific setting considered involves a multi-issue bargaining scenario in which a representative of a city council and a representative of small business owners negotiate over the implementation of new anti-smoking regulations. The negotiation involves four issues, each with four or five different options (see Figure 1). The task of the negotiators is to negotiate an agreement, which assigns exactly one option to each issue. Despite this simple set up, this setting allows for 400 different possible negotiation outcomes in addition to the opt-out outcome.

Each experiment involves a pair of participants that perform a number of separate negotiation scenarios. One of the participant is randomly assigned the role of city council, the other participant to the role of small business. Each participant receives their cover story and instructions, as well as their preference profiles for each scenario. For each preference profile, each option was assigned one of nine possible values, which was communicated to the participant through colours, as shown in Figure 1. Brighter red colours indicated increasingly more negative options, while brighter blue colours - increasingly more positive options. The use of colour rather than numbers introduces a form of uncertainty in the exact value of a given agreement, which is closer to real-life negotiations.

Participants were asked to negotiate for an agreement with the highest possible value according to their preference information. They were not allowed to accept agreements that had a negative value, and participants were not allowed to show their preference information to each other. No further rules on the negotiation process were imposed. During the data collection experiment, the conversational speech was captured with two headset microphones to record the speech of the participants separately (mono, 96000Hz sample rate, 24-bit sample format). 16 unique subjects, undergraduates of age between 19 and 25 participated in these experiments. The resulted data collection consists of 50 dialogues with total duration of 8 hours comprising about 4.000 speaking turns.

Participants' speech has been transcribed semi-automatically by (1) running the Automatic Speech Recognizer (ASR) Kaldi (Povey et al., 2011) and (2) correcting automatic transcriptions manually. For this purpose the transcription tool was designed which takes wav files cut per speaker/per turn as input (process known as *speaker-diarization*), runs the ASR system on them and returns the recognized string to human transcribers for corrections. Corrected transcriptions are fed back to the ASR system to re-train/improve language models. All types of transcriptions were stored for each participant and each dialogue separately in format compliant with TEI standard (ISO, 2006).

4. Annotation Design

Analyses of human dialogue commonly model speaker's intentions. For this, the notion of dialogue act plays a crucial role. Dialogue acts have two main components: a *semantic content*, which specifies what the act is about; and a *communicative function*, which specifies how an addressee updates his information state with the semantic content when he understands the corresponding aspect of the meaning of a dialogue utterance. The formal definition of dialogue acts allows computational modelling of most dialogue phenomena. Communication in general and negotiation in particular is a complex activity in the sense that it involves not only the understanding and performance of actions for pursuing a certain goal or task; among other

Utt_ID	Speaker	Start-End time	Utterance (wording)	DA_ID	DA tag[dependence]	Negotiation Move	Rhetorical
u1	p1	00.00-00.16	in this city I would suggest all outdoor smoking allowed	da1	task;suggest	offerValue	
u2	p2	00.16-00.17	uh-uhu	da2	autoPositive[u1]		
u3	p1	00.17-00.25	no changes in tobacco taxes and then anti-smoking television advertisement	da3	task;suggest	offerValue	list[da1]
u4	p1	00.25-00.30	and police fines for minors again	da4	task;suggest	offerValue	list[da1,da3]
u5	p2	00.30-00.31	uh-uhu	da5	autoPositive[u3,u4]		
u6	p1	00.31-00.33	so what do you think	da6	task;setQuestion	elicitOfferValue	
u7	p2	00.32-00.33	uhm	da7	turnTake;stal		
u8	p2	00.33-00.34	yeah	da8	autoPositive[u1,u3,u4]		
u9	p2	00.34-00.36	that's bit difficult for me	da9	task;setAnswer[da6]	declineOfferValue[da6]	
u10	p2	00.36-00.42	because that really doesn't meet our goals	da10	task;inform		justify[da9]
u11	p2	00.41-00.49	but we can sure look if we can find a solution maybe	da11	task;suggest		contrast[da10]
u12	p2	00.49-00.56	maybe I start with the worst points for me	da12	discourseStructuring; suggest		
u13	p1	00.55-00.56	okay	da13	discourseStructuring; acceptSuggest[da12]		
u14	p2	00.55-01.01	it's the scope of the smoking ban	da14	discourseStructuring; topicShift		
u15	p1	01.01-01.02	uh-uhu	da15	discourseStructuring; agreement[da14]		
u16	p2	01.00-01.12	only to allow outdoor smoking is not enough	da16	task;inform	declineOfferValue[da1]	
u17	p2	01.13-01.28	i think it would be fine if we stop smoking in public transportation	da17	task;inform	counterOfferValue[da1]	
u18	p1	01.36-01.37	okay i would go for that point	da18	task;agreement[da17]	acceptOfferValue[da17]	

