Discourse Structure and Performance Analysis: Beyond the Correlation

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Abstract

This paper is part of our broader investigation into the utility of discourse structure for performance analysis. In our previous work, we showed that several interaction parameters that use discourse structure predict our performance metric. Here, we take a step forward and show that these correlations are not only a surface relationship. We show that redesigning the system in light of an interpretation of a correlation has a positive impact.

1 Introduction

The success of a spoken dialogue system (**SDS**) depends on a large number of factors and the strategies employed to address them. Some of these factors are intuitive. For example, problems with automated speech recognition can derail a dialogue from the normal course: e.g. non-understandings, misunderstandings, end-pointing, etc. (e.g. (Bohus, 2007; Raux and Eskenazi, 2008)). The strategies used to handle or avoid these situations are also important and researchers have experimented with many such strategies as there is no clear winner in all contexts (e.g. (Bohus, 2007; Singh et al., 2002)). However, other factors can only be inferred through empirical analyses.

A principled approach to identifying important factors and strategies to handle them comes from *performance analysis*. This approach was pioneered by the PARADISE framework (Walker et al., 2000). In PARADISE, the SDS behavior is quantified in the form of *interaction parameters*: e.g. speech recognition performance, number of turns, number of help requests, etc. (Möller, 2005).These parameters are then used in a multivariate linear regression to predict a SDS performance metric (e.g. task completion, user satisfaction: (Singh et al., 2002)). Finally, SDS redesign efforts are informed by the parameters that make it in the regression model.

Conceptually, this equates to investigating two properties of interaction parameters: **predictiveness** and **informativeness**[1]. Predictiveness looks at the connection between the parameter and system performance via predictive models (e.g. multivariate linear regression in PARADISE). Once the predictiveness is established, it is important to look at the parameter informativeness. Informally, informativeness looks at how much the parameter can help us improve the system. We already know that the parameter is predictive of performance. But this does not tell us if there is a causal link between the two. In fact, the main drive is not to prove a causal link but to show that the interaction parameter will inform a modification of the system and that this modification will improve the system.

This paper is part of our broader investigation into the utility of *discourse structure* for performance analysis. Although each dialogue has an inherent structure called the discourse structure (Grosz and Sidner, 1986), this information has received little attention in performance analysis settings. In our previous work (Rotaru and Litman, 2006), we established the predictiveness of several interaction parameters derived from discourse structure. Here we take a step further and demonstrate the informativeness of these parameters.

We show that one of the predictive discourse structure-based parameters (PopUp-Incorrect) informs a promising modification of our system.

[1] Although this terminology is not yet established in the SDS community, the investigations behind these properties are a common practice in the field.

Proceedings of SIGDIAL 2009: the 10th Annual Meeting of the Special Interest Group in Discourse and Dialogue, pages 178–187,
Queen Mary University of London, September 2009.

We implement this modification and we compare it with the original version of the system through a user study. Our analyses indicate that the modification leads to objective improvements for our system (e.g. performance improvements for certain users but not at the population level and fewer system turns).

2 Background

ITSPOKE (**I**ntelligent **T**utoring **Spoke**n Dialogue System) (Litman et al., 2006) is a speech-enabled version of the text-based Why2-Atlas conceptual physics tutoring system (VanLehn et al., 2007). The interaction between ITSPOKE and users is mediated through a graphical web interface supplemented with a headphone-microphone unit. ITSPOKE first analyzes a user typed essay response to a physics problem for mistakes and omissions. Then it engages in a spoken dialogue to remediate the identified problems. Finally, users revise their essay and ITSPOKE either does another round of tutoring/essay revision if needed or moves on to the next problem.

While for most information access SDS performance is measured using task completion or user satisfaction, for the tutoring SDS the primary performance metric is learning. To measure learning, users take a knowledge test before and after interacting with ITSPOKE. The Normalized Learning Gain (**NLG**) is defined as (posttest-pretest)/(1-pretest) and measures the percentage improvement relative to the perfect improvement: an NLG of 0.0 means no improvement while an NLG of 1.0 means maximum improvement.

2.1 Discourse structure

We use the Grosz & Sidner theory of discourse (Grosz and Sidner, 1986). According to this theory, dialogue utterances naturally aggregate into discourse segments, with each segment having an associated purpose or intention. These segments are hierarchically organized forming the discourse structure hierarchy. This hierarchical aspect of dialogue has inspired several generic dialogue management frameworks (e.g. RavenClaw (Bohus, 2007)). We briefly describe our automatic annotation of this hierarchy and its use through discourse transitions. A sample example is shown in Appendix 1. For more details see (Rotaru and Litman, 2006).

