Advances in Writing Analytics: Mapping the state of the field

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ABSTRACT: Writing analytics as a field is growing in terms of the tools and technologies developed to support student writing, methods to collect and analyze writing data, and the embedding of tools in pedagogical contexts to make them relevant for learning. This workshop will facilitate discussion on recent writing analytics research by researchers, writing tool developers, theorists and practitioners to map the current state of the field, identify issues and develop future directions for advances in writing analytics.

Keywords: writing analytics, learning analytics, collaborative writing, writing theories, writing analytics advances

1 BACKGROUND

As technological capabilities progress in the field of understanding natural language, there is increasing interest in their application to study and improve writing. *Writing analytics* has emerged as a sub-domain of learning analytics to support the analysis of written products and processes in educational contexts (Buckingham Shum et al., 2016). The time-consuming and labor-intensive process of assessing writing makes it hard for educators to provide formative feedback on students' writing, which could be supported by writing analytics. An application of writing analytics that has gained traction is the use of tools that provide automated feedback and writing instruction to improve students' writing skills (Allen, Jacovina, & McNamara, 2015; Liu, Li, Xu, & Liu, 2017; Woods, Adamson, Miel, & Mayfield, 2017). Such tools developed across different educational levels engage students directly to aid in the improvement of their writing skills. Another objective of writing analytics tools and techniques is to understand the writing *products* and *processes* deeper to contribute to the theory and research on writing, which can then lead to its application in writing contexts (McNamara, Graesser, McCarthy, & Cai, 2014). In addition to studying user behavior and interaction through log data, this can inform design choices in writing tool development. These applications build on the main notion of developing a synergy between writing analytics technology and pedagogical practice, so that the educational context is meaningfully embedded in the use of these technologies. Three previous workshops run on this topic have focused on critical perspectives and community building around writing analytics in LAK (Buckingham Shum et al., 2016), developing a writing analytics literacy and practitioner capacity (Knight, Allen, Gibson, McNamara, & Buckingham Shum, 2017) and a hands-on-training for developing this literacy by understanding technical affordances and aligning them to pedagogical feedback (Shibani, Abel, Gibson, & Knight, 2018).

2 WORKSHOP FOCUS

The proposed fourth workshop in the series will build on the previous writing analytics workshops to develop writing analytics literacy and map the field for the future. The focus will be on critically assessing the current state of work being done in the field, and how it could be directed towards the future by considering key issues. The key thread of integrating writing analytics with pedagogy will be emphasized, by connecting theory, pedagogy and assessment to close the feedback loop (Knight, Shum, & Littleton, 2014; Shibani, Knight, Buckingham Shum, & Ryan, 2017). The pedagogic relevance and the question of why writing analytics is employed and what it can add to the existing system will be brought into discussion by practitioners. In this way, we maintain a productive dialogue among different stakeholders like educators, researchers and developers for effective implementation of learning analytics in the classroom (Thompson et al., 2018; Shibani, Knight, & Buckingham Shum, 2019).

The landscape of tools that offer support for writing is constantly changing with new tools getting introduced and the existing ones getting updated, to incorporate the technical advances and the data made available over time (Liu, Calvo, Pardo, & Martin, 2015; McDonald, Moskal, Gunn, & Donald, 2018; Rapp & Ott, 2017; Woods et al., 2017). The ways in which we study writing, and respective systems that support its instruction and practice, have also considerably changed with technological affordances like keystroke-level analysis which allow for a more fine-grained level of analysis, and multiple sources of data which allow for triangulation and validation while studying writing processes. It is important to share knowledge from related work on writing, for instance process-mining and temporal analysis, that can contribute to writing analytics research. This will expand the knowledge base of the community and find relevant opportunities to meaningfully collect, analyze, visualize and use data to derive insights that are relevant for the learning contexts. Hence, the workshop will encourage presentations on various tools and techniques to understand and improve writing.

With growth in the field of Writing Analytics, the multidisciplinary of the field, and the different ways in which researchers engage with its development, it is important to align the goals of the field within the community. Community building generates a shared understanding and common goals to work towards the future of the field. While considering the potential pathways for the field to progress, we will also include discussions on the pushbacks and critical perspectives that can affect how the field moves forward. This includes legal and ethical considerations on the use of students' data, development of learning theories to support writing analytics technology, and evaluation methods to assess these advances for their real impact to meaningfully contribute to writing.

Thus, the fourth workshop is intended to:

1. Build on the existing dialogue around developing writing analytics literacy and pedagogic integration by connecting different stakeholders like practitioners and researchers.

2. Expand the knowledge of the field by discussing about novel approaches and tools being developed by different researchers that contribute to writing analytics research.

3. Move the field forward by building a community for writing analytics research and thinking about pushbacks and potential future steps.