Table 1: Example of multi-level negotiation dialogue annotation.

things, dialogue participants also constantly have to evaluate whether and how they can (and/or wish to) continue, perceive, understand and react to each others intentions. It has been shown by Bunt (2000) and Petukhova (2011) that many complexities of natural human dialogue are handled by analysing dialogue behaviour as having communicative functions in several dimensions. Some dialogue act taxonomies are designed in order to capture meaning of dialogue contributions in multiple dimensions resulting in multi-layered annotations. For instance, the ISO 24617-2 taxonomy (ISO, 2012) distinguishes 9 dimensions, addressing information about a certain (*Task*); the processing of utterances by the speaker (*Auto-feedback*) or by the addressee (*Allo-feedback*); the management of difficulties in the speaker's contributions (*Own-Communication Management*) or that of the addressee (*Partner Communication Management*); the speaker's need for time to continue the dialogue (*Time Management*); the allocation of the speaker role (*Turn Management*); the structuring of the dialogue (*Dialogue Structuring*); and the management of social obligations (*Social Obligations Management*). These dimensions are proven to be useful to model many dialogue conversations, successfully applied to analyse and model two-party task oriented dialogues as TRAINS, HCRC MapTask, OVIS, DIAMOND corpora (Petukhova, 2011), spontaneous free conversations as SWBD-DAMSL (Fang et al., 2012), AMI meetings (Petukhova, 2011), and quiz games (Petukhova et al., 2014). Analysing the collected negotiation data we noticed that the ISO 24617-2 dialogue acts inventory is not sufficient to interpret and model negotiation interactions, and requires some extensions. Consider the following example:

(1) P1: What's your opinion on scope of smoking ban?
P2: I think there shouldn't be smoking in public transportation and parks

Analyses according to the ISO 24617-2 dialogue acts standard will result in assigning to P1 *Set Question* tag and to P2 *Set Answer*. Dialogue context model will be updated accordingly. For negotiation analysis, P1 is rather an *Offer Elicitation* act and P2 is an *Offer*. It is very common to analyse negotiations in terms of offers, counter-offers, commitments, concessions, etc. (see (Watkins, 2003), (Afantenos et al., 2012), (Hindriks et al., 2007)). For the system to know that an *offer* was elicited and performed is more important than to know that it was done in the form of a *SetQuestion*. Information about a **Negotiation Move** allows the system to interpret partners and to generate adequate communicative behaviour, to interpret partners negotiation strategies, and to take correct decisions in negotiation. Thus, we propose to have an additional set of acts which will be assigned to negotiators actions by extending the ISO 24617-2 tag set with negotiation moves as Task domain-related communicative functions. Such extension is eligible according to the standard guidelines (see Section 12 of the ISO 24617-2 standard). To avoid, however, confusions with the general-purpose *offer* dialogue act defined in ISO to describe the speaker's commitment to perform a certain action, we define *offerValue* as a dimension-specific negotiation move and assign it for speaker's expressions of commitments or preferences concerning a certain value (i.e. utility value).[1]

4.1. Dialogue Acts

As stated above dialogue acts are annotated using the ISO 24617-2 dialogue act annotation scheme. Table 2 provides an overview of the dialogue act tags distribution per dimension. As it can be observed, along with task-related and auto-feedback acts that are important and occur frequently in any conversation, discourse structuring acts occur often in negotiations. They are mainly concerned with topic

[1]Note that the selected negotiation moves names are domain dependent and fit our negotiation types the best. One can choose different names for different negotiation types, e.g. for selling-buying bargaining, *bid* would be more appropriate one.

ISO 24617-2 dimension	Relative frequency (in %)
Task	47.6
AutoFeedback	18.7
AlloFeedback	2.3
Turn Management	6.6
Time Management	6.6
Discourse Structuring	14.9
Own Communication Management	2.1
Partner Communication Management	na
Social Obligation Management	1.2

Table 2: Distribution of dialogue acts per ISO 24617-2 dimension in multi-issue bargaining corpus.

switches (e.g. moving from one issue to another) and decisions to continue, delay, reschedule or terminate the ongoing discussion and/or whole interaction. A negotiation dialogue example is provided in Table 1.