Since dialogues with ITSPOKE follow a "tutor question - user answer - tutor response" format, which is hand-authored beforehand in a hierarchical structure, we can easily approximate the discourse structure hierarchy. After the essay analysis, ITSPOKE selects a group of questions which are asked one by one. These questions form the top-level discourse segment (e.g. DS1 in Appendix 1). For incorrect answers to more complex questions (e.g. applying physics laws), ITSPOKE will engage in a *remediation subdialogue* that attempts to remediate the student's lack of knowledge or skills. These subdialogues form the embedded discourse segments (e.g. DS2 in Appendix 2).

We define six *discourse transitions* in the discourse structure hierarchy and use them to label each system turn. A *NewTopLevel* label is used for the first question after an essay submission. If the previous question is at the same level with the current question we label the current question as *Advance*. The first question in a remediation subdialogue is labeled as *Push*. After a remediation subdialogue is completed, ITSPOKE will pop up and a heuristic determines whether to ask again the question that triggered the remediation dialogue. Reasking is labeled as a **PopUp**, while moving on to the next question is labeled as *PopUpAdv*. Rejections due to speech problems or timeouts are labeled as *SameGoal*.

Our transitions partially encode the hierarchical information of discourse structure: they capture the position of each system turn in this hierarchy relative to the previous system turn.

2.2 Discourse structure-based interaction parameters

To derive interaction parameters, we look at *transition–phenomena* and *transition–transition* bigrams. The first type of bigrams is motivated by our intuition that dialogue phenomena related to performance are not uniformly important but have more weight depending on their position in the dialogue. For example, it is more important for users to be correct at specific places in the dialogue rather than overall in the dialogue. We use two phenomena related to performance in our system/domain: user correctness (e.g. correct, incorrect) and user certainty (e.g. uncertain, neutral, etc.). For example, a PopUp-Incorrect event occurs whenever users are incorrect after being reasked the question that initially triggered the remediation dialogue. The second type of bigrams is motivated by our intuition that "good" and "bad" dialogues have different discourse structures. To compare two dialogues in terms of the discourse structure we look at consecutive transitions: e.g. Push-Push.

For each bigram we compute 3 interaction parameters: a total (e.g. the number of PopUp-Incorrect events), a percentage (e.g. the number of PopUp-Incorrect relative to the number of turns) and a relative percentage (e.g. the percentage of times a PopUp is followed by an incorrect answer).

3 Predictiveness

In (Rotaru and Litman, 2006), we demonstrate the predictiveness of several discourse structure-based parameters. Here we summarize the results for parameters derived from the PopUp–Correct and **PopUp–Incorrect** bigrams (Table 1). These bigrams caught our attention as their predictiveness has intuitive interpretations and generalizes to other corpora. Predictiveness was measured by looking at correlations (i.e. univariate linear regression) between our interaction parameters and learning[2]. We used a corpus of 95 dialogues from 20 users (2334 user turns). For brevity, we report in Table 1 only the bigram, the best Pearson's Correlation Coefficient (R) associated with parameters derived from that bigram and the statistical significance of this coefficient (p).

Bigram	R	p
PopUp-Correct	**0.45**	**0.05**
PopUp-Incorrect	**-0.46**	**0.05**

Table 1. Several discourse structure-based parameters significantly correlated with learning (for complete results see (Rotaru and Litman, 2006))

The two bigrams shed light into user's learning patterns. In both cases, the student has just finished a remediation subdialogue and the system is popping up by reasking the original question again (a PopUp transition). We find that correct answers after a PopUp are positively correlated with learning. In contrast, incorrect answers after a PopUp are negatively correlated with learning. We hypothesize that these correlations indicate whether the user took advantage of the additional learning opportunities offered by the remediation subdialogue. By answering correctly the original system question (PopUp–Correct), the user demonstrates that he/she has absorbed the information from the remediation dialogue. This bigram is an indication of a successful learning event. In contrast, answering the original system question incorrectly (PopUp–Incorrect) is an indication of a missed learning opportunity; the more such events happen the less the user learns.

In (Rotaru and Litman, 2006) we also demonstrate that discourse structure is an important source for producing predictive parameters. Indeed, we found that simple correctness parameters (e.g. number of incorrect answers) are surprisingly not predictive in our domain. In contrast, parameters that look at correctness at specific places in the discourse structure hierarchy are predictive (e.g. PopUp–Incorrect).

4 Informativeness

We investigate the informativeness of the PopUp–Incorrect bigram as in (Rotaru, 2008) we also show that its predictiveness generalizes to two other corpora. We need 3 things for this: an interpretation of the predictiveness (i.e. an interpretation of the correlation), a new system strategy derived from this interpretation and a validation of the strategy.