3 SUBMISSIONS AND WORKSHOP FORMAT

Workshop activities and schedule

The full-day workshop will include a number of presentations and demonstrations from researchers to share their work within the writing analytics community (depending on the interest generated). It will include round-table and open discussions throughout the day to steer the direction of writing analytics work and possible pathways for future advances in the field. The provisional program is given below:

Introductions (30 minutes): Introductions of workshop organizers and participants, and a quick background to the field of writing analytics.
Presentations (10-15 minutes each): Presentations and demonstrations from accepted papers and invited researchers on their writing analytics tool or technology, the data collected by the tool, analysis of writing data and how it contributes to writing theory, and the direction of future work.
Discussion Blocks (5-10 minutes each): Discussion blocks will follow each presentation to ask critical questions on what can be done and analyzed from the tool/data, how and why.
Round-table discussion (1 hour): Key topics for discussion from the presentations will be selected for round-table discussion. Participants can move around tables to discuss more in detail on the topic they are interested in. Potential topics include collaborative writing analytics, analytical and reflective writing analytics, writing feedback visualization and writing theories.
Open discussion (30 minutes): Open discussion facilitated among all participants on the advances in writing analytics and its potential future, co-creation of shared notes and resources.
Writing analytics community engagement (30 minutes): Building the community of writing analytics researchers by connecting existing and new researchers in the field. Formation of a formal writing analytics committee if participants are interested.
Concluding remarks and future directions (15 minutes): Brief summary and closing remarks on the workshop with future steps.

Program Committee

Co-chairs of the workshop will invite researchers and companies active in the field of writing analytics to present their work in the form of tool demonstrations or presentations. They will also review submissions for presentations by extending an open call for participation.

Participation, Required Equipment and Dissemination

Participation will be ‘mixed’ – in addition to participants who are invited to present their work, any interested delegate may register to attend. An invitation will be extended to participants of previous workshops, writing researchers who are not (yet) involved with the technology side, and international researchers active in the field to share their work and different perspectives on Writing Analytics. An open call for participation will be put out to encourage others to present their research and become more actively involved in the LAK writing analytics community. A website setup for the workshop will archive the event and disseminate the notes to participants. Papers accepted for presentation will be published in the companion proceedings and linked to the website.

The workshop will be of interest to a wide range of LAK delegates including: students and researchers engaged in writing research and the use of writing tools; educators in schools, universities and businesses; data analysts; and companies active or potentially active in the field. The workshop does not require any special equipment (WiFi, data projector and power strips aside). Flexible seating is preferred for breakout discussion groups. Participants will be encouraged to bring their own devices to contribute to shared notes. Workshop organizers will make use of listservs (SoLAR, Learning Analytics Google group, EDM-announce, ISLS, SIG-LS, ICCE) and their own personal networks to advertise the workshop.

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WAT: Writing Assessment Tool

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This presentation describes our progress on a project to develop the Writing Assessment Tool (WAT): an on-line platform to provide students, teachers, and researchers access to automated writing analytics. WAT will comprise three access points, each tailored to the needs of these three types of end-users. From a single-entry point: *Students* will receive summative and formative feedback via automated writing evaluation (AWE) on three types of essays: persuasive (independent) essays, summaries, and source-based (integrative) essays. *Teachers* will have access to a teacher interface allowing them to administer essay assignments, which they can choose to be scored using AWE or grade themselves using scaffolded rubrics. *Researchers* will have access to a web-based tool, a downloadable tool, and editable software, which will allow them to conduct computational analyses of writing. WAT will be packaged and disseminated such that researchers and software developers can easily integrate components of WAT into existing tools to provide natural language processing (NLP) extensions in educational software.

Our aim is to provide students, teachers, and researchers with writing analytics that will directly contribute to their knowledge of writing. For researchers, this knowledge may be theoretical or computational; for teachers, this knowledge may be pedagogical and relate to developing a better understanding of linguistic and semantic features of higher quality writing and pedagogical approaches to improve writing; finally, for students, this knowledge may be metacognitive, such that they develop a better understanding of how features of language affect their audience and essay scores. Our overall aim is to provide a writing analytics tool that will enhance students' ability to produce high-quality texts across multiple genres. Thus, we aim to develop a tool with broad impact on current practices in writing research and instruction across multiple dimensions.

One of our objectives with WAT is to provide students and teachers with writing tasks that provide automated feedback. Previous projects have informed our natural language processing (NLP) algorithms to drive feedback for persuasive essays and summaries. As such, our main focus currently is to collect additional corpora of source-based essays, analyze those essays to identify important linguistic and semantic features, and develop NLP algorithms. We will discuss work with our collaborators in which we are conducting NLP analyses of source-based essays collected in previous projects as well as on-going projects.

