The MaDrIgAL project: Multi-Dimensional Interaction Management and Adaptive Learning

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Simon Keizer and Verena Rieser

Interaction Lab
School of Mathematical and Computer Sciences
Heriot-Watt University, Edinburgh, Scotland
{s.keizer,v.t.rieser}@hw.ac.uk

Abstract. Recent statistical approaches have improved the robustness and scalability of spoken dialogue systems. However, they still lack in two main aspects: 1) their perceived naturalness and social intelligence, and 2) their cross-domain scalability. In this paper, we argue that both of these shortcomings can be addressed effectively by extending current models to reflect and exploit the multi-dimensional nature of human dialogue. In order to investigate this, the MaDrIgAL project aims to develop multi-dimensional versions of data-driven models for spoken dialogue systems. In doing so, we 1) incorporate a richer set of dialogue acts into the learning process, leading to more natural and socially appropriate dialogues, and 2) learn transferable skills by separating out domain-independent dimensions of communication, leading to more efficient cross-domain adaptation.

Keywords: spoken dialogue, machine learning, domain adaptation

1 Introduction

Virtual personal assistants, such as Apple's Siri or Microsoft's Cortana, have made commercial use of interactive spoken language technology. However, it seems that users do not find them engaging due to their lack of natural and social behaviour. Furthermore, commercial exploitation of advanced spoken dialogue technology requires new methods for cost-effective development and efficient adaptation to new domains. In this position paper, we argue that a *multi-dimensional* approach has the potential to address both of these problems.

Existing systems focus almost exclusively on the primary task underlying the conversation, for example travel booking. The behaviour resulting from such an approach is quite different from natural human dialogue, where several other aspects besides the task itself are addressed as well, such as giving and eliciting feedback, following social conventions, and managing turn-taking and timing. Humans frequently perform *multi-functional* utterances, where several of these aspects, or *dimensions*, are addressed simultaneously [2]. Consider the following example interaction (annotated with different functions for each turn):

User: ***Hi, what time is the next train to Glasgow?***	
SOCIAL:GREET; TASK:QUESTION; TURN:RELEASE	
System: ***Let me see, . . .***	
TURN:TAKE; TIME:PAUSING; TASK:INFORMSEARCH	
System: ***the next one to Glasgow will be at 11:25***	
AUTO-FEEDBACK:INFORM; TASK:ANSWER	

The user both greets the system and asks for a departure time, before releasing the turn; the system then takes the turn and indicates that it needs more time to retrieve the requested information; in the second part the system both provides this information and gives feedback about understanding the user's question (see underlining). Current approaches to statistical dialogue optimisation, however, only consider a single, task-oriented function of dialogue interaction in each utterance. This limits the capacity for learning good interaction strategies, and often results in a discrepancy between the generated surface form and the intended meaning by the dialogue manager, causing the user to misinterpret the system's behaviour [14].

In our project, we will explicitly account for these different dimensions of communication, using Bunt's notion of multi-dimensionality of dialogue [2]. We believe that a principled multi-dimensional approach is needed for building statistical dialogue systems that support more natural interactions and therefore get higher user satisfaction rates. Our proposal therefore is to extend existing, one-dimensional, state-of-the art statistical techniques to support multi-dimensional action selection natural language generation. This will allow us to consider a wider range of system actions, whilst addressing tractability issues by exploiting the modularity of multi-dimensional design. In addition, this modularity enables *better portability to different domains*: dimensions that are relevant across domains (such as feedback and turn management) represent interaction skills that can be transferred to new domains and adapted directly.

2 Multi-dimensional Dialogue Modelling

We will make use of Dynamic Interpretation Theory (DIT), a theory of dialogue developed by Prof. Harry Bunt, in which the distinction between different aspects of communication, called ***dimensions***, plays a central role [1]. In his approach, utterances in a dialogue are represented as combinations of dialogue acts from a multi-dimensional dialogue act taxonomy, thus accounting for their multifunctional nature [2]. Several annotation campaigns have resulted in the development of an ISO standard for dialogue act annotation [8]. The core dimensions in the established standard are: *Task/Activity*, *Auto-*, and *Allo-Feedback*, *Turn-*, and *Time-Management*, *Partner-* and *Own Processing Management*, *Discourse Structuring*, and *Social Obligations Management*. Also, our work builds upon other work by Bunt and colleagues involving incremental recognition of dialogue acts from this taxonomy [13], and a proof-of-concept multi-dimensional dialogue manager [9, 10].

3 POMDP-based dialogue systems

Recent advances in statistical dialogue systems have investigated Reinforcement Learning to optimise dialogue policies [15, 18]. The underlying problem is modelled as a Partially Observable Markov Decision Process (POMDP) to account for uncertainty introduced by automatic speech recognition and spoken language understanding (ASR&SLU). A conventional POMDP-based SDS typically consists of a pipeline of components for ASR and SLU, dialogue management (DM), and natural language generation and speech synthesis (NLG&TTS), see Fig. 1, where DM consists of belief monitoring (updating the *belief state* $b(s)$, i.e., a distribution over state hypotheses, based on an N-best list of user act hypotheses $\tilde{a}_u^i$) and action selection (deciding which system act a_m to generate, given the current belief state).