As mentioned in Section 3, our interpretation of the correlation between PopUp–Incorrect events and learning is that these events signal failed learning opportunities. The remediation subdialogue is the failed learning opportunity: the system had a chance to correct user's lack of knowledge and failed to achieve that. The more such events we see, the lesser the system performance.

How can we change the system in light of this interpretation? We propose to *give additional explanations after a PopUp–Incorrect event* as the new strategy. To arrive at this strategy, we hypothesized why the failed opportunity has occurred. The simplest answer is that the user has failed to absorb the information from the remediation dialogue. It is possible that the user did not understand the remediation dialogue and/or failed to make the connection between the remediation dialogue and the original question. The current ITSPOKE strategy after a PopUp–Incorrect is to give away the correct answer and move on. The negative correlations indicate that this strategy is not working. Thus, maybe it would be better if the system will engage in additional explanations to correct the user. If we can make the user understand, then we transform the failed learning opportunity into a successful learning opportunity. This will be equivalent to a PopUp–Correct event which we have seen is *positively* correlated with learning (Section 3).

[2] As it is commonly done in the tutoring research (e.g. (Litman et al., 2006)), we use partial Pearson's correlations between our parameters and the posttest score that account for the pretest score.

While other interpretation and hypotheses might also be true, our results (Section 5) show that the new strategy is successful. This validates the interpretation, the strategy and consequently the informativeness of the parameter.

4.1 Modification

To modify the system, we had to implement the new PopUp–Incorrect strategy: provide additional explanations rather than simply giving away the correct answer and moving on. But how to deliver the additional explanations? One way is to engage in an additional subdialogue. However, this was complicated by the fact that we did not know exactly what information to convey and/or what questions to ask. It was crucial that the information and/or the questions were on target due to the extra burden of the new subdialogue.

Instead, we opted for a different implementation of the strategy: interrupt the conversation at PopUp–Incorrect events and offer the additional explanations in form of a *webpage* that the user will read (recall that ITSPOKE uses in addition a graphical web interface – Section 2). Each potential PopUp–Incorrect event had an associated webpage that is displayed whenever the event occurs. Because the information was presented visually, users can choose which part to read, which meant that we did not have to be on target with our explanations. To return to the spoken dialogue, users pressed a button when done reading the webpage.

All webpages included several pieces of information we judged to be helpful. We included the tutor question, the correct answer and a text summary of the instruction so far and of the remediation subdialogue. We also presented a graphical representation of the discourse structure, called the Navigation Map. Our previous work (Rotaru and Litman, 2007) shows that users prefer this feature over not having it on many subjective dimensions related to understanding. Additional information not discussed by the system was also included if applicable: intuitions and examples from real life, the purpose of the question with respect to the current problem and previous problems and/or possible pitfalls. See Appendix 2 for a sample webpage.

The information we included in the PopUp–Incorrect webpages has a "reflective" nature. For example, we summarize and discuss the relevant instruction. We also comment on the connection between the current problem and previous problems. The value of "reflective" information has been established previously e.g. (Katz et al., 2003).

All webpages and their content were created by one of the authors. All potential places for PopUp–Incorrect events (i.e. system questions) were identified and a webpage was authored for each question. There were 24 such places out of a total of 96 questions the system may ask during the dialogue.

5 Results

There are several ways to demonstrate the success of the new strategy. First, we can investigate if the correlation between PopUp–Incorrect and learning is broken by the new strategy. Our results (5.2) show that this is true. Second, we can show that the new system outperforms the old system. However, this might not be the best way as the new PopUp–Incorrect strategy directly affects only people with PopUp–Incorrect events. In addition, its effect might depend on how many times it was activated. Indeed, we find no significant effect of the new strategy in terms of performance at the population level. However, we find that the new strategy does produce a performance improvement for users that "needed" it the most: users with more PopUp–Incorrect events (5.3).

We begin by describing the user study and then we proceed with our quantitative evaluations.

5.1 User study

To test the effect of the new PopUp–Incorrect strategy, we designed and performed a between-subjects study with 2 conditions. In the control condition (***`R`***) we used the regular version of ITSPOKE with the old PopUp–Incorrect strategy (i.e. give the current answer and move on). In the experimental condition (***`PI`***), we had the regular version of ITSPOKE with the new PopUp–Incorrect strategy (i.e. give additional information).

The resulting corpus has 22 *`R`* users and 25 *`PI`* users and it is balanced for gender. There are 235 dialogues and 3909 user turns. The experiment took 2½ hours per user on average.