We also invite our colleagues to join the Distributed Literacy Coalition (DLC; distributedliteracy.org), which aims to integrate laboratories distributed across the world focused on understanding and improving literacy. Distributed literacy refers to the multiple, intertwined aspects of literacy including reading and writing, as well as science, health, math, and social media literacies. DLC members work together on the common objective to improve literacy worldwide, recognizing the vital societal importance of literacy and the need for multidisciplinary and multicultural approaches to solve literacy problems.

Understanding the 'Black-Box' of Automated Analysis of Communicative Goals and Rhetorical Strategies in Academic Discourse

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Despite the appeal of automated writing evaluation (AWE) tools, many writing scholars and teachers have disagreed with the way such tools represent writing as a construct. This talk will address two important objections – that AWE heavily subordinates rhetorical aspects of writing, and that the models used to automatically analyze student texts are not interpretable for the stakeholders vested in the teaching and learning of writing. The purpose is to promote a discussion of how to advance research methods in order to optimize and make more transparent writing analytics for automated rhetorical feedback. AWE models will likely never be capable of truly understanding texts; however, important rhetorical traits of writing *can* be automatically detected (Cotos & Pendar, 2016). To date, AWE performance has been evaluated in purely quantitative ways that are not meaningful to the writing community. Therefore, it is important to complement quantitative measures with approaches stemming from a humanistic inquiry that would dissect the actual computational model output in order to shed light on the reasons why the 'black box' may yield unsatisfactory results.

Drawing on an ongoing project, which involves a systematic analysis of a collection of erroneous feedback produced by a genre-based AWE tool (Cotos, 2016), I will describe a hybrid – computer--driven/human-informed – approach with an exponential interpretive strand. The approach entails a linguistic investigation of the communicative goals analyzed both by AWE and the human. New heuristic taxonomies were developed to compare AWE detection and human interpretation of rhetorical intent, examine differences, and construe the nature of AWE errors. The resulting qualitative insights describe error patterns and reveal the role of linguistic features in automated detection of communicative goals. These insights help describe and interpret the reasons why error patterns in automated rhetorical analysis occur and how they may hinder computational representation of the writing construct. The findings can inform future interdisciplinary research aimed at developing augmented approaches for improving the quality of automated rhetorical feedback on student writing. In terms of immediate practical implications, the outcomes of this work can be translated to teaching and learning materials addressing possible feedback errors and providing strategies for how to use the feedback more effectively. More broadly, interpretable writing analytics can potentially power paradigmatic shifts and drive innovation at the level of research methodology, computational operationalization, interdisciplinary collaborations, and writing pedagogy – all interconnected to serve the purpose of students' writing development.

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Learning with Text: Toward a Multi-Dimensional Perspective on Text-Based Communication

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A commonly held belief among educators, researchers, and students is that high-quality texts are easier to read than low-quality texts, as they contain more engaging narrative and story-like elements. Interestingly, these assumptions have typically failed to be supported by the writing literature. Research suggests that higher quality writing is typically associated with decreased levels of text narrativity and readability. Although narrative elements may sometimes be associated with high-quality writing, the majority of research suggests that higher quality writing is associated with decreased levels of text narrativity, and measures of readability in general.

One potential explanation for this conflicting evidence lies in the situational influence of text elements on writing quality. In other words, it is possible that the frequency of specific linguistic or rhetorical text elements alone is not consistently indicative of essay quality. Rather, these effects may be largely driven by individual differences in students' ability to leverage the benefits of these elements in appropriate contexts. Indeed, recent research points to the contextual variability of linguistic features across different audiences, prompts, and assignments (Allen, Snow, & McNamara, 2016; Crossley, Roscoe, & McNamara, 2014). Crossley and colleagues (2014) for example, found that there were multiple profiles of high-quality writing, which demonstrated different linguistic properties. This evidence points toward the need to examine writing in more situated contexts.

This presentation will further explore the hypothesis that writing proficiency is associated with an individual's flexible use of text properties, rather than simply the consistent use of a particular set of properties. Across three experiments, this study relies on a combination of natural language processing, dynamic methodologies, and behavioral methodologies to examine the role of linguistic flexibility during the writing process. Overall, this study provides important insights into the role of flexibility in writing skill and develop a strong foundation on which to conduct future research and educational interventions.

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A Novel Writing Analytics Approach to Study Multiple Information Sources Integration by Students

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ABSTRACT: This poster describes a work in progress (WIP) research project that will explore the way students merge and summarize multiple information sources. The experiment examines the effect of merging digital versus analog texts on the digital writing process, the quality of the written outcomes, and the level of plagiarism in summaries written by students. The project incorporates a novel writing analytics approach that uses a logger which tracks not only keystrokes and timestamps, but also their impact on the evolving text, allowing an in-depth analysis of writing and editing processes. The study contributes to the writing analytics literature by improving our understanding of multiple information source integration and of plagiarism in student writing, as well as by offering a novel method to track and analyze computer-based writing processes.