4.2. Negotiation Structure and Acts

As pointed out in Section 2, bargaining structure may shape strategies that negotiators follow and may influence the overall outcome. Negotiation starts with the **anchoring** phase, in which participants bring up early offers and counter-offers establishing jointly possible values contributing to the **Zone of Possible Agreement** (or bargaining range). The Zone of Possible Agreement (ZOPA) describes the intellectual zone in negotiations between parties where an agreement can reached. Within this zone, an agreement is possible. Outside of the zone, no amount of negotiation will yield an agreement. The actual bargaining occurs in *Claim Value* phase, potentially leading to (1) adaptation of the originally established ZOPA, (2) Negotiation Outcome, or (3) Negotiation Termination. Negotiation moves observed here are *BargainIn, BargainDown, BlockOfferValue*, and *Concession(-s)*. **Negotiation Outcome** is the phase associated with all walk-away positions for each partner. This phase is mainly concerned with stating *(partial) Deals* on a certain value set. Negotiations might be terminated. **Termination** is the phases associated with *deadlock* situations in which two or more competing actions are each waiting for the other to finish, and thus neither ever does. No other actions are further possible and interaction stops without any result (either positive or negative) can be reached. Specific acts that can be observed here are *Breakdown(-s)* and *Withdraw(-s)*. Negotiators can move to **Secure** (LockIn) the outcome reached so far and either go to another issue or new negotiation round, where previous *BreakDown(-s)* may be cancelled, e.g. *ExitBreakDown*. Secure phase is concerned with summing up, restating reached negotiation or termination outcomes. Participants take decisions to move with another issue, or continue or re-start the discussion later. Figure 2 depicts the observed negotiation structure.

Further, analysing the collected data, we observed and defined 18 negotiation moves, which are presented in the Table 3 along with their relative frequencies in our data.

Additional to dialogue acts and negotiation moves we annotated relations between them according to ISO 24617-2: *functional dependence*, *feedback dependence* and *rhetorical* relations as illustrated in Table 1.

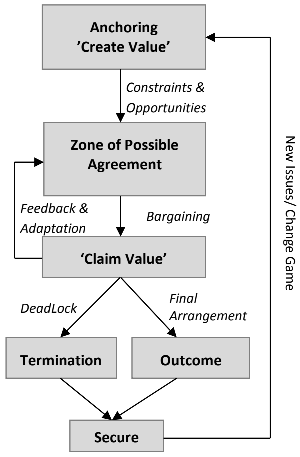

Figure 2: Negotiation phases associated with negotiation structure or certain negotiation strategy.

Negotiation Move	Relative frequency (in %)
ElicitOfferValue	19.3
OfferValue	28.7
AcceptOfferValue	14.7
DeclineOfferValue	6.0
CounterOfferValue	7.3
Concession	1.3
BargainIn	2.5
BargainDown	2.6
Deal	14.0
Withdraw	1.8
BreakDown	0.2
ExitDeal	0.7
ExitBreakDown	0.2
BlockOfferValue	0.7

Table 3: Defined negotiation moves and their relative frequencies in the collected multi-issue bargaining corpus.

Moreover, qualifiers are attached to the main function to specify the semantic/pragmatic meaning more accurately: ISO 24617-2 for certainty, conditionality and sentiment. For example:

(2) P1: If you insist on ten percent tax increase we would insist on anti-smoking television advertisement[$< task; inform >$; offerValue; conditional]
P2: Well, I am not sure we can give you this [$< task; disagreement >$; declineOfferValue; uncertain]

5. Initial Multi-Issue Bargaining Dialogue Models

As discussed in Section 4, participation in dialogue is a complex activity in the sense that it involves not only the understanding and performance of actions for pursuing a certain goal or task, but also many interactional aspects. When modelling dialogues as a part of dialogue system design process, dialogue management tasks for *interaction control* and *task control* actions are often separated. It has been done successfully by implementing multi-agent archi-