5.2 Breaking the correlation

The predictiveness of the PopUp–Incorrect bigram (i.e. its negative correlation with learning) means that PopUp–Incorrect events signal lower performance. One way to validate the effectiveness of the new PopUp–Incorrect strategy is to show that it breaks down this correlation. In other words, PopUp–Incorrect events no longer signal lower performance. Simple correlation does not guarantee that this is true because correlation does not necessarily imply causality.

In our experiment, this translates to showing that that PopUp–Incorrect bigram parameters are still correlated with learning for *R* students but the correlations are weaker for *PI* students. Table 2 shows these correlations. As in Table 1, we show only the bigrams for brevity.

	R users		*PI* users	
Bigram	R	p	R	p
PopUp-Correct	**0.60**	**0.01**	0.18	0.40
PopUp-Incorrect	**-0.65**	**0.01**	-0.18	0.40

Table 2. Correlation with learning in each condition

We find that the connection between user behavior after a PopUp transition and learning continues to be strong for *R* users. PopUp–Incorrect events continue to signal lower performance (i.e. a strong significant negative correlation of -0.65). PopUp–Correct events signal increased performance (i.e. a strong significant positive correlation of +0.60). The fact that these correlations generalize across experiments/corpora further strengthens the predictiveness of the PopUp–Incorrect parameters.

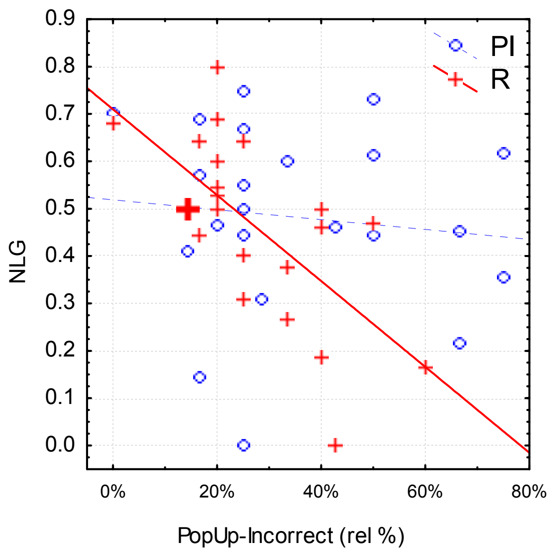

Figure 1. Correlations between a PopUp-Incorrect parameter and NLG

In contrast, for *PI* users these correlations are much weaker with non-significant correlation coefficients of -0.18 and 0.18 respectively. In other words the new PopUp–Incorrect strategy breaks down the observed correlation: PopUp–Incorrect events are no longer a good indicator of lower performance.

It is interesting to visualize these correlations graphically. Figure 1 shows a scatter plot of the PopUp–Incorrect relative percentage parameter and NLG for each *PI* and *R* user. The regression lines for the correlation between PopUp–Incorrect and NLG for *PI* and *R* are shown. The graph shows that users with less PopUp–Incorrect events (e.g. less than 30% relative) tend to have a higher NLG (0.5 or higher) regardless of the condition. However, for users with more PopUp–Incorrect events, the behavior depends on the condition: *R* users (crosses) tend to have lower NLG (0.5 or lower) while *PI* users (circles) tend to cover the whole NLG spectrum (0.2 to 0.73). Our next analysis will provide objective support for this observation.

5.3 Performance improvements

The simplest way to investigate the effect of the new PopUp–Incorrect strategy is to compare the two systems in terms of performance (i.e. learning). Table 3 shows in the second column the learning (NLG) in each condition. We find that the new strategy provides a small 0.02 performance improvement (0.48 vs. 0.46), but this effect is far from being significant. A one-way ANOVA test finds no significant effect of the condition on the NLG ($F(1,45)=0.12$, $p<0.73$).

		PI Split	
	All	Low	High
PI	0.48 (0.19)	0.49 (0.21)	0.48 (0.17)
R	0.46 (0.19)	0.56 (0.13)	0.30 (0.18)

Table 3. System performance (NLG) in each condition
(averages and standard deviation in parentheses)

There are several factors that contribute to this lack of significance. First, the new PopUp–Incorrect strategy is only activated by users that have PopUp–Incorrect events. Including users without such events in our comparison could weaken the effect of the new strategy. Second, the impact of the new strategy might depend on how many times it was activated. This relates back to our hypothesis that that a PopUp–Incorrect is an instance of a failed learning opportunity. If this is true and our new PopUp–Incorrect strategy is effective, then we should see a stronger impact on *PI* users with a higher number of PopUp–Incorrect events compared with the similar *R* users.