Keywords: writing analytics, text integration, logger, plagiarism

1 MERGING AND SUMMARIZING MUTLIPLE INFORMATION SOURCES

One of the top skills required by participants in the knowledge economy is that of reading multiple information sources and creating a new document that integrates these information sources in a coherent and effective manner (Barzilai, Zohar, & Mor-Hagani, 2018). A study of this skill intersects with several research themes related to reading and writing, including research on the differences between reading from paper versus from digital sources (e.g. Fortunati & Vincent, 2014; Mangen, Walgermo, & Brønnick, 2013), research on the cognitive and metacognitive processes that are associated with these integration tasks (Barzilai & Zohar, 2012), research on writing processes and their evaluation (e.g. Shibani, Knight, & Shum, 2018), and research on academic integrity in the use of information sources (e.g. Blau & Eshet-Alkalai, 2017).

2 RESEARCH QUESTIONS

The study described in this WIP poster is an experiment that requires participants to merge and summarize three texts into a single coherent digital text. The study explores three research questions:

a. Are there differences between the processes of creating a summary document from digital sources versus paper-based information sources?

b. Are there differences between the quality of outcomes - a summary document from digital sources versus paper-based information sources?

c. Is there a difference in the extent of plagiarism between creating a summary document from digital sources versus paper-based information sources?

3 EDIT-TRACKING KEYSTROKE LOGGER

A unique keystroke logger is currently under development in order to study the writing process of the participants in the study. Like a regular keystroke logger, this logger tracks every keystroke performed by users as they type within an HTML window. Furthermore, with each keystroke (both down-stroke and up-stroke) the logger also records the text that is in the HTML window when the keystroke occurred. These timestamped records are then exported in a json file which contains a highly detailed record of the writing process. This json file is then analyzed using scripts that identify the various writing and editing activities performed by the users.

4 THE EXPERIMENT

In the experiment, sixty participants will be recruited and randomly assigned into two groups. Both groups will be asked to merge and summarize three identical texts, either digital (group A) or paper based (group B). Both groups will perform the merging using the logger described in section 3 above. The three RQs will be explored by analyzing the writing process as well as the resultant text written by the participants. This novel writing analytics approach contributes to our understanding of multiple information source integration, of digital versus paper-based reading and writing, and of student plagiarism. It also presents a novel method for tracking and analyzing computer-based writing processes.

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Am I planning smart? – Analyzing student goals

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ABSTRACT: Goal setting is an important step in Self-Regulated Learning. Setting goals is not a straight forward task. Some types of goals are more useful than others. The SMART goal setting guideline helps to generate more meaningful goals. In this paper, we present a research roadmap designed to assist learners with the generation of meaningful learning goals. The roadmap consists of a three-stage process: structure goal extraction, continuous text goal extraction, and dialogue-based goal extraction. Findings from each of the stages will support with the implementation of the next one.

Keywords: NLP, Learner Goals, Recommender Systems, Self-Regulated Learning, Chatbot

1 BACKGROUND

Self-regulated Learning (SLR) describes the area of learning strategies, self-assessments, and self-reflection of learners. Learning planning and goal setting is a crucial process of SRL that allows learners to draw conclusions from the learning process through self-reflection (Zimmerman & Moylan, 2009). Goals can be defined in many ways, nevertheless not every formulation is of equal value. By the requirements of the well-known SMART Framework (Doran, 1981), they can be evaluated through a simple set of rules.

With the increasing digitalization of our everyday lives, written texts are gaining more and more importance. For many students, writing text messages has become the preferred method of communication, which they use to communicate with others (Rideout & Robb, 2018). Popular extensions of these classic text messages are chatbots and digital assistants. They open up new possibilities in the networking of learners and learning support systems by using the same communication channels (Winkler & Söllner, 2018).

We want to help learners with their goal setting by offering a system that can be operated in natural language. Such a dialogue-oriented system should give students the opportunity to compose goals and track their achievements in the context of SRL (Locke & Latham, 1990).

In this article, we present our research roadmap of a system that starts with the evaluation of written learning goals and leads into a dialogue-based learning tool for goal setting. This research roadmap follows the design-oriented approach (Wang & Hannafin, 2005), in which context and theory are examined in an iterative process.

2 THEORETICAL BACKGROUND

The basis of the following goal extraction is the SRL theory. A popular model in SRL is the three phases model of (Zimmerman & Moylan, 2009). It describes an SRL cycle with Forethought Phase, Performance Phase and Self-Reflection Phase (fig. 1).

