Combining Structural, Process-oriented and Textual Elements to Generate Awareness Indicators for Graphical E-discussions

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Moderation of e-discussions can be facilitated by online feedback promoting awareness and understanding of the ongoing discussion. Such feedback may be based on indicators, which combine structural and process-oriented elements (e.g., types of connectors, user actions) with textual elements (discussion content). In the ARGUNAUT project (IST-2005027728, partially funded by the EC, started 12/2005) we explore two main directions for generating such indicators, in the context of a synchronous tool for graphical e-discussion. One direction is the training of machine-learning classifiers to classify discussion units (shapes and paired-shapes) into pre-defined theoretical categories, using structural and process-oriented attributes. The classifiers are trained with examples categorized by humans, based on content and some contextual cues. A second direction is the use of a pattern matching tool in conjunction with e-discussion XML log files to generate "rules" that find "patterns" combining user actions (e.g., create shape, delete link) and structural elements with content keywords.

Introduction

The term *awareness* is defined as “an understanding of the activities of the others which provides context for your own activity” (Dourish & Belloti, 1992). A great variety of tools for e-discussion and e-collaboration are available today, many of which offer awareness features for participants or moderators of discussions (for a review, see Soller, Martinez, Jermann, & Muehlenbrock, 2005). Awareness feedback in the different awareness tools has been based on various properties of the discussion, such as social interaction patterns, participation information, temporal stages and text analysis. An interesting example of feedback on structural issues in e-discussions is the DREW system (Baker, Quignard, Lund & Sejourne, 2003), which highlights opposing opinions in discussion graphs Yet, a systematic integration and combination of structural, process-oriented, and textual aspects has only recently been discussed in initiatives such as the Interaction Analysis project in the European Kaleidoscope network (http://www.noe-kaleidoscope.org).

One of the goals of the ARGUNAUT project (IST-2005027728, http://www.argunaut.org) is to obtain more meaningful indicators upon which to base online feedback to the moderators of synchronous graphical e-discussions. The methods described here were applied to the discussion products of a graphical e-discussion tool called Digalo (http://dunes.gr), but are relevant to other synchronous discussion tools, particularly graphical e-discussion tools.

Digalo discussions are held within an object space called a "map". Within this space, users contribute to the discussion by adding shapes representing argumentative ontology (e.g., rectangle for claims) and typing their text into them. Users may also link shapes to other shapes, using arrows of different types (support, opposition. reference). The shape and arrow objects may be modified or deleted. All user actions are logged, and XML log files are generated detailing all the actions taken by the users (e.g., user_1 created a claim shape at time_x). For each such discussion map, we can investigate structural, process-oriented and textual elements. The *structural elements* are the direct or computable attributes of each shape or arrow object (such as type, creator, number of characters) and any combination using these attributes as building blocks. The *process-oriented elements* are comprised of user actions on the discussion objects, and sequences thereof (stressing the dimension of time and the *process* of discussion rather than the end product). The *textual elements* are the free text contributions typed within each shape.

Within the context of the ARGUNAUT project, we are confronted with the challenge of combining some of the above-mentioned elements to generate awareness indicators. These awareness indicators will help us discover meaningful patterns in e-discussions. This approach is facilitated by the collaboration of specialized teams with expertise in various fields (pedagogy, argumentation, linguistics, software development, and machine learning). We believe our ongoing progress in this endeavor will have theoretical, pedagogical and technological implications for the evaluation of graphical e-discussions and for supporting the moderation of collaborative work and discussions.

Analyzing Graphical E-discussions: Methods and Initial Results

We have focused on two approaches to the analysis of e-discussions, combining structural, procedural and textual elements: machine-learning classifications and a rule-based approach for the definition and discovery of action patterns. These approaches are expected to yield complementary analysis results for e-discussions. We have applied these two approaches to Digalo log files of classroom e-discussions with some promising initial results. The following sections present both approaches and a brief summary of our progress so far.

During the conference, we plan on demonstrating both methods described below: the application of machine learning to our pre-annotated examples and the definition of action sequence patterns and pattern-matching log-file search for these patterns, using a specialized tool (also described below).

Machine-learning classifications

Taking a cue from previous work on automated analysis of collaborative argumentation (e.g., Domnez, Rosé, Stegmann, Weinberger, & Fischer, 2005), we applied machine-learning algorithms to the task of classifying the content of e-discussion contributions.

Graphical e-discussions (and specifically Digalo maps), may be coded or annotated at different levels of granularity. We began by focusing on *individual contributions (shapes)* as the classified units. We also classified contributions at a more complex unit of analysis, *paired shapes*, comprised of two contributions (shapes) and the link between them (arrow). This unit goes beyond a single utterance: it includes two distinct but related pieces of texts, and can only be interpreted or categorized using both contributions. Additionally, its definition includes structural relationships (a connector), and the interpretation of the intent behind the text must also consider the order of their appearance, a process-oriented element.