To test if the impact of the strategy depends on how many times it was engaged, we split users based on their PopUp–Incorrect (**PISplit**) behavior into two subsets: *Low* and *High*. We used the mean split based on the PopUp–Incorrect relative percentage parameter (see the X axis in Figure 1): users with a parameter value less than 30% go into the Low subset (15 `PI` and 14 `R` users) while the rest go into the High subset (10 `PI` and 8 `R` users).

Results are shown in the third and the fourth columns in Table 3. To test the significance of the effect, we run a two-way factorial ANOVA with NLG as the dependent variable and two factors: PISplit (Low vs. High) and Condition (`PI` vs. `R`). We find a significant effect of the combination PISplit × Condition ($F(1,43)=5.13$, $p<0.03$). This effect and the results of the posthoc tests are visualized in Figure 2. We find that `PI` users have a similar NLG regardless of their PopUp–Incorrect behavior while for `R`, High PISplit users learn less than Low PISplit users. Posthoc tests indicate that High PISplit `R` users learn significantly less than Low PISplit `R` users ($p<0.01$) and both categories of `PI` users ($p<0.05$). In other words, there is an inherent and significant performance gap between `R` users in the two subsets. The effect of the new PopUp–Incorrect strategy is to bridge this gap and bring High PISplit users to the performance level of the Low PISplit users. This confirms that the new PopUp–Incorrect strategy is effective where it is most needed (i.e. High PISplit users).

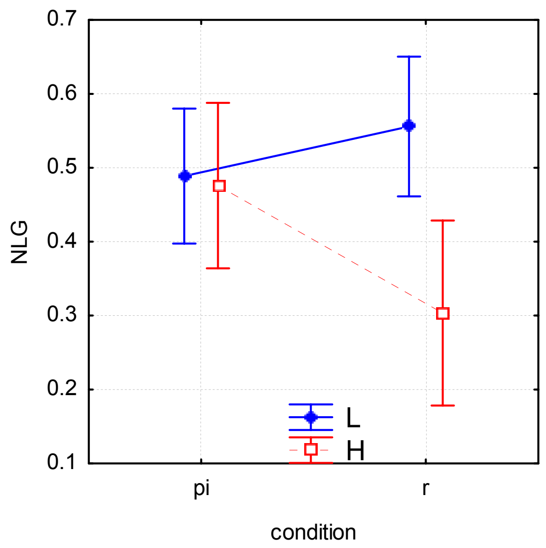

Figure 2. PISplit × Condition effect on NLG (bars represent 95% confidence intervals)

It is interesting to note that Low PISplit `R` users learn better than both categories of `PI` users although the differences are not significant. We hypothesize this happens because not all learning issues are signaled by PopUp–Incorrect events: a user might still have low learning even if he/she does not exhibit any PopUp–Incorrect events. Indeed, there are two `PI` users with a single PopUp–Incorrect event but with very low learning (NLG of 0.00 and 0.14 respectively). It is very likely that other things went wrong for these users rather than the activation of the new PopUp–Incorrect strategy (e.g. they might have other misconceptions that are not addressed by the remediation subdialogues). In fact, removing these two users results in identical NLG averages for the two low PISplit subsets.

5.4 Dialogue duration

We also wanted to know if the new PopUp–Incorrect strategy has an effect on measures of dialogue duration. The strategy delivers additional explanations which can result in an increase in the time users spend with the system (due to reading of the new instruction). Also, when designing tutoring systems researchers strive for learning efficiency: deliver increased learning as fast as possible.

	Total time (min)	No. of sys. turns
`PI`	44.2 (6.2)	86.4 (6.8)
`R`	45.5 (5.7)	90.9 (9.3)

Table 4. Dialogue duration metrics (averages and standard deviation in parentheses)

We look at two shallow dialogue metrics: dialogue time and number of turns. Table 4 shows that, in fact, the dialogue duration is shorter for `PI` users on both metrics. A one way ANOVA finds a non-significant effect on dialogue time ($F(1,45)=0.57$, $p<0.45$) but a trend effect for number of system turns ($F(1,45)=3.72$, $p<0.06$). We hypothesize that 2 factors are at play here. First, the additional information activated by the new PopUp–Incorrect strategy might have a positive effect on users' correctness for future system questions especially on questions that discuss similar topics. As a result, the system has to correct the user less and, consequently, finish faster. Second, the average total time `PI` users spend reading the additional information is very small (about 2 minutes) compared to the average dialogue time.

6 Related work

Designing robust, efficient and usable spoken dialogue systems (**SDS**) is a complex process that is still not well understood by the SDS research community (Möller and Ward, 2008). Typically, a number of evaluation/performance metrics are used to compare multiple (versions of) SDS. But what do these metrics and the resulting comparisons tell us about designing SDS? There are several approaches to answering this question, each requiring a different level of supervision.

