Discovering Discourse Motifs in Instructional Dialog

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Abstract. We propose a method to analyze conversational interaction using discourse motifs (sequence of labels). We focus specifically on instructional transactive discourse. We first describe the characteristics of transactive discourse, its relationship to other frameworks of instructional discourse, and introduce a refined taxonomy of transactive discourse. Based on this new taxonomy, we construct a set of classifiers to automatically label instructional dialog segments. After labeling, we search for salient patterns of discourse common to these chains of labels using Multiple EM for Motif Elicitation and Gapped Local Analysis of Motifs (which are two techniques available for DNA and protein motif discovery). From our analysis of a corpus of classroom data, a set of Transactive-Participatory-Coherent motifs emerge. This approach to interaction-motif discovery and analysis can find application in dialog and discourse analysis, pedagogical domains (e.g., assessment and professional development), automatic tutoring systems, meeting analysis, problem solving, etc.

1 Introduction

We focus on the analysis of classroom discourse particularly when the focus is on solving mathematical problems. While the analysis of classroom discourse and mathematical problem solving is useful in providing pedagogical insight into teaching practices (see for example Huerta (2008), Blanton (2008)), its analysis can also shed light into interaction mechanisms used in more general collaborative problem solving.

Research in human dialog has been approached from various viewpoints using frameworks and methodologies of analysis that have been tailored to address the specific requirements of these viewpoints (examples of relatively recent perspectives to dialog analysis include Stolcke (2000), Stent (2000) among others, and a good summary can be found in Moore (2003)).

More problem-solving specific frameworks have also been proposed to analyze planning-oriented and instructional dialog in the classroom (Linden (1995)). Additionally, there have also been other efforts in the manual analysis of classroom interaction from purely pedagogical and sociological perspectives (Blanton (2008), Mehan (1985), Stark (2002), Haussman (2003)). There has been also work focusing on specific theoretical frameworks of interaction and the correlation of their elements to individual learning (e.g., Haussman (2006) and elaborative discourse, Meyer (2002) and scaffolding and self-regulation) as well as development of discourse frameworks

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for the analysis of tutoring speech and implementation of tutoring systems (e.g., Marineau (2000)) .

The specific focus of this paper is around discourse that occurs inside a classroom when the teacher guides and regulates problem-solving activities with the students. We look into Mathematics classes when the classroom is collaboratively solving a problem under the guidance of the instructor. We propose a taxonomy of instructional discourse acts that is specific to this domain and focus on transactive and coherence elements and use this taxonomy to label discourse. The result of this labeling is a set of strings, or linear sequences of labels. We then apply techniques for the discovery of motifs (strong patterns) in these strings. The goal is to extract motifs that can be of interest and help us identify strong or salient patterns. Because our taxonomy is based specifically on transactive and coherent discourse, the motifs that emerge during our data analysis strongly highlight these characteristics. Motifs discovered in this fashion can be used as features of further stages of discourse analysis in support of applications in the areas of problem solving, tutoring systems, meeting analysis, as well as purely pedagogical ones.

While the techniques developed for essay analysis (e.g., Burstein (2003) and Burstein (2003b)) address a different series of issues (due to the differences between essay discourse and classroom interaction), some basic ideas (like the relevance of coherence discourse) can be utilized for the analysis of classroom interaction.

This paper is organized as follows, in Section 2 we present a general overview of the main existing approaches that are relevant to this paper; specifically, we describe the framework of transactive discourse based on Blanton (2008) and Huerta (2008). In section 3 we describe in detail the particular taxonomy labels that we use in later sections of this paper and describe the classification techniques we used in order to label our data. In section 4 we describe the methods we use to discover motif sequences in the labels of classroom discourse. In section 5 we describe the results of the analysis of data and the most salient motifs of this discourse and illustrate how these motifs can be utilized in dialog analysis applications. And finally in section 6 we conclude our paper with a summary of the contributions of this paper, a discussion of results observed and a discussion of future directions.

2 Relevant Approaches

In this section we briefly describe some of the existing theories and abstractions that are most related to this paper, specifically RST, elaborative-collaborative dialog, and transactive dialog.