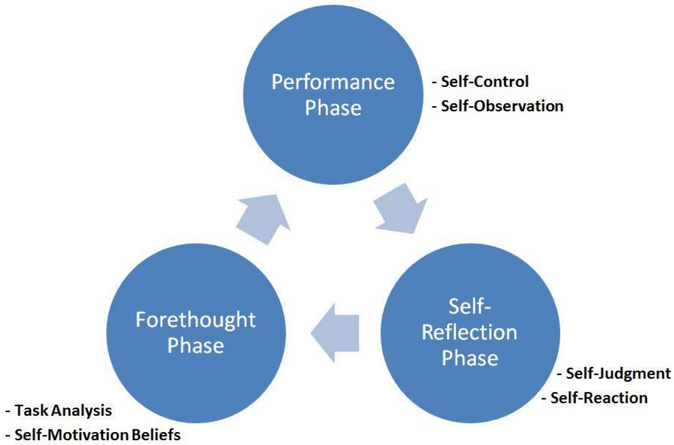

Figure 1: A cyclical phase model of self-regulation (Zimmerman & Moylan, 2009)

Many applications of student facing Learning Analytics can be assigned to the second phase, where learners observe themselves within the learning process. With the introduction of a goal dialogue system, we plan to contribute to the learning planning phase of SRL, which is in many cases overlooked (Jivet, Scheffel, Drachsler, & Specht, 2017).

3 SMART GOAL SETTING

In order to be meaningful, goals should inherit several features as defined by (Doran, 1981). This guideline consists of the acronym "SMART", which says that goals should be:

- **S**pecific
- **M**easurable

- **A**ssignable
- **R**ealistic
- **T**ime-related

The following example (fig. 2) is intended to illustrate the features of a SMART goal:

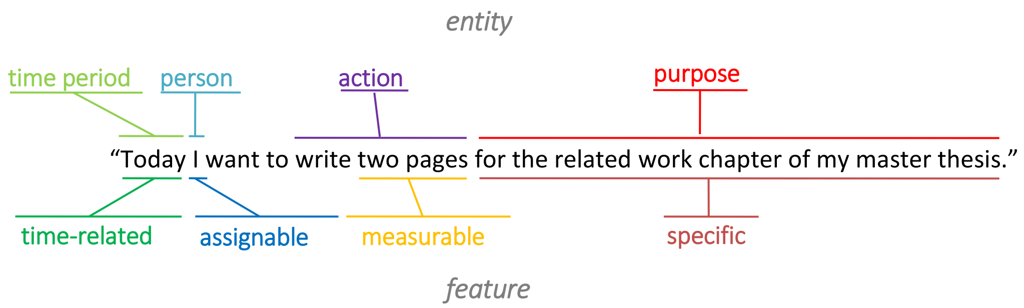

Figure 2: SMART goal example

As this example shows, many features match entities. It turns out, the assessment of the realistic feature is not included in the wording and strongly dependent on author and context. The SMART guideline contains the idea that the progress of goal achievement has to be assessed in the future. Therefore, the measure is strongly related to the defined time period, which represents a deadline. The specificity feature can be described as a connection between the actual action and a superior intention. It can be seen as a hierarchy of goals, in which the achievement of subordinate goals also benefits superior goals (Cropanzano, James, & Citera, 1993).

4 RESEARCH ROADMAP

Our Research roadmap has the purpose to create a system that helps learners to set smart learning goals. It consists of a three-stage process, which leads from a structured to a dialogue-oriented input (fig. 3). These stages are defined as:

- Stage 1 – Structured Goal Extraction
- Stage 2 – Continuous Text Goal Extraction
- Stage 3 – Dialogue-based Goal Extraction

In the transition from one stage to another, learners gain degrees of freedom in the possibility of defining goals. This increases the variability of the used wording and requires more complex extraction rules and procedures.

Figure 3: Research Roadmap for extracting learning goals

Stage 1 - Structured Text Goal Extraction

This stage is the beginning of the roadmap and focuses on the extraction of goals from a predefined wording. It simplifies the definition of learning goals to one sentence, which has to be completed by the learners. As already seen in fig. 2, SMART features are comprised by textual entities. The most variable entities in this context are actions and purposes. With actions, learners describe conditions for achieving a goal, while purposes are used to place goals in a higher context.

Actions should be examined for measures (see chapter 3). These measures could be countable numbers or a set of verbs describing a state of progress (like *"finish"* or *"complete"*).

In the following two subsections (4.1.1 and 4.1.2) we present some example structures which enable a SMART analysis of learning goals. They are exemplarily designed for one week, in order to create a useful SRL cycle. The assessment of the closeness to reality can only be covered by an additional input field. As mentioned in chapter 3, this information is not included in the goal formulation.

