Generating Socially Appropriate Tutorial Dialog

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Abstract. Analysis of student-tutor coaching dialogs suggest that good human tutors attend to and attempt to influence the motivational state of learners. Moreover, they are sensitive to the social face of the learner, and seek to mitigate the potential face threat of their comments. This paper describes a dialog generator for pedagogical agents that takes motivation and face threat factors into account. This enables the agent to interact with learners in a socially appropriate fashion, and foster intrinsic motivation on the part of the learner, which in turn may lead to more positive learner affective states.

1 Introduction

Animated pedagogical agents, or guidebots, exploit human-like communication modalities, such as speech and nonverbal gesture, in order to promote more effective learning [10]. Learning materials incorporating animated agents can engender a higher degree of learner interest than similar learning materials that lack such agents [16], and reduce the perceived difficulty of the learning material [1]. They can also produce a positive affective response on the part of the learner, sometimes referred to as the persona effect [13]. This is attributed to the natural tendency for people to relate to computers as social actors [23], a tendency that animate agents exploit.

Educational researchers increasingly recognize the importance of learner affective states in promoting effective learning. Of particular importance factors such as self-confidence and interest that contribute to learner intrinsic motivation [25]. Expert human tutors are also able to recognize when learners have negative affective states due to poor motivation or low sense of self-efficacy, and can try to influence learner motivation through encouragement and other motivational tactics [12]. Since animated agents can display emotion via speech and gesture, it is reasonable to suppose

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that they could be well suited to promoting positive affective states. Yet clearly doing this properly involves more than generating emotional displays per se, but generating the appropriate type of display at the right time in order to influence the learners in the appropriate way.

This paper describes a model for dialog generation in guidebot designed to emulate tactics that human tutors use to influence learner motivation. It takes into account characteristics of the social relationship between the guidebot and the learner, as well as learner motivational factors and individual learner characteristics. The work is the combined effort of several students of the University of Twente, each of whom performed internships of a few months in duration at the Center for Advanced Research in Technology for Education (CARTE) at USC / Information Sciences Institute. It is part of a larger project building a socially intelligent pedagogical agent able to monitor learner performance and provide socially sensitive coaching and feedback and appropriate times [9].

2 Background Studies on Tutor-Learner Interaction

To investigate the role that social intelligence plays in learner-tutor interaction, we videotaped interactions between learners and a human tutor while the students were working with a particular on-line learning environment, the Virtual Factory Teaching System (VFTS) [7]. Students read through an on-line tutorial in a Web browser, and carried out actions on the VFTS simulation as indicated by the tutorial. Learners were supposed to analyse the history of previous factory orders in order to forecast future demand, develop a production plan, and then schedule the processing of jobs within the factory in order to meet the demand. The tutor sat next to the students as they worked, and could interact with them as the student or the tutor felt appropriate. Completing the entire scenario required approximately two hours of work, divided into two sessions of around one hour. Three video cameras were used: one focused on the learner's face, one focused on the computer screen, and one provided a view of the learner and tutor together. This made it possible to track the learner's actions and focus of attention, as well as verbal and nonverbal interactions between the learner and the tutor. The tutor was a USC professor who has won awards for teaching excellence, and who uses the VFTS in his courses.

To analyse the interactions, and use them in designing learner-agent dialog, we transcribed them and annotated them using the DISCOUNT scheme [19]. DISCOUNT represents the structure of educational dialogs as a series of *episodes*, each pertaining to a particular topic. Episodes are divided into *exchanges* between the parties in the dialog, which are composed of a series of *turns* (e.g., initiate, respond, reinitiate). Each turn consists of one or more dialog moves, classified according to speech act (hint, support, contradict, etc.) and marked with predicate labels that indicate the function of the move in the dialog.

2.1 Interaction Tactics and Learner Motivation

A striking feature of these dialogs was that although they involved many episodes where the tutor was offering advice as to what to do, in very few cases did the tutor give explicit instructions of what to do. Rather, the tutor would phrase his comments so as to subtly engage the learner's interest and motivation, while leaving the learner the choice of what to do and how. These include hints phrased as questions, e.g.:

Tutor: Want to look at your capacity?