In the area of theories of discourse analysis, Rhetorical Structure Theory is quite relevant to the type of discourse we focus on; specifically, Stent (2000) proposed the application of RST for content-planning of mixed-initiative task-oriented dialogs (TRIPS dialogs). RST is a descriptive theory of hierarchical structure in discourse that identifies functional relationships between discourse parts based on the intentions behind their production (Mann (1987)). While the discourse activity that occurs in the classroom in the context of mathematic problem solving to have many commonalities with the sort of mixed-initiative, task oriented, content-planning characteristics of a domain like TRIPS, a much simpler taxonomy to the classroom data suffices.

Hausmann (2006), focuses on measuring the effect that elaborative and collaborative dialogs have on learning and understanding. In his literature review, he says that previous research has found that *only certain* collaborative dialogs have been found to have strong gains in understanding. He says that while elaborative dialog has been shown to impact individual learning, for collaborative learning the results have shown no correlation with deeper measure techniques can be trained and lead to deep learning outcomes.

Transactive reasoning is defined as discourse in which the participant continues the reasoning, analysis or interpretation of the discussion and which possibly leads into or motivates further transactive discourse (Blanton 2008). Berkowitz (1983) describe transactive dialogs as, “reasoning that operates on the reasoning of another”. Co-construction qualifies as a transactive dialog because the listener takes the speaker’s message as input, manipulates it, and produces an output based on, yet separate from, the original input (Salomon, 1993).

We can see then, that elaborative dialog is a subset of the transactive discourse and that frameworks focusing on transactive discourse are adequate for analyzing mathematical problem solving in the classroom.

In terms of abstractions for analysis, Truxaw (2004) and DeFranco (2007) describes recursive discourse cycles as components of a cyclical process. The authors describe that in their observed data this cyclical process serves an inductive purpose (to move from the particular to the general hypothesis and rules). For this purpose they rely on the concept of a sequence map, which is a machine that produces the observed sequence. In Truxaw and DeFranco (2002) a sociolinguistic framework is used to analyze classroom speech using sequence maps.

We have defined as an interaction motif as sequence of labels that describe the discourse given a taxonomy and a coherent portion of discourse. A sequence map is the finite state machine that accepts such motif. In this paper we will focus on the mechanisms of discovery of motifs, and such motifs can be abstracted into sequence maps.

3 Taxonomy of Transactive Discourse

In this section we describe the basic taxonomy of problem-solving oriented classroom discourse that we use in this paper. It is based in (Blanton (2008) and Huerta (2008)).

3.1 Taxonomy

The basic components of the taxonomy are described in terms of mutually exclusive characteristics or labels. The basic characteristics/labels are:

- **Transactive Teacher Prompt:** Question or prompt in which the instructor *elicits* continued reasoning, analysis or interpretation of the discussion and which response possibly leads into or motivates further transactive discourse

- **Transactive and Non-transactive Student Response:** A student participates in a non-trivial way. It can be both transactive response, as in providing further elaboration to the thinking and discussion process, or it can be non-transactive, like a direct yes-no response to a question.
- **Student-Coherence Teacher Discourse:** The instructor implicitly validates or emphasizes the student utterance by repeating verbatim or paraphrasing part, or the whole, of what the student has said. This is related to coherence in essays and in text to work by Barzilay (2006), Higgins (2004) , Grosz (1995), and Higgings (2006).
- **Explicit Teacher Validation:** The Instructor explicitly validates a student response by using yes-no utterances or equivalent expressions (e.g., 'sure", "of course", etc).
- **Other (Instructive+Directive):** This is a catch-all category absorbs all the teacher's utterances that fall mostly in the instructive and directive categories. Instructive utterances are those that the teacher uses to lecture, or teach. Directive utterances are those that the teacher uses to provide overall direction of activities.

The labels above are not meant to be exhaustive; hence, the *other* category. In the discourse there are other possible labels, but for now we focus on these. A single utterance can combine more than one of the characteristics above: e.g., a teacher might say in a single utterance: "That's quite a good guess, anybody else has a different answer?" which would simultaneously correspond to Explicit Validation and Transactive Teacher Question categories. We will explain further below how we code this.

Thus, we map sentences with the characteristics above to sequences of 5 characters (or labels). The character order is very important for motif analysis. Table 1 shows the maps from characteristics or labels to characters for each utterance.

3.2 Classification and Labeling Approaches

Here we describe how the labels are generated. Due to the relative simplicity of the classroom speech, most of these classifiers are quite simple.