The attributes selected for single-shape classification included: the type of shape, the length of text within it, and the presence or absence of several classes of links (e.g., presence of outgoing links to a shape by the same user). We selected three sets of attributes at the paired-shape level for analysis: a basic set that did not consider the order of shapes (e.g., whether the shapes were created by the same user, their combined text length, type of connector), a set that assumed the shapes appeared in a particular order (e.g., whether the link created by the same user as the first shape), and a set that relied on our previous annotations for the shape level.

For each level of analysis, we created coding schemes based on theoretical, pedagogical and empirical considerations related to fostering productive collective argumentation. The coding schemes included, for example, labels such as 'task management' (shape level), and 'contribution followed by counter-argument' (paired-shapes level). The coding schemes are content-oriented, but take into account other elements (e.g., type of link), in some cases where the text's intention is unclear. The initial coding schemes were fine-tuned via a process of 2 or 3 coders annotating a small number of maps and subsequent discussion between them. The resulting schemes were used to code 42 Digalo discussion maps at the shape level, and 21 of those maps at the paired shapes level. Inter-rater reliability was assessed and coding differences were resolved by discussion or decision rules.

The coded sheets were then analyzed by a variety of machine-learning schemes, implemented within the WEKA framework (Witten and Frank, 2005, e.g., C4.5 Decision Tree, OneR, AdaBoost with OneR, PART), to try and generate accurate classifiers for new contributions. The initial results have been promising, in particular for the shape-level label of ‘critical reasoning’ (the C4.5 Decision Tree had 86% of overall accuracy) and the paired-shapes label of ‘question followed by answer’ (the PART algorithm had 94% overall accuracy). Some of the other classifiers also resulted in high accuracy, but relied too much on biased data (e.g., 89% of the shapes were 'on topic').

The Pattern Discovery Tool: Creating Rules to Detect Meaningful Action Sequences

The Pattern Discovery Tool, developed by the COLLIDE research group (Harrer, Vetter, Thür, & Brauckmann, 2005), was applied to the task of searching for patterns of user actions in e-discussion logs.

Sequences of actions, units comprised of sequential user actions logged by the discussion tool, can be considered process-oriented elements. Each action can be defined using the type of action (e.g., create, delete), the type of object(s) involved, the user(s) involved, and keywords to search for in the text parts of the objects. The generated PROLOG rule defining a sequence of such actions also includes a temporal element of order (first action, second action, etc.), and referencing information (for users and objects). For example, you can define a sequence in which a 'claim' shape is created by a user, modified by the same user, and later deleted by another user.

Our approach in the ARGUNAUT project is to pre-define possible action sequences which we think may be meaningful, i.e. representing specific theoretical or pedagogical phenomena, and to look for such sequences in XML logs of discussions. For example, consider a sequence in which one user creates a shape, another user creates a question shape (or a shape containing a question keyword) and then links it to the first user's shape, followed by the first user creating a shape with keywords such as 'because', 'reason', 'therefore' and linking it to the question shape. This could represent a request for clarification or reason (perhaps the initial contribution was an unsupported claim), which prompted the first user to give reasons for his or her opinion. This is exactly the type of pedagogical phenomenon within e-discussions that interests us.

However, the 'hits' for a particular rule in the discussion logs may not always reflect the phenomenon we wish to capture. We may therefore attempt to annotate the hits received according to whether they truly represent the semantic interpretation assigned to them ('good hits'), and then to use machine learning on these annotations (pending a sufficient number of coded examples to serve as a training set for classification learning).

Future Directions in the Support of e-discussion Moderation

Our vision is to utilize the products of the approaches described above to support the ARGUNAUT system, a tool currently in development. This tool is aimed at supporting online moderation of graphical e-discussions (e.g., Digalo discussions), providing meaningful feedback and advice to the moderators. The first prototype of the system, to be completed in January 2007, is expected to integrate an AI classifier for 'critical reasoning' as well as a few PROLOG rules that can identify action patterns.

It will take further theoretical and empirical work to reach a close-to-optimal set of indicators. To reach this goal, we plan to use an iterative process of experimentation and refinement, in which we will receive feedback from end users (moderators) about the effectiveness of the produced indicators. We also plan to observe and analyze the effect of the use of our awareness tools on the quality of e-moderation and e-discussion. However, we can already say that these innovative approaches to combining structural, process-oriented and textual elements have displayed great potential for analyzing graphical e-discussions and providing support to moderators of such discussions.

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