The tutor's comments often would reinforce the learner's sense of being an active participant in the problem solving process, e.g., by phrasing suggestions as activities to be performed jointly by the tutor and the learner, e.g.:

Tutor: So why don't we go back to the tutorial factory…

Following the work of Sansone, Harackiewicz, and Lepper and others [25, 12], we analyze these comments as intended to influence learner intrinsic motivation. Learners tend to learn better and more deeply if they are motivated by an internal interest and desire to master the material, as opposed to extrinsic rewards and punishments such as grades. Researchers in motivation have identified the following factors as conducive to intrinsic motivation among others:

- *Curiosity* in the subject matter,
- An optimal level of *challenge* – neither too little nor too much,
- *Confidence*, i.e., a sense of self-efficacy, and
- A sense of *control* – being free to choose what problems to solve and how, as opposed to being told what to do.

The tutorial comments observed in the dialogs tend to be phrased in such a way as to have an indirect effect on these motivational factors, e.g., phrasing a hinted action as a question reinforces the learner's sense of control, since the learner can choose whether or not to answer the question affirmatively. These motivational factors in turn are closely linked to learner affect, e.g., confidence and optimal challenge reduce the fear of problem solving failure and increase the satisfaction of success.

Although these comments indicated that the tutor was sensitive to the learner's motivational state, and post-session interviews confirmed this, there were hardly any instances in the dialogs of explicit comments aimed explicitly and solely at influencing learner motivation, such as "Good job!" or "You can do it!" To model this type of interaction in a guidebot, it was clearly necessary to develop a dialog generation model that would allow learner motivation to have a pervasive influence, without requiring a separate repertoire of tactics with purely motivational intent.

3 Generating Interaction Tactics

Based upon these analyses, Sander Kole and Wauter Bosma developed a natural language generator for producing appropriate interaction tactics. The generator takes as input a set of language elements – short noun phrases and short verb phrases in the target domain – and predicates describing the desired dialog move. It chooses an utterance pattern that matches the dialog move predicates most closely, instantiates it with the language elements, and synthesizes an utterance, which is then passed to the guidebot persona for uttering using text-to-speech synthesis.

The underlying generation scheme utilizes DISCOUNT as a way of classifying dialog moves. It operates on a set of move templates, each of which includes a set of DISCOUNT predicates and a template for expressing the move in natural language. The templates specify slots for language elements, which are filled from the language elements supplied to the generator. The move templates and language elements are specified using an XML syntax and all defined in one language definition file. Fig. 1 shows an example move from the language definition file. The moves are based upon utterances found in the dialog transcripts; the comments at the top of the move template show the original utterance and the transcript and time code where it was found. The move template may classify the move in multiple ways, reflecting the fact that the same utterance may have multiple communicative roles, and different coders may code the same utterance differently.

```
<move>
        <!-- 7S P1 47:11  T  -->
<!-- So number 2, the number of seasons may not be 2 then.-->
        <predicate role="initiating" move="all" name="action1"/>
        <predicate role="initiating" move="all" name="noun1"/>
        <predicate role="initiating" move="hint" name="suggest"/>
        <predicate role="initiating" move="inform" name="identify"/>
        <predicate role="initiating" move="reason" name="explain"/>
        <template>
                So <nounphrase case="object" type="parameter"
                                name="noun1.nounphrase1"/>
                may not
                <verbphrase type="parameter" name="action1.action1"
                                form="infinite"/>
                .
        </template>
</move>
```

Fig. 1. An example dialog move template

Using this generation framework, it is possible to present the same tutorial comment different ways. For example, a suggestion to perform an action, such as saving the current factory description, can be stated either directly (e.g., “Save the factory now”), as a hint, (“Do you want to save the factory now?”), as a suggestion of what the tutor would do (“I would save the factory now”), as a suggestion of a joint action (“Why don’t we save our factory now?”), etc.