- Transactive teacher prompt: We could have relied on bag-of-words Maximum Entropy approaches to utterance classification (like Wu et al., 2003), but we noticed that most of the time, in classroom speech, simple rule-based approaches suffice (key-words, key-phrases, and lexical patterns), i.e., we look for words like "what is" (Spoerleder (2005) analogously looks into lexical cues for rhetorical relations)
- Student: Trivial mapping generated from the speaker identification.
- Student-Coherence Teacher discourse: Substantial work has been done in this area for document/essay coherence (Higgins 2004, Higgins 2006, Barzilay 2008). Bag of word comparisons based on frequencies or on word rank orders (Huerta 2008) are possible.
- Explicit teacher validation: Similarly, simple keyword suffices, but also other classification approaches (like Maximum Entropy) could be used.

- Other (Instructive+Directive): This is not performed using an actual classifier, but rather is the remainder of the teacher's utterances that are not transactive, coherent-student, or validation. An utterance will fall in this category if none of the features used to identify the other teacher labels are found.

Table 1. Label-to-string mapping

	Transactive Teacher Prompt	Student Response	Student Coherence Teacher	Explicit Reaffirmation	Directive+ Instructive Teacher
S		1			
T	1				
C			1		
YC			1	1	
YCT	1		1	1	
YT	1			1	
CT	1		1		
Y				1	
X					1

4 Methods for Motif Discovery

We have defined a motif as a strong recurring pattern in the sequence of characters. As our taxonomy defines labels in terms of transactive roles in the discourse, we expect that the patterns that emerge reflect transactive motifs that provide insight into the interaction. Depending on the approach, a Motif can be permitted to have gaps and insertions and deletions, as well as to make various assumptions regarding the minimum and maximum times a motif occurs as well as the location of the motif (context). We used specifically the MEME and GLAM approaches which we detail below.

4.1 Multiple EM for Motif Elicitation

The MEM method (Bailey 1994, Bailey 2006) [1] is a Maximum Likelihood based approach to motif discovery. It works with the assumption that motifs occur zero or more times in the data. It uses a two component finite mixture model. One component models the probability that each position in a segment of length n in the sequence was generated *independently* by a position-specific multinomial random trial variable. The background model has a similar multinomial random variable but it is not position specific. The dataset over which the models are trained consists of all possible over-

[1] http://meme.nbcr.net/meme4/cgi-bin/meme.cgi

lapping segments of length *n* in the data. There are constraints in place to ensure that the model does not predict that two overlapping sequences were predicted by the same motif, as well as to reduce its bias to sequences of one or two letters.

4.2 Gapped Local Analysis of Motifs

GLAM (Frith 2008) [2] searches for key positions in the input sequences optimizing this number of key positions. Each sequence string contributes only zero or one substrings to the alignment. GLAM maximizes the alignment score which includes penalizations for insertions and deletions, penalizing less if these are clustered together. The model has position specific residue (character generation) probabilities as well as position-specific insertion and deletion probabilities. A Beta distribution for priors is assumed. Search is performed using stochastic annealing.

5 Experiments

In this section we describe the experiments we perform on motif discovery. We used as a corpus data from a college course on Discrete Mathematics at freshman level that was recorded and manually transcribed (Blanton 2008). Four segments were identified for analysis. These segments originated in four different lectures. These segments comprised a total of 1000 turns (utterances), more than 18,000 words (tokens) and around 100 minutes of classroom interaction.

5.1 Discourse Labeling and Sequence Generation

Each segment was classified as described in section 3.2. Labels were converted into sequences of characters (one utterance was allowed to generate more than one character). Figure 1 below shows a level plot corresponding to the instructional discourse labels found in one of the for segments, which consisted of 331 events (or utterances). In this figure, each dot at level 0.8 represents a Transactive and non-transactive student response, a dot at level 1.0 represents a Transactive-Teacher prompt, a dot at level 1.1 represent a student-coherence teacher response, a dot at level 1.2 represents an explicit teacher validation, and a dot at level zero represents *other*. In this example, it is very clear from the figure that there *are* patterns of interaction present in the classroom data. Through motif analysis, we will show how to identify those motifs. Motifs can be used as features in analysis that address questions like: what is the effect or correlation of a certain motif in the future student response? What are the characteristic discourse patterns that emerge for a specific teacher? Are teachers A and B using similar interaction strategies in the classroom?