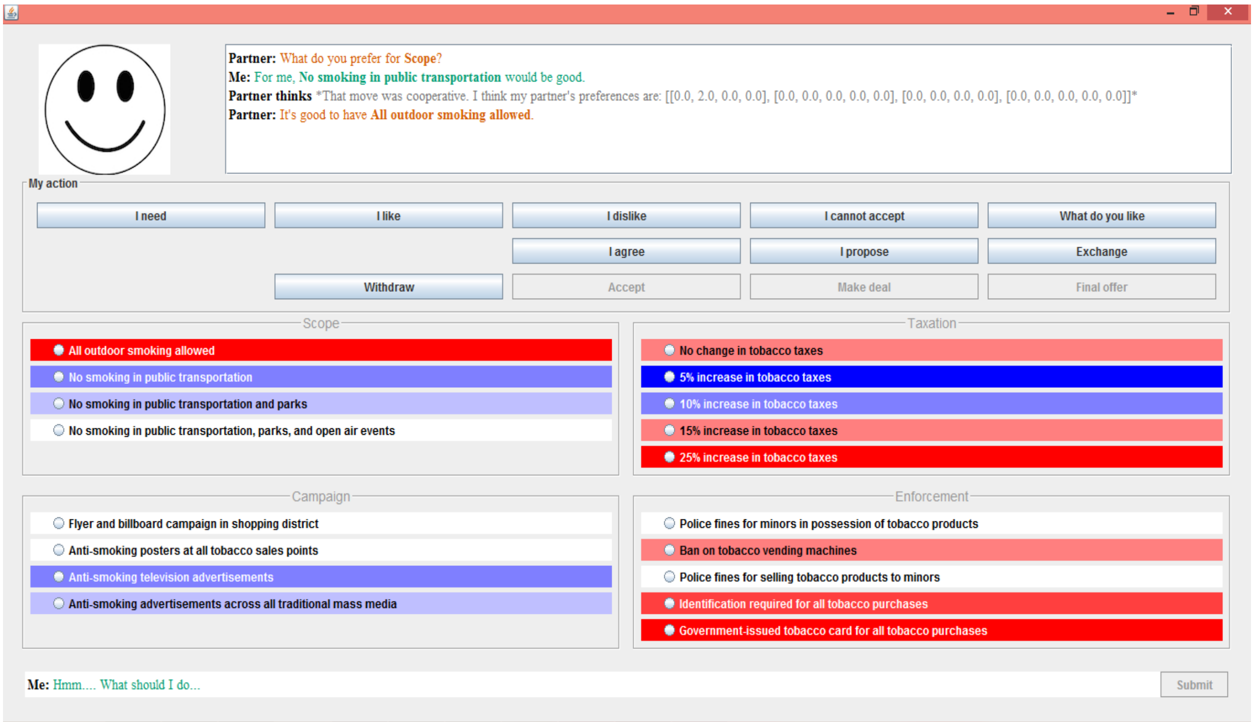

Figure 3: Screenshot of the Task Agent graphical user interface.

tectures for adaptive and flexible human-computer interactions (e.g. see JASPIS speech application architecture of Turunen et al, 2005). Moreover, dialogue participants do not only process and perform several actions but they use linguistic and nonverbal elements in order to address these several aspects at the same time. Thus, parallel processing and generation of multiple actions need to be allowed by the dialogue system. As consequence, a rather complex but also flexible dialogue model is required to deal with potentially complex communicative scenarios, see e.g. (Malchanau et al., 2015). Based on the analysis of collected and annotated data we developed the METALOGUE Dialogue Manager (DM) that is designed to handle multiple aspects ('dimensions') simultaneously. The DM is able to track multiple updates of the participants' information states specified by dialogue acts, see also Bunt (2000), Keizer et al. (2011) and Petukhova (2011). This gives rise to the generation of multiple dialogue acts. The DM's decision what acts to generate, in what order and combination is motivated by the preceding and current states of the communicative context and those of the underlying cognitive task model.