One approach that requires little human supervision is to use reinforcement learning. In this approach, the dialogue is modeled as a (partially observable) Markov Decision Process (Levin et al., 2000; Young et al., 2007). A reward is given at the end of the dialogue (i.e. the evaluation metric) and the reinforcement learning process propagates back the reward to learn what the best strategy to employ at each step is. Other semi-automatic approaches include machine learning and decision theoretic approaches (Levin and Pieraccini, 2006; Paek and Horvitz, 2004). However, these semi-automatic approaches are feasible only in small and limited domains though recent work has shown how more complex domains can be modeled (Young et al., 2007).

An approach that works on more complex domains but requires more human effort is through performance analysis: finding and tackling factors that affect the performance (e.g. PARADISE (Walker et al., 2000)). Central to this approach is the quality of the interaction parameters in terms of predicting the performance metric (predictiveness) and informing useful modifications of the system (informativeness). An extensive set of parameters can be found in (Möller, 2005).

Our use of discourse structure for performance analysis extends over previous work in two important aspects. First, we exploit in more detail the hierarchical information in the discourse structure through the domain-independent concept of discourse structure transitions. Most previous work does not use this information (e.g. (Möller, 2005)) or, if used, it is flattened (Walker et al., 2001). Also, to our knowledge, previous work has not employed parameters similar to our transition–phenomena (transition–correctness in this paper) and transition–transition bigram parameters. In addition, several of these parameters are predictive (Rotaru and Litman, 2006).

Second, in our work we also look at the informativeness while most of the previous work stops at the predictiveness step. A notable exception is the work by (Litman and Pan, 2002). The factor they look at is user's having multiple speech recognition problems in the dialogue. This factor is well known in the SDS field and it has been shown to be predictive of system performance by previous work (e.g. (Walker et al., 2000)). To test the informativeness of this factor, Litman and Pan propose a modification of the system in which the initiative and confirmation strategies are changed to more conservative settings whenever the event is detected. Their results show that the modified version leads to improvements in terms of system performance (task completion). We extend over their work by looking at a factor (PopUp–Incorrect) that was not known to be predictive of performance beforehand. We discover this factor through our empirical analyses of existing dialogues and we show that by addressing it (the new PopUp–Incorrect strategy) we also obtain performance improvements (at least for certain users). In addition, we are looking at a performance metric for which significant improvements are harder to obtain with small system changes (e.g. (Graesser et al., 2003)).

7 Conclusions

In this paper we finalize our investigation into the utility of discourse structure for SDS performance analysis (at least for our system). We use the discourse structure transition information in combination with other dialogue phenomena to derive a number of interaction parameters (i.e. transition–phenomena and transition–transition). Our previous work (Rotaru and Litman, 2006) has shown that these parameters are predictive of system performance. Here we take a step further and show that one of these parameters (the PopUp–Incorrect bigram) is also informative. From the interpretation of its predictiveness, we inform a promising modification of our system: offer additional explanations after PopUp–Incorrect events. We implement this modification and we compare it with the original system through a user study. We find that the modification breaks down the negative correlation between PopUp–Incorrect and system performance. In addition, users that need the modification the most (i.e. users with more PopUp–Incorrect events) show significant improvement in performance in the modified system over corresponding users in the original system. However, this improvement is not strong enough to generate significant differences at the population level. Even though the additional explanations add extra time to the dialogue, overall we actually see a small reduction in dialogue duration.

Our work has two main contributions. First, we demonstrate the utility of discourse structure for performance analysis. In fact, our other work (Rotaru and Litman, 2007) shows that discourse structure is also useful for other SDS tasks. Second, to our knowledge, we are the first to show a complete application of the performance analysis methodology. We discover a new set of predictive interaction parameters in our system and we show how our system can be improved in light of these findings. Consequently, we validate performance analysis as an iterative, "debugging" approach to dialogue design. By analyzing corpora collected with an initial version of the system, we can identify semi-automatically problems in the dialogue design. These problems inform a new version of the system which will be tested for performance improvements. In terms of design methodology for tutoring SDS, our results suggest the following design principle: "do not give up but try other approaches". In our case, we do not give up after a PopUp-Incorrect but give additional explanations.

In the future, we would like to extend our work to other systems and domains. This should be relatively straightforward as the main ingredients, the discourse transitions, are domain independent.

Acknowledgments

This work is supported by the NSF grants 0328431 and 0428472. We would like to thank the ITSPOKE group.