[2] http://meme.sdsc.edu/meme4/cgi-bin/glam2.cgi

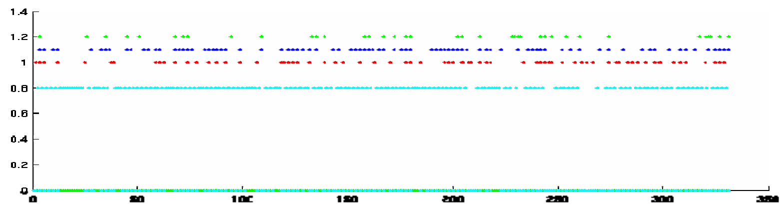
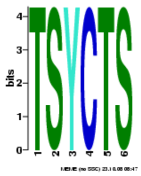


Fig. 1. Level plot of instructional discourse labels for a lecture segment.

5.2 Motif Discovery

We now analyze the four segments using MEM and GLAM. MEM allows for any number of repetitions to be present in the data. We first specified a minimum motif length of 4, a maximum of 6. The main pattern found is TCYCTS, which means a Transactive teacher prompt, followed by student participation, followed by explicit affirmation, then coherent teacher discourse (and then a fresh Transactive and Coherent labels).



The relative entropy of the motif relative to a uniform background frequency model is 25.9 bits. It was found 20 times in the data. When we limited our search exclusively to motifs of length 4, the result is CTSY, which is essentially included in the 6 character pattern originally found. One could argue that the core of this pattern is TSYC, or even more simply TSC. The block diagram, showing the occurrences of exactly the TSYCTS motif in the data is shown below:

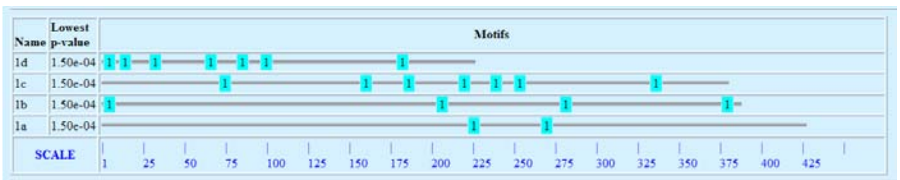
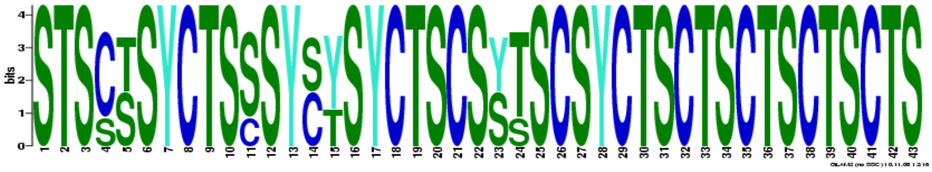
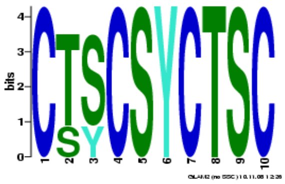


Fig. 2. Block diagram displaying the location of the occurrences of the TSYCTS motif in the data.

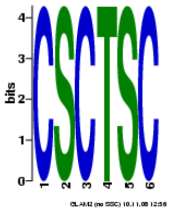
GLAM allows for insertions and deletions and thus is able to provide longer runs. The results of the GLAM analysis are very different from the MEM results and can be used to supplement each other. The parameters we used initially for GLAM are: Minimum number of sequences in the alignment=2, Min. Num. of aligned columns=50, Initial num of aligned cols =4, num alignment runs=40. The Result is shown below.



When constrained to find a shorter motif the result is:



Reducing further the length of the found motif:



GLAM provides, in addition to the best motif, the top alignments in the data allowing for deletions and insertion. The motif found by MEME is alignment #40 in GLAM with score 58.49. In other words CSCTSC is the most generalizable pattern under insertions and deletions.

Considering this alignment that exist in both MEME and GLAM both approaches produced very consistent results.

So far, we have just applied two techniques to extraction and discovery of motifs. Now we are interested in applying these newly discovered motifs to further analyze the data.