To design task models, many approaches have been developed. Often domain/task-specific processes are modelled as knowledge bases (*domain ontologies*) with constant values. Major disadvantage of using ontologies is that their construction may be quite expensive, and they are hardly ever complete. Another tradition is to perform *task analysis*, originally proposed by Annett et al. (1971). The method requires to describe a task in terms of a hierarchy of operations and plans. This framework was successfully applied to human decision-taking training. In dialogue management, it was also deployed in the form of hierarchical task decomposition and expectation agenda generation within the RavenClaw framework (Bohus and Rudnicky, 2003) and tested successfully in many systems. Examples include the use of a tree-of-handlers in Agenda Communicator (Xu and Rudnicky, 2000), activity trees in WITAS (Lemon et al., 2001) and recipes in Collagen (Rich et al., 1998). Yet another approach is the *plan-based* approach. For instance, in the TRIPS system (Allen et al. (2001) the implemented task manager relies on plan recognition and planning, and coordinates actions with dialogue manager. The Task Manager (or Problem Solving Manager) is defined as a set of actions that can be carried out: objectives (goals that are pursued), solutions to the objectives, resources available at their disposal (objects used in solutions) and situations (settings in which solutions are used to reach objectives).

In METALOGUE, we do not pre-define knowledge bases for system actions generation. We also do not rely on plan-recognition, since it has been proven be problematic in the past. Models based on task analysis are too generic and static. Our goal is to capture the dynamics related to frequently changing participants' goals. Thus, the system needs to support active identification of partner's goals and to balance between its own and partner's goals. Moreover, the system is required to be aware of partner errors and is able to propose improvements. The METALOGUE Task Agent operates on a structured dynamic context and generates actions based on system's beliefs about the partner's goals providing control over multiple possibilities/strategies.

5.1. Task Model

The METALOGUE cognitive task model is based on instance-based learning approach (Gonzalez & Lebiere, 2005), a well-established cognitive theory that has been validated against human decision-making data in a variety of contexts. The model reasons about the overall negotiation state, and attempts to identify the best negotiation move for the next step. A negotiation move is mapped to one or many possible task dialogue acts that changes the state of the negotiation. For instance, making an offer is a negotiation move because it signals that a player is willing to commit to a certain value if the other player is also willing to do so. The speaker can perform a SetQuestion act as in (1) or Inform act as in (2).

The cognitive model takes as an input the user's last negotiation move. The model returns the agent's counter-move information. Additionally, the model provides feedback on the user's strategies, where it shares the system's beliefs about the user's preferences and its evaluation of the user's strategy. Figure 3 illustrates the stand-alone Task Agent application which is used for evaluation and for supplementary data collection rounds.

In more details, a negotiation move is encoded in the form of OFFER(ISSUE-1,VALUE-A). The Dialogue manager calls the agent's `observeMove` method and passes the move as a parameter. The agent then updates its own representation of the negotiation state by retrieving an instance from memory. As an example, suppose it retrieves the following instance:

instance-a	
strategy cooperative	(The agent's strategy is cooperative)
my-offer-value-me 4	(The agent's current offer is worth 4 points to him)
opp-offer-value-me 1	(The opponent's offer is worth 1 point to the agent)
next-offer-value-me 2	(The next best option for the agent is worth 2 points)
satisfaction 0.0	(This represents the extent to which the agent is happy with the current offer on a -10 to +10 scale)
opp-move concede	(On the opponent's last move, she changed her offer to one that was less valuable to her)
my-move concede	(In this situation, the agent believes it should repay its opponent by also selecting a less valuable option)

This instance may have several slots that encode information about the state of the negotiation. The model extracts two important pieces of information from these instances: the strategy (cooperative vs. aggressive) of the user and an estimate of the user's preference for the options mentioned in the move. In other words, the model knows that, when there are other good options available, a cooperative negotiator will explore those options first before insisting on their current position. From this behaviour, the model infers that it is dealing with a cooperative negotiator with positive preferences on at least two issues.

The model uses its own context to choose an appropriate response to the user. Depending on how the user has played, and what the model knows about the user's preferences, the model may choose to respond aggressively or cooperatively. It will cooperate when the user is cooperative but it will be aggressive when the user is aggressive. Suppose, based on the user's actions, the model believes the user is cooperative. It will then be more likely to retrieve instances that encode cooperative behaviours. These include returning concessions, openly sharing information, and actively seeking information about the opponents preferences. Aggressive actions, by contrast, will include withholding information (or offering misleading information), rigidly committing to its positions, and issuing ultimatums ('take it or leave it'). Having decided on a specific negotiation move, the dialogue manager will translate it into the most appropriate dialogue act(-s) with certain communicative function and semantic content, place them into the candidate list along with other not-task-related dialogue acts, order them according to their importance given the current dialogue state (or other constraints either logical or pragmatic, or linguistic, see Petukhova, 2011), and pass them for generation.