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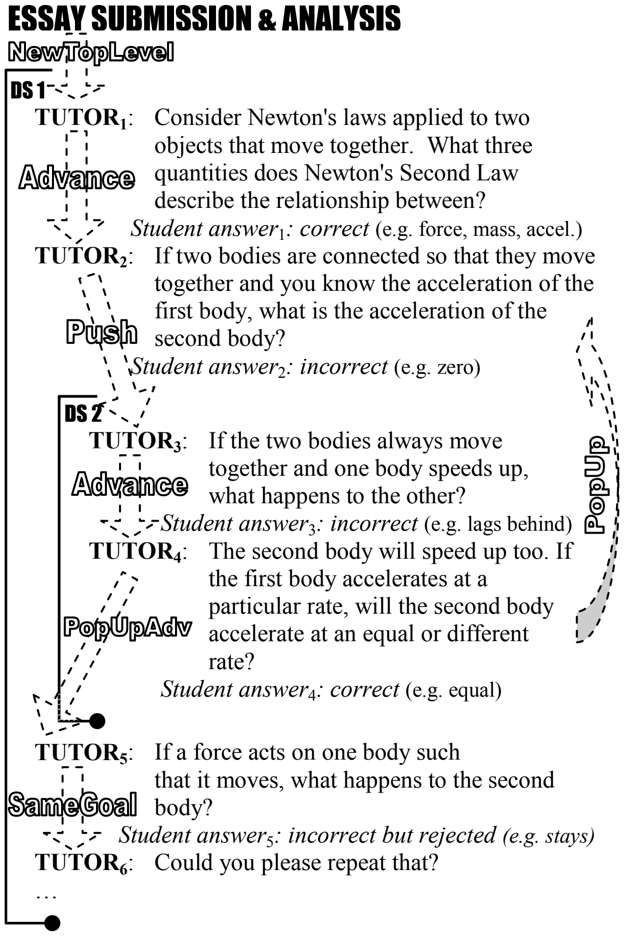
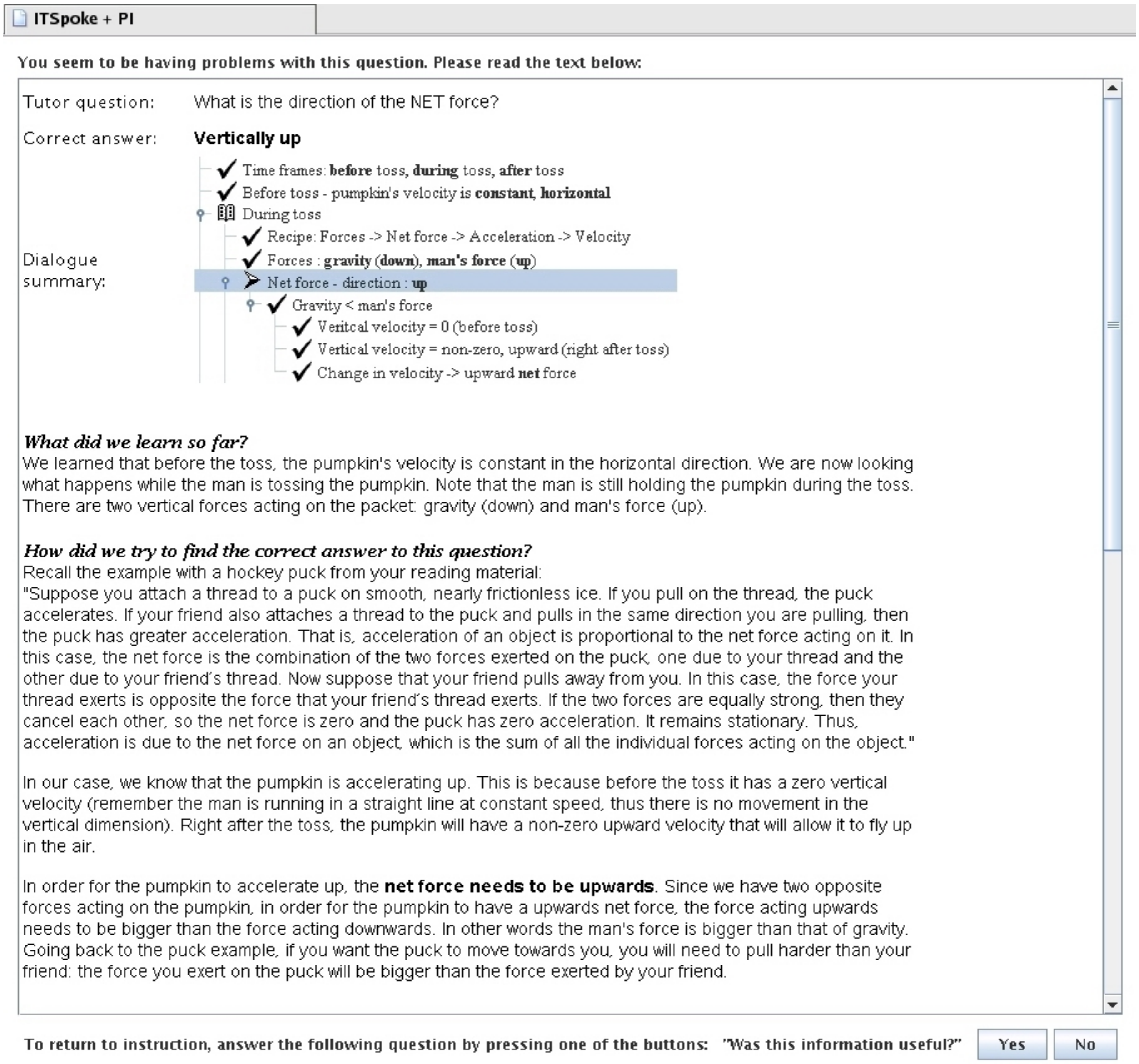