4 Politeness as a Framework for Selecting Interaction Tactics

Having defined this set of dialog moves and implemented a generator that can produce them, the next challenge is to determine which tactic to employ in which circumstances. How does the choice of interaction tactic depend upon the learner, the topic being discussed, and the state of the social interaction between the learner and the tutor?

The politeness theory of Brown and Levinson [5] helps provide a rationale for these decisions. In this theory, social actors are motivated by a set of wants, including social wants: *negative face*, the want to be autonomous and unimpeded by others, and *positive face*, the want to be desirable to others. Common speech acts between social actors, such as requests and offers, can threaten the hearer's negative face, positive face, or both, and therefore are referred to as *face threatening acts* (FTAs). Speakers use various types of politeness strategies to mitigate face threats, depending upon the severity, or *weightiness,* of the potential face threat.

The following are some examples of politeness strategies in the context of tutoring a student in operating the VFTS. Consider a critique of the learner such as "You didn't save your factory. Save it now." This is an example of what Brown and Levinson term a *bald on record* FTA; there is no attempt to use politeness to mitigate the face threat. There are two types of face threat in this example: the criticism of the learner's action is a threat to positive face, and the instruction of what to do is a threat to negative face.

There are various politeness tactics that can be employed to mitigate the face threat. One is simply to avoid the face threatening act altogether if the cost of making the threat is greater than the potential benefit. In the above case the tutor could omit the criticism of the learner and focus on the suggested action, i.e., to save the factory. Alternatively the tutor could perform the face-threatening act *off record*, i.e., so as to avoid assigning responsibility to the hearer. An example of this would be "The factory parameters need saving." The face threat of the instruction can be mitigated using negative politeness tactics, i.e., phrasing that gives the hearer the option of not following the advice, e.g., "Do you want to save the factory now?" Positive politeness strategies can also be employed that emphasize common ground and cooperation between the tutor and learner, e.g., "How about if we save our factory now?" Other positive politeness strategies include overt expressions of approval, such as "That is very good," however as noted above such strategies were uncommon in the interactions that we studied.

In the Brown and Levinson model evaluation of face threat depends upon several factors. First, the relative weightiness of different face threats is culturally dependant. The weightiness of a face-threatening act also depends upon the relative power P between the speaker and the listener. Tutors generally have power relative to learners, so we would generally expect tutors to make use of weaker politeness strategies when speaking to learners than the learners use in reverse. Finally, the weightiness of a face threat depends upon the social distance between the two parties. As two people interact over time their social distance often decreases, reducing the severity of face threatening acts and increasing the likelihood that bald-on-record strategies will be used.

Although the Brown and Levinson model is not specifically aimed at modeling tutorial dialog, it provides a good means of accounting for variability in tutorial dialog. The interaction tactics observed in the recorded dialogs, when other than bald-on-record statements, have the effect of mitigating face threats. Since offers of advice and requests to perform actions are face threatening acts, the theory predicts that tutors will employ face mitigation strategies for these kinds of interactions, but not for other dialog moves such as explanatory comments. This is consistent with the observed data. The theory predicts that the incidence of face threat mitigation strategies will decrease as tutor and learner interact for longer periods of time. This trend is also observable in the data that we have collected; the incidence of bald-on-record tactics was greater in the follow-on tutorial sessions than in the initial sessions.

Although politeness theory and motivation theory come out of distinct literatures, their predictions regarding the choice to tutorial interaction tactics are broadly consistent. This is not surprising, since the wants described by politeness theory have a clear motivational aspect; negative face corresponds to control, and positive face corresponds somewhat to confidence in educational settings. To bring the two frameworks together, we extend the Brown & Levinson model in certain respects. First, whereas Brown & Levinson's model assigns a single numeric value to each face threat, we extend their model to consider positive face threat and negative face threat separately. This enables us to select a redressive strategy that is appropriate to the type of face threat. For example, if an FTA threatens negative face but not positive face, then the politeness model should choose a redressive strategy that mitigates negative face threat; in contrast the basic Brown & Levinson model would consider a redressive strategy aimed at positive face to be equally appropriate. Second, we allow for the possibility that the tutor might wish to explicitly enhance the learner's face, beyond what is required to mitigate immediate face threats. For example, if the tutor judges that the learner needs to feel more in control, he or she will make greater use of redressive strategies that augment negative face.