$$
\begin{bmatrix}
\mathit{LingContext}: \begin{bmatrix}
\mathit{speaker}: \begin{bmatrix}
\mathit{dialogue\_history}: \{\ \langle \mathit{previous\_segments}\ \rangle\ \} \\
\mathit{latest\_segment}: \begin{bmatrix} \mathit{FS}: \mathit{current\_segment} \\ \mathit{state} = \mathit{opening}|\mathit{body}|\mathit{closing} \end{bmatrix} \\
\mathit{dialogue\_future}: \mathit{plan}: \begin{bmatrix} \mathit{candidates}: \langle \mathit{list\_DAs} \rangle \\ \mathit{order}: \langle \mathit{ordered\_list\_DAs} \rangle \end{bmatrix}
\end{bmatrix} \\
\mathit{partner}: \langle \mathit{partner\_linguistic\_context} \rangle\ (\mathit{according\ to\ speaker}) \\
\mathit{shared}: \langle \mathit{shared\_linguistic\_context} \rangle
\end{bmatrix} \\
\mathit{SemContext}: \begin{bmatrix}
\mathit{task\_progress}: \mathit{initiated}|\mathit{ongoing}|\mathit{suspended}|\mathit{completed}|\mathit{aborted} \\
\mathit{speaker\_task\_model}: \langle \mathit{beliefs} \rangle \\
\mathit{partner\_task\_model}: \langle \mathit{beliefs} \rangle\ (\mathit{according\ to\ speaker}) \\
\mathit{shared\_task\_model}: \langle \mathit{mutual\_beliefs} \rangle
\end{bmatrix} \\
\mathit{CogContext}: \begin{bmatrix}
\mathit{speaker\_own\_proc\_state}: \begin{bmatrix} \mathit{proc\_problem}: \mathit{yes}|\mathit{no} \\ \mathit{problem\_input}: \mathit{FS} \\ \mathit{time\_need}: \mathit{negligible}|\mathit{small}|\mathit{substantial} \end{bmatrix} \\
\mathit{partner\_proc\_state}: \langle \mathit{partner\_cognitive\_context} \rangle (\mathit{according\ to\ speaker}) \\
\mathit{shared}: \langle \mathit{shared\_cognitive\_context} \rangle
\end{bmatrix} \\
\mathit{PercContext}: \begin{bmatrix}
\mathit{speaker}: \begin{bmatrix} \mathit{own\_presence}: \mathit{positive}|\mathit{negative} \\ \mathit{own\_readiness}: \mathit{positive}|\mathit{negative} \end{bmatrix} \\
\mathit{partner}: \langle \mathit{partner\_perceptual\_context} \rangle (\mathit{according\ to\ speaker}) \\
\mathit{shared}: \langle \mathit{shared\_perceptual\_context} \rangle
\end{bmatrix} \\
\mathit{SocContext}: \begin{bmatrix}
\mathit{speaker}: \begin{bmatrix} \mathit{interactive\_pressure}: \mathit{none}|\mathit{greet}|\mathit{apology}|\mathit{thanking}|\ldots \\ \mathit{reactive\_pressure}: \{\langle \mathit{dialogue\_acts} \rangle\} \end{bmatrix} \\
\mathit{partner}: \langle \mathit{partner\_social\_context} \rangle (\mathit{according\ to\ speaker}) \\
\mathit{shared}: \langle \mathit{shared\_social\_context} \rangle
\end{bmatrix}
\end{bmatrix}
$$

Figure 4: Feature structure representation of the context model.

5.2. Interaction Control Model

Along with the task-related actions handled by the task model as discussed above and triggering updates in **Semantic Context (SemC)** of the whole dialogue context model, the proposed model has four further components: (1) **Linguistic Context (LC)** with information about (a) 'dialogue history'; (b) 'latest state'; and (c) 'dialogue future' or 'planned state'; (2) **Cognitive Context (CC)** representing information about the current and expected participants' processing states; (3) **Perceptual/Physical Context (PC)** having information about the perceptible aspects of the communication process and the task/domain; (4) **Social Context (SocC)** containing information about current speaker's and partner's social obligations and rights. Figure 4 shows the proposed context model with its component structure.