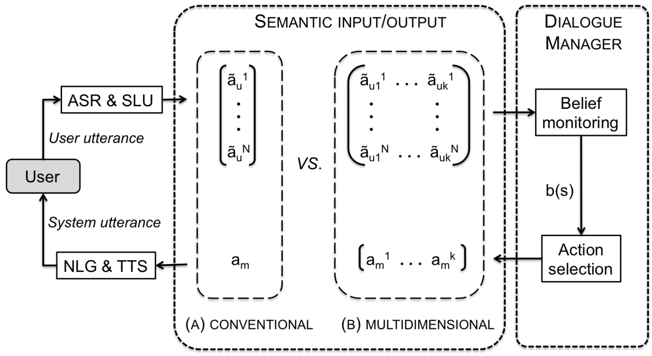

Fig. 1. Typical dialogue system architecture, contrasting conventional statistical dialogue manager with a multi-dimensional version.

In the POMDP framework, the process of belief monitoring can be expressed using the graphical model depicted in Fig. 2, where the observations o represent the N-best list of user dialogue act hypotheses and their confidence scores, a_m represents the system action, r represents the reward function $r(s, a) \in \mathbb{R}$, and the state s is factored into the user goal s_u, dialogue history s_d and true user act a_u. Based on the updated belief state, a system act is selected using a policy which is optimised w.r.t. the long-term expected cumulative rewards for each state-action pair. After an action is executed, the state at time $\mathbf{t}$ transitions to the next state at time $\mathbf{t+1}$.

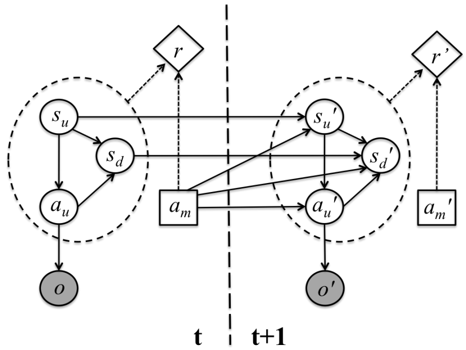

Fig. 2. Graphical model of a POMDP based SDS.

4 Multi-dimensional architecture

Conventional statistical dialogue managers in each turn select one dialogue act a_m out of a set of possible acts, whereas the proposed dialogue manager selects responses that consist of combinations of dialogue acts a_m^i, see settings (A) resp. (B) in the lower middle part of Fig. 1. A naive approach would be to collapse the dimensions of dialogue acts into a single set of actions, and then follow the conventional approach. However, under this architecture the state-action spaces, and thus computing time, grow exponentially and are unlikely to tractably accommodate the proposed richness of interaction. We therefore propose to extend the graphical model of Fig. 2 to incorporate multiple action nodes, each corresponding to a separate dimension, as depicted in Fig. 3. According to DIT,the state can be represented in such a way that decision making in each dimension is based on its own separate state component. As such, each state node s' would be connected to at most one action node a_m, resulting effectively in a multi-agent design [4, 3]. We will compare this with a more general model where this kind of factorisation is more flexible and can potentially be learned. Although a multi-agent approach might have computational advantages and be more efficient for porting to new domains, the factored approach more accurately models any dependencies between the dimensions, thus resulting in better coordination of action selection across the dimensions and therefore better system performance.

Recent work on **Domain Adaptation** in a one-dimensional SDS framework has focused on identifying and exploiting similarities between task domains [5, 6, 11, 17]. In contrast, our proposed multi-dimensional framework distinguishes domain-independent dimensions such as social conventions and turn-taking, which can be transferred directly between domains. These transferable skills are trained jointly in one domain, and can be adapted in a new domain. Using such types of *transfer learning* [16, 12], building and optimising an SDS for a new domain promises to be more efficient.

In our proposed framework, the **Natural Language Generation** (NLG) component will take combinations of dialogue acts as input and generate (po-

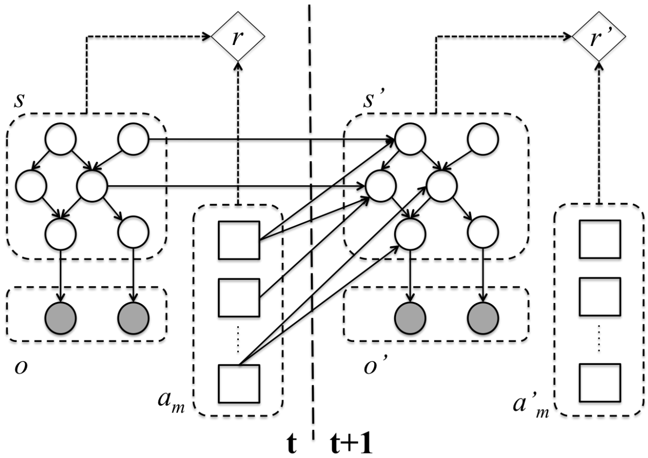

Fig. 3. Graphical model of a POMDP based SDS with factored action space.

tentially multi-functional) natural language utterances. In previous work [14] we found that separately optimised NLG and DM can lead to sub-optimal system performance; in this work, we therefore propose to *jointly optimise DM and NLG*, e.g. by using Multi-Objective Optimisation (MOO), which showed promising first results for content selection [7]. We use MOO to find a surface form which can simultaneously satisfy multiple communicative goals as specified by the input list of dialogue acts.

5 Conclusion

We have argued for a multi-dimensional approach to dialogue system development, in order to 1) support more natural and socially acceptable dialogues, and 2) enable more efficient cross-domain adaptation by learning transferable conversational skills. The MaDrIgAL project aims to develop a novel framework for spoken dialogue systems, extending current machine learning approaches to support multi-dimensional input processing and output generation, featuring for example (variants of) multi-agent reinforcement learning, multi-task learning, multi-objective optimisation and domain adaptation. We believe that this approach will result in conversational interfaces with improved user satisfaction rates from the consumer's point of view, and in more cost-effective development and adaptation of such interfaces from the industry's point of view.

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