Altogether, the amount of face threat redress is determined by the following formulas, which are slight elaborations of the weightiness formulas proposed by Brown & Levinson [5]:

$$W_{x+} = D(T,S) - P(T,S) + R_{x+} + \Delta_{+}$$

$$W_{x-} = D(T,S) - P(T,S) + R_{x-} + \Delta_{-}.$$

Here W_{x+} and W_{x-} are the amounts of positive and negative face threat redress, respectively, T represents the tutor and S represents the student. D(T,S) is the social distance between the tutor and the student, and P(T,S) is the amount of social power that the tutor has over the student. R_{x+} is the inherent positive face threat of the communicative act (e.g., advising, critiquing, etc.,), R_{x-} is the inherent negative face threat of the act, Δ_{+} is the amount of augmentation of positive face desired by the tutor, and Δ_{-} is the desired augmentation of learner negative face.

Additional factors clearly need to be taken into account besides politeness theory in order fully account for the influence of interaction tactics on learner motivation. For example, politeness theory per se does not explain the relative infrequency of comments aimed solely at positive face, e.g., expressions of praise. In our analyzed dialogs, positive praise is confined to the ends of VFTS sessions, when the learner has completed the assigned tasks. One way to account for this is to note that learners are motivated not just by positive face, i.e., to be approved of by the tutor, but by a desire for self-efficacy, i.e., to approve of their own performance. Since VFTS tasks take a long time to complete, it is difficult to tell whether the learner is doing well until after the learner has worked on the task for a significant amount of time. If a learner recognizes this, then frequent praise from the tutor might be regarded as insincere. This is an account that needs to be tested in other domains, where there are there are more frequent opportunities to evaluate learner work.

5 Implementing the Politeness Model

Mattijs Ghijsen and Herwin van Welbergen have developed a politeness module that implements the politeness / motivation model described above, and interfaces to the natural language generator. The combined dialog generator takes as input the desired utterance type, language elements, and a set of parameters governing face threat mitigation (social distance, social power, and motivational support) and generates an utterance with the appropriate degree of face threat redress.

The utterance types are classified in accordance with Bloom's taxonomy of educational goals [4]. Bloom categorizes instructional actions into three groups: cognitive, concerning the development of intellectual abilities and skills; affective, comprising interests, attitudes, and values; and psycho-motor, regarding the manipulative or motor-skill area. The three objectives most relevant to the VFTS are from the cognitive category: Knowledge, i.e. the recall of specifics, universals, methods and processes – such as mastering the concept of forecast, or the planning process; Application, i.e. the use of abstractions in concrete situations –for instance the application of a specific forecasting method to the simulated factory; and Synthesis, i.e. the putting together of elements and parts so as to form a whole –such as producing a plan of operations to perform on the VFTS interface.

These cognitive goals, applied to the set of interface objects in the VFTS interface, and to the concepts and tasks described in the tutorial materials for the VFTS, determine the set of possible communicative acts that the dialog generator needs to generate. The repertoire of utterance patterns and language elements was extended as needed in order to cover this set.

To choose the appropriate interaction tactic, politeness generator first computes target positive and negative politeness values for the desired utterance. The positive and negative politeness values are computed in order to counteract the weightiness of the face threat, as well as to achieve additional motivational influence, as indicated in the formulas in the previous section. Social distance, social power, and motivational influence are all parameters that are supplied to the politeness generator and are potentially adjustable.

Once the target politeness values are chosen, the generator chooses from a library of natural language templates one that matches the target politeness values most closely. Each template, as in Figure 1, is assigned a positive and negative politeness value. A template is chosen that minimizes the sum of the distances between desired and chosen politeness values, for both positive and negative politeness. When multiple templates have an appropriate politeness value one is chosen that matches the greatest number of move predicates.