Appendix 1. Automatic annotation of discourse structure hierarchy and of discourse structure transitions

Discourse structure hierarchy annotation: DS1 is the top level discourse segment. Its purpose is to correct misconceptions in user's essay and/or to elicit more complete explanations for the essay. DS2 is an embedded discourse segment which corresponds to the remediation subdialogue for question $Tutor_2$.

Discourse structure transition annotation: Each transition labels the system turn at the tip of the arrow (e.g. $Tutor_2$ is labeled with Advance). Please note that $Tutor_2$ will not be labeled with PopUp because, in such cases, an extra system turn will be created between Tutor4 and Tutor5 with the same content as Tutor2. This extra turn also includes variations of "Ok, back to the original question" to mark the discourse segment boundary transition.



ITSpoke + PI

You seem to be having problems with this question. Please read the text below:

Tutor question: What is the direction of the NET force?

Correct answer: **Vertically up**

Dialogue summary:

- Time frames: **before** toss, **during** toss, **after** toss
- Before toss - pumpkin's velocity is **constant**, **horizontal**
- During toss
  - Recipe: Forces -> Net force -> Acceleration -> Velocity
  - Forces : **gravity** (**down**), **man's force** (**up**)
  - Net force - direction : **up**
    - Gravity < man's force
      - Veritcal velocity = 0 (before toss)
      - Vertical velocity = non-zero, upward (right after toss)
      - Change in velocity -> upward **net** force

What did we learn so far?
We learned that before the toss, the pumpkin's velocity is constant in the horizontal direction. We are now looking what happens while the man is tossing the pumpkin. Note that the man is still holding the pumpkin during the toss. There are two vertical forces acting on the packet: gravity (down) and man's force (up).

How did we try to find the correct answer to this question?
Recall the example with a hockey puck from your reading material:
"Suppose you attach a thread to a puck on smooth, nearly frictionless ice. If you pull on the thread, the puck accelerates. If your friend also attaches a thread to the puck and pulls in the same direction you are pulling, then the puck has greater acceleration. That is, acceleration of an object is proportional to the net force acting on it. In this case, the net force is the combination of the two forces exerted on the puck, one due to your thread and the other due to your friend's thread. Now suppose that your friend pulls away from you. In this case, the force your thread exerts is opposite the force that your friend's thread exerts. If the two forces are equally strong, then they cancel each other, so the net force is zero and the puck has zero acceleration. It remains stationary. Thus, acceleration is due to the net force on an object, which is the sum of all the individual forces acting on the object."

In our case, we know that the pumpkin is accelerating up. This is because before the toss it has a zero vertical velocity (remember the man is running in a straight line at constant speed, thus there is no movement in the vertical dimension). Right after the toss, the pumpkin will have a non-zero upward velocity that will allow it to fly up in the air.

In order for the pumpkin to accelerate up, the **net force needs to be upwards**. Since we have two opposite forces acting on the pumpkin, in order for the pumpkin to have a upwards net force, the force acting upwards needs to be bigger than the force acting downwards. In other words the man's force is bigger than that of gravity. Going back to the puck example, if you want the puck to move towards you, you will need to pull harder than your friend: the force you exert on the puck will be bigger than the force exerted by your friend.

To return to instruction, answer the following question by pressing one of the buttons: "Was this information useful?" Yes No

Appendix 2. Sample additional instructions webpage

Problem discussed by ITSPOKE: Suppose a man is running in a straight line at constant speed. He throws a pumpkin straight up. Where will it land? Explain.

Location in the dialogue: For this problem, ITSPOKE discusses what happens during three time frames: before pumpkin toss, during pumpkin toss and after pumpkin toss. ITSPOKE is currently discussing the forces and the net force on the pumpkin during the toss.