Each of the parts of the model can be updated independently while other parts remain unaffected. For instance, Linguistic Context is updated when dealing with presentational aspects and some interactional aspects, such as turn management. In the Cognitive Context participant's processing states are modelled (Auto- and Allo-Feedback acts), as well as aspects related to time and own commu-

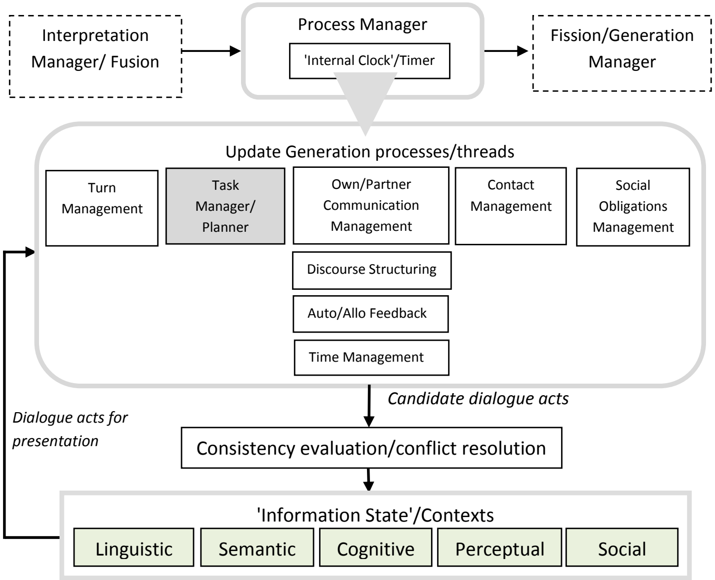

Figure 5: Multi-thread Dialogue Manager architecture.

Type	Content	Format	Comment
Preference cards	9 negotiation cases	html for web-presentation stand-alone GUI (Java)	defined for each negotiator
Metadata	participants (id, native language sex, age at collection)	xml	
Signals	sound recordings wav files	mono, 96000Hz sample rate 24-bit sample format mono, 16-bit sample format	1 channel per speaker cut per speaker/per turn
Automatic Speech Recognition Transcriptions Typed interactions	turn (id, start, end, string) turn (id, start, end, string) turn (id, string)	plain text TEI compliant csv format	automatic manual
DA annotations	dialogue act (sender, dimension, communicative function, qualifier functionalDependenceRelation feedbackDependenceRelation) rhetoricalLinks negotiation moves (separately)	Anvil and DiAML	manual

Table 4: METALOGUE Multi-Issue Bargaining Corpus overview.

nication management (e.g. error in speech production). Along with task-related negotiation acts, Semantic Context is updated with information concerning structure and progress of negotiation task associated with negotiation phases depicted in Figure 2.

5.3. Dialogue Manager Implementation

The Dialogue Manager is designed as a set of processes (threads) that receive data, update the information state and generate output. The DM architecture is, therefore, updated as shown in Figure 5. Firstly, DM receives data produced by the Dialogue Recognition module. Next, an update of information state is performed based on the received input. What part of context model to update is decided by Process Manager. In parallel, to receiving and updating, the output based on the analysis of the information state is generated. The DM keeps track of its own dialogue history in the Linguistic Context of the context model. The planned ordered dialogue acts list are checked for logical and pragmatic consistencies (see Petukhova, 2011) and passed to the Generation Manager.

6. Conclusion and Future Work

In this paper we discussed the nature and complexities of multi-issue bargaining dialogues. We presented the approach to data collection and proposed the annotation design. We showed that carried out analyses provided us with a well-defined inventory of the majority of possible acts that occur in this type of negotiations and that are necessary for successful computational modelling of such interactions.
The fact that we based our analysis on the internationally accepted annotation and representation standards extending those for our specific purposes supports the previous statement. We would also like to note that the data, metadata, used graphical material, and semantic and pragmatic annotations in standard xml-format will be released to the research community as METALOGUE multi-issue bargaining corpus (end 2016). Table 4 provides corpus overview specifying type of data planned for release.
Designed initial dialogue models (task and interaction con-

trol) provide the basis for interpreting the speaker's behaviour and for decisions about future actions. The proposed approach opens the perspective for an adequate and rich human-system interaction. The models will be evaluated as part of the whole dialogue system that is able to perform accurate understanding and multimodal and multitasking behaviour generation tasks. The proposed models can be re-trained when more data arrives, offer possibilities for sophisticated refinements and structured extensions, but also for specific constraints, if required.

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