Time-period-based Goal Formulation

With a time-period-based goal formulation, learners can set an action to a purpose. It can be formulated as follows and is a flexible structure for one-time conditions:

> " This week I want to ***[action]*** to ***[purpose]***. "

Event-based Goal Formulation

Through an event-based goal formulation, learners can define focus events within a time period. Every time this event occurs, the learner defines a specific action to perform. The wording can be chosen as follows:

> " Every time I ***[event]*** this week, I want to ***[action]*** to ***[purpose]***. "

In contrast to time-period-based extraction, an additional condition (event) is involved. It should, therefore, be chosen in such a way that it occurs frequently in the time period. A predefined selection of events can, therefore, be considered as a simple solution.

Stage 2 - Continuous Text Goal Extraction

This stage is concerned about goal extraction from continuous text. By further opening the goal formulation, it extends the structured text goal extraction through goal extractions from textboxes. This enables learners to freely define goals in their preferred sentence structures. The Continuous Text Goal Extraction stage has to deal with more varieties of SMART learning goals and should include sentence analysis, POS analysis, and entity extraction. It should include feedback in the form of recommendations to improve learning goals (Verbert et al., 2012), which can be achieved by a set of tips. These can be shown if a particular feature of the SMART guideline could not be found in the goal formulation.

Stage 3 - Dialogue-based Goal Extraction

This stage is the end of the roadmap and marks the dialogue-based goal extraction. It defines a conversational extension to the continuous text goal extraction, which is able to extract goals from a conversational dialogue, question on goal formulations and provide examples how to define SMART goals. This stage should ideally be integrated in a chatbot-system that tries to model goals as described in (Brusilovsky & Millán, 2007).

5 USE CASE SCENARIO

Our roadmap of goalsetting and applied goals could be integrated into SRL diaries. They should enable not only to document one's own learning progress but also to set goals and evaluate their achievement. A dialogue-based goal extraction with an intuitive interface would enhance these systems. It would help students in defining meaningful goals for their SRL cycle by asking questions and recommending improvements.

6 OUTLOOK

The goal extraction mechanisms proposed in this paper can help learners to define and keep track of meaningful goals. In the next step, we plan to follow our research roadmap in order to implement such a system and study its effects. It should show insights about the possibilities and limitations of its use, which result from the entire roadmap process.

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Towards knowledge-transforming in writing argumentative essays from multiple sources: A methodological approach

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ABSTRACT: Skillful essay writers successfully transform knowledge from multiple sources. However, when post-secondary writers draft essays after researching the articles, they often face challenges to engage in knowledge transforming, a complex process simultaneously involving reading comprehension, writing production and metacognitive monitoring (Bereiter & Scardamalia, 1987). We describe a two-facet methodological approach to model linguistic properties that distinguish knowledge-telling evidential sentences from knowledge-transforming ones in disciplinary argumentative writing. We collected and coded 40 post-secondary disciplinary argumentative essays based on an assigned argumentation framework and Bloom's taxonomy (Sadker & Sadker, 2006). We use these coded argumentation schemes to develop a computational tool to generate writing analytics to scaffold writers towards more knowledge transforming processes.

Keywords: Argumentation, writing, text analysis, knowledge telling, knowledge transforming

1 INTRODUCTION

To develop well-structured arguments in essays, students need to form and present claims and adjoin credible evidence to support arguments. This entails successfully navigating between a rhetorical problem space and a content problem space (Bereiter & Scardamalia, 1987). In the rhetorical problem space, students work to design, structure, and precisely and coherently communicate claims and supportive evidence. Solving rhetorical problems accomplishes argumentative goals. Simultaneously, in the content problem space, students process information they identify and mine from multiple sources. As they compare facts, reasons and explanations, evaluate and generalize findings, and establish semantic relationships among key concepts, opportunities arise to coordinate evidence relating to claims positioned in the rhetorical space.

In this process, students actively rework drafts to fit parameters of the writing task and its goals. Bereiter & Scardamalia (1987) modeled interactions among discourse and content processing, and metacognitive monitoring as a composite process called knowledge transforming. Because this process triggers reflective thinking while writing, Bereiter & Scardamalia (1987) argue that knowledge transforming promotes learning.

Producing knowledge-transforming texts is a challenge for many post-secondary writers. Research indicates student writers often fail to paraphrase, interpret, and evaluate content in sources; construct novel associations across multiple sources; and integrate multiply-sourced information into a coherent structure (Bereiter & Scardamalia, 1987; Aull, 2015; Boscolo, Ariasi, Favero, & Ballarin, 2011; Dong, 1996; Flower et al, 1990; Petrić, 2007). As a result, under-skilled post-secondary writers often engage in a more limited text production process termed knowledge telling. Writers who generate knowledge-transforming text typically use monitoring and planning strategies that develop a coherent text. In contrast, writers who produce knowledge-telling texts focus overly on generating basic text, e.g., staying on topic and repeating facts from sources. In the knowledge-telling process of writing, interactions between the content problem space and the rhetorical problem space are few, limited in complexity and unproductive. We hypothesise writing analytics can be generated to help struggling writers move from knowledge telling toward knowledge transforming. Such analytics should invite writers to engage in knowledge transforming processes while practicing writing, reading, and arguing strategies that help them navigate between the content and rhetorical spaces.