5.3 Motifs as Discourse Analysis Features

We have shown how to discover and extract interaction motifs. These motifs can be then used as features in the analysis of the discourse. In this section we present a simple example of such analysis. For this purpose, we define two parameters we are interested in analyzing: the smoothed participation index and the smoothed transactive coherent (TSC) pattern. The smoothing of the TSC pattern is defined simply as a sort of asymmetrically *charging* and discharging a virtual capacitor in which if either motifs TSYC and YSC are found in the dialog the value of function increases (charges) at a certain rate and if not it decreases (discharges) at another rate, i.e. if the smoothed TSC at time i is denoted by s_i,

$$s_i = \begin{cases} 0.8 + 0.2 s_{i-1} & \text{if TSC patterns occur at time i} \\ 0.9 s_{i-1} & \text{if TSC pattern does not occur at time i} \end{cases}$$

The participation index is defined similarly as the smoothed TSC pattern, except that it will charge at time *i* if a student event occurs then and it will discharge otherwise. Ideally, for balanced participation, this index should have value 0.5. Below we show the

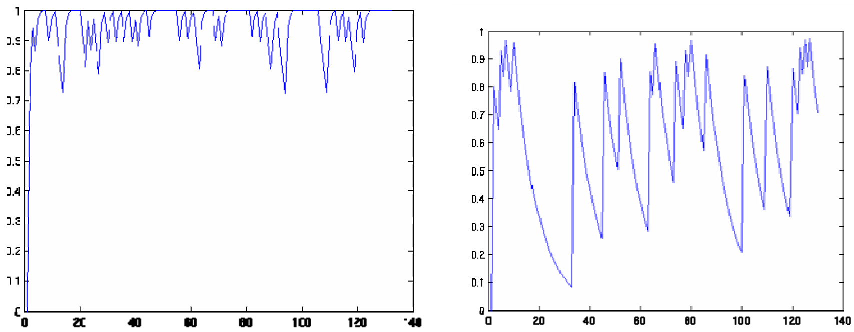


Fig. 3. Sample smoothed TSC (top) and participation functions for a segment of classroom discourse.

We now show the scatter plot between the log values of the two variables observed above except that we provide a time lag of 10 events. This scatter plot shows us the extent of the predictability of the logarithm of the balanced interaction coefficient and the logarithm of the smoothed occurrences of the TSC motif. As we can see, there is a region of correlation in which there seems to be strong.

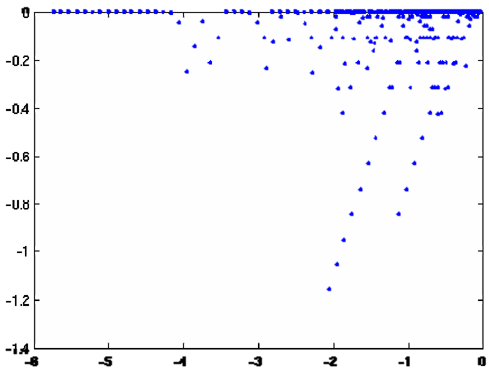


Fig. 4. Scatter plot of the log values of the delayed (time lagged) smoothed student participation index smoothed vs. smoothed TSC values.

6 Conclusions

In this paper we have looked at instructional mathematical discourse, and we have introduced a simple taxonomy to label classroom discourse events based on transactive and coherence discourse. We have discussed how classroom discourse events (utterances) can be classified into these categories using simple lexical feature classifiers, which can be easily extended to Logistic Regression/Maximum Entropy classifiers. We discussed to approaches to Motif discovery in biological sequences (MEM and GLAM) and introduced the utilization of these approaches to the sequences created by the interaction discourse labelers. Analysis of classroom data using both the Maximum Likelihood computation of finite mixtures and the Gapped local analysis using stochastic annealing revealed a common basic pattern: the TSC (which also generates TSYC and TSYCT). We demonstrated how based on motifs discovered using MEM and GLAM it is possible to use these motifs for other purposes, like prediction of interaction coefficient balance, or other predictive or analytic applications.

The main contribution of this paper is the introduction of a motif-based analysis of sequence of discourse labels and the application of motif discovering approaches used for DNA and protein motif discovery.

Future work should integrate motif discovery with other discourse analysis approaches including, for example, the modeling of discourse using dynamical systems, etc. Applications of the motif discovery approach includes: feature discovery for Tutoring systems, problem solving systems, meeting summarization as well as pedagogy-specific applications like teacher assessment, student assessment, professional development, portfolio creation and analysis, et cetera.

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