To apply this politeness module, it is necessary to assign politeness values to each template in the library. To assign these values, we grouped templates according to the politeness strategies that they exhibit, as shown in Table 1. These categories were derived from analysis of the background dialog transcripts, and then mapped onto the general strategies identified by Brown & Levinson such as bald-on-record. We then assumed that all templates employing a given strategy should be assigned the same level of politeness—not strictly true, since perceived politeness depends upon context, but adequate as a first approximation. We then created a questionnaire containing examples of different politeness strategies, and had subjects evaluate each example in terms of negative and positive politeness. The mean negative and positive politeness scores were then assigned to the templates in the library.

Table 1. Face threat redress strategies for different utterance types

Utterance Type	Politeness strategies
Suggest action	Bald on record, conventional indirectness, joint goal, student goal, question, suggestion, tutor goal
Explain concept	Bald on record, positive politeness, attend to hearer, student's goal, impersonalize, off record
Explain tutorial	Bald on record, tutor goal, joint goal, suggestion
Suggest interface operation	Bald on record, conventional indirectness
Explain interface object	Bald on record
Socratic hint	Socratic hint
Action feedback	Bald on record, positive politeness

The politeness module and dialog generator are used as part of an overall pedagogical agent architecture, which includes other modules to detect learner focus of attention, including eye gaze tracking, and to recognize plans that the learner is carrying out, as described in [22]. This information can be provided to a remote tutor, operating a Wizard-of-Oz interface, so that the tutor can decide when it is appropriate for the guidebot to interact with the learner; we are also developing a control module that can make these decisions automatically. Either way, the interactions are realized by the dialog generator, which selects appropriate dialog moves in accordance with the social distance and the intended effects on learner motivation. The synthesized utterances are then output by the agent persona, by means of a text-to-speech generator and persona control system [24].

6 Related Work

There is a growing body of research relating to the expression of affect-related states in animated agents in animated agents (e.g., [6; 14; 21]. There also is some work in recognizing user affect [18; 28]. However following the work of theorists such as Lazarus [11] we draw a distinction between emotions, on one hand, and attitudes and mental states that engender emotions in certain circumstances, and focus on the latter. The focus here is help make learners confident and motivated, rather than make them happy per se, although the expectation that a favorable motivational state will lead to favorable emotional states.

Although there is relatively little work on learning systems designed to detect and influence learner motivational state, the topic is beginning to attract more interest, particularly in the work of del Soldato et al [26] and de Vicente [27]. Heylen et al. [17] highlight the importance of affective and motivational factors in tutors, and examine the interpersonal factors that should be taken into account when creating sociallly intelligent computer tutors. Baylor [2] has conducted experiments in which learners interact with multiple pedagogical agents, one of which seeks to motivate the learner. User interface and agent researchers are also beginning to apply the Brown & Levinson model to human-computer interaction in other contexts [6; 15].

Porayska-Pomsta [20] has also been using the Brown & Levinson model to analyze teacher communications in classroom settings. Although there are similarities between her approach and the approach described here, her model makes relatively less use of face threat mitigating strategies. This may be due to the differences in the social contexts being modeled: one-on-one coaching and advice giving is likely to result in a greater degree of attention to face work.

7 Conclusions and Future Work

In this paper we have presented an approach to generating coaching dialogs characterized by politeness. Real tutors use politeness as a means for respecting the student's social face, and for indirectly fostering his intrinsic motivation. Our goal is to replicate the tutor's behavior by means of a natural language generator coupled with a politeness module, that chooses templates according to their level of politeness and to a set of pedagogical goals relevant to the VFTS.

Using this framework we now plan evaluations to test the impact of politeness in learning settings. We plan to compare guidebots that exhibit politeness against guidebots in which politeness considerations are disregarded, so that all guidebot comments are bald on record. We predict that the polite version will be regarded more favorably, and will result in an improved learner motivational state, compared to a comparable impolite version.

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