We present a methodological approach to identify knowledge transforming in evidential sentences situated in disciplinary argumentative essays generated by post-secondary students. Specifically, we seek to identify when students transform source information by applying evidence to promote argumentative claims. Hemberger, Kuhn, Matos, & Shi (2017) posited that coordinating evidence with claims is essential to skilled argumentative writing. Thus, the final goals of our research are (a) to develop an ensemble off computational algorithms to analyze linguistic properties of evidential sentences in an argumentative essay relative to information available in sources, and (b) generate learning analytics that scaffold knowledge transforming as writers bring evidence to support claims. The computational tool will use linguistic properties of evidential sentences as standards for tailoring learning analytics in form of metacognitive prompts to writers helping them go beyond merely restating information borrowed from sources to engage in knowledge transforming.

2 RELATED WORK AND THEORETICAL MODEL

Citations in an essay – references to and quotes of source information – have been classified with respect to various linguistic functions (see Petrić, 2007). We elaborated Bereiter and Scardamalia’s (1987) model contrasting knowledge telling and knowledge transforming by additionally categorizing evidential sentences in argumentative writing in terms of Bloom’s taxonomy of the cognitive domain (Sadker & Sadker, 2006; Table 1). The taxonomy describes a progression of thinking processes across knowledge, comprehension, application, analysis, synthesis and evaluation. While not without criticism (e.g., see Darwazeh, 2017) it has potential to supply an underlying framework for developing informative, specific and useful learning analytics to guide learners in advancing from knowledge-telling to knowledge transforming. According to Bereiter and Scardamalia’s (1987) writing model, students engaged in knowledge telling neglect cognitive and metacognitive operations that transform knowledge. Using Bloom’s taxonomy to classify writers’ evidential sentences could reflect underlying cognitive and metacognitive processes writers engage in. Bloom’s knowledge classification aligns with

Table 1: Framework for classifying evidential sentences in argumentative writing

Category	Operationalization	Writing Mode
Knowledge	paraphrased/copied information from a source	Knowledge telling
Comprehension	elaborated source information	Knowledge transforming
Application	source information applied to the real-world context	Knowledge transforming
Analysis	inferential additions to information mentioned in sources	Knowledge transforming
Synthesis	integrating information from different sources or a proposition	Knowledge transforming
Evaluation	evaluating or discrediting source information	Knowledge transforming

Bereiter and Scardamalia's knowledge-telling model where writers focus on generating basic text. Bloom's comprehension, application, analysis, synthesis and evaluation categories reflect Bereiter and Scardamalia's knowledge transforming category where writers coordinate and create knowledge. Thus, classifying students' evidential sentences in terms of Bloom's taxonomy forms a basis for analytics to guide students toward producing knowledge transforming texts with arguments strengthened by more thorough articulation of content with evidence.

3 METHOD

3.1 Corpus and writing task

Our corpus was 40 argumentative essays written by undergraduates enrolled in various disciplinary majors and registered in an introductory educational psychology course in a Western Canadian university. Students were assigned a 1500-2000 word argumentative essay on a specific disciplinary issue of their choice. Essays were required to present (a) at least three arguments supported with evidence gathered from 5-7 sources students selected from 160 sources in the course repository, (b) at least one counterargument with evidence, and (c) rebuttal(s) to the counterargument(s).

3.2 Hand coding – codebook

Sentences were sampling units. Since we focus on analyzing arguments and evidence, we coded sentences in the essay body (excluding the introduction paragraph, conclusion paragraph, and headings) in terms of argumentation, writing mode and relationality.

For argumentation, we coded sentences in one of five categories: *Argument (A)*, a sub claim supporting the thesis statement (main claim); *Evidence (E)*, sentences providing support to the argument; *Counterargument (C)*, counter claims; and *Rebuttal (R)*, sentences discrediting the counterargument; *Not applicable (NA)*, a sentence that did not fit any argumentation category, e.g., definition or background information. For Writing mode, categories (Table 1) referred to Bereiter and Scardamalia's knowledge transforming model (1987) elaborated by Bloom's taxonomy of the cognitive domain following Sadker & Sadker (2006). A 3-point scale quantified relationality in terms of each argument's (or sub argument's) linkage to the thesis statement (or main argument), and the relation of evidence to arguments (sub arguments): 0 indicated *not related*, 1 described *far-fetched*, and 2 described *related.* The coding method is illustrated in the Figure 1. The sentence coded as argument (A) receives a rating on its relation to thesis statement. The sentence coded as evidence receives a rating on its relation to the preceding argument.

3.3 Hand coding – interrater agreement

To reach high interrater agreement among three coders, coding proceeded in three rounds of train together → code independently → calculate reliability. In round 1, two randomly selected essays were collaboratively coded followed by independently coding four randomly selected essays. Altogether,

Sentence	Macro Structure	Argumentation	Writing mode	Relation to thesis statement/ argument
Meeting the different needs of learners and allowing them to be included in classrooms can result in children achieving educational success.	Intro			
Learner differences should be a primary concern when it comes to educating teachers and achieving inclusion, as the failure to incorporate learning needs can be disastrous for all students.	Intro			
While most schools focus on bringing underachieving students up, individuals who are of high ability are neglected.	Body	A		2
According to Northwestern University (2017), children are then left to rely on their parents to provide them with advanced instruction.	Body	E	Knowledge	2
Therefore, many students miss out on opportunities for achievement as many families cannot provide them with the resources such as tutoring services or enrichment activities.	Body	E	Comprehension	2
When teachers are given appropriate instruction, they are able to teach learners who need support.	Body	NA		

Figure 1: Codebook

those four essays comprised 28 paragraphs (per text: M=7, SD =1.41) and 245 sentences (per paragraph: M=8.75, SD =3.63). After independent coding, we calculated reliability using the AC1 statistic (Gwet, 2002) as this method corrects agreement among raters for the probability of chance agreement. Although inter-rater reliability was lower for Argumentation and Writing mode (0.67 and 0.77, respectively), differences arose in identifying argumentation categories because coders' failed to reliably identify evidential sentences. In addition, for Writing mode, coders struggled to discriminate synthesis from analysis, and analysis from comprehension. For round 2, we sharpened coding of Argumentation and Writing mode. In round 2, three coders coded two randomly selected student essays collaboratively followed by independently coding four randomly selected essays. Altogether, the four essays comprised 26 paragraphs (per text: M=5.2, SD=1.3) and 247 sentences (per paragraph: M=9.27, SD=2.47). Reliability of the argumentation mode was still low (0.76). Round 3 included collaboratively coding two randomly selected student essays followed by independently coding six randomly selected essays. Table 2 presents final inter-rater reliability results.

Table 2: IR reliability after the 3 rounds of "train together-code independently-calculate reliability"

Code	AC1 Reliability	Standard Error	95% CI
Macro-structure	0.97	0.01	[0.95, 0.99]
Argumentation	0.81	0.02	[0.77, 0.84]
Writing mode	0.83	0.02	[0.78, 0.87]
Relation to arguments/thesis	0.82	0.02	[0.78, 0.86]

In the Appendix, we illustrate codes within the Writing mode for each category of Bloom's taxonomy (Sadker & Sadker, 2006).

3.4 Extracting linguistic indices for sentences coded in Writing mode scheme

We propose modeling the following linguistic indices for each identified evidential sentence. The variables are grouped into: anaphoric devices, semantic overlap, and rhetorical connectives.

First, high accessibility (unstressed pronouns) and low accessibility anaphoric devices (full noun phrases and indefinite articles) will be computationally extracted. Sanders & Spooren (2007) pinpoint high accessibility markers in a sentence indicate continuation with previous topic, or the writer's tendency to stay on topic. Both are signs of knowledge-telling. Low accessibility markers, on the other hand, signal termination of current and activation of other topics. They indicate knowledge-transforming.

For each evidential sentence we will compute its semantic overlap with source text and with the preceding sentence (argument/counterargument/rebuttal/evidence). We hypothesize knowledge-telling sentences have higher semantic overlap with a source while knowledge-transforming sentences have lower semantic overlap with the source and the preceding sentence.

Seventeen rhetorical connectives will be calculated using the TAACO tool (see Crossley, Kyle & McNamara, 2016). We anticipate subsets of rhetorical connectives will predict knowledge telling and transforming. The analysis will provide substantial details.

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APPENDIX

Sample coded sentences

Category	Example Sentence
Knowledge	*When institutions and classrooms integrate self-directed learning into their curriculum, long term benefit have been observed through increased student retention and graduation rates (University of Texas at Austin, 2016).*
Comprehension	*With this type of learning, students can fully control their educational experience and focus on information they would like to explore.*
Application	*Having different interpretations based on cultural differences is a concern, particularly for schools in British Columbia and other Canadian metropolitan centers where we have and are projected to receive more international students particularly from Asia.*
Analysis	*Meaning engagement in some form of unstructured play could also result in an increase in academic performance.*
Synthesis	*However, this is not the case, because praise is not overly useful feedback, and if it is undeserved, it can cause students to feel like their teachers do not expect much from them.*
Evaluation	*One of the limitations is that the research is centered on a questionnaire survey which may result in certain biases including social desirability bias.*