Can you tell if they're learning?

Using a pedagogical framework to measure pedagogical activity

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***Abstract* — The proliferation of Web-based learning objects makes finding and evaluating online resources problematic. While established Learning Analytics methods use Web interaction to evaluate learner engagement, there is uncertainty regarding the appropriateness of these measures. In this paper we propose a method for evaluating pedagogical activity in Web-based comments using a pedagogical framework, and present a preliminary study that assigns a Pedagogical Value (PV) to comments. This has value as it categorises discussion in terms of pedagogical activity rather than Web interaction. Results show that PV is distinct from typical interactional measures; there are negative or insignificant correlations with established Learning Analytics methods, but strong correlations with relevant linguistic indicators of learning, suggesting that the use of pedagogical frameworks may produce more accurate indicators than interaction analysis, and that linguistic rather than interaction analysis has the potential to automatically identify learning behaviour.**

Keywords *Web-based learning, pedagogical frameworks, learning analytics, language analysis, MOOC, discussion forums*

I. INTRODUCTION

The emergence of Massive Open Online Courses (MOOCs) in recent years has added to the proliferation of learning objects (LO) online, making finding and evaluating online learning resources a significant hurdle to overcome. While discoverability may be improved by applying relevant metadata tags, web objects are rarely effectively tagged, and ensuring tags remain relevant is problematic [1].

Analysis of networked learner interactions is recognised as a valuable tool for providing useful feedback [2]. The practice of Learning Analytics prioritises the use of trace data to make evaluations of learner engagement, however studies that compare methods are rarely undertaken [3].

In this paper we present an approach to coding Web-based comments based on the Digital Artefacts for Learning Engagement Framework (DiAL-e) [4] which we compare with established Learning Analytics and Language Analysis methods. We believe Dial-e has importance for the analysis of online discussion in terms of actual focus on learning activity rather than Web-based interaction. We use the term 'pedagogical activity' to describe comments that demonstrate active involvement in learning in contrast with non-relevant discussion.

II. BACKGROUND

Developing effective pedagogic practice in e-learning environments is a dynamic and evolving area of study. Pedagogic frameworks bring together different approaches, for example: constructivism (building on prior knowledge), experiential (learning by doing), and reflection (learning through internal dialogue) [5]. Generic frameworks like DiAL-e employ pragmatic methods to map out theoretically consistent learning designs.

Language Analysis typically involves the study of linguistic data [6] where the content and style of language used in everyday communications can provide indicators of psychological and social meaning. Characteristic quantitative methods identify similar patterns, and interpret content through statistical tests of significance [7], which, in terms of this study, may suggest pedagogically meaningful dialogue.

The underlying assumptions of Learning Analytics are based on the understanding that Web-based proxies for behaviour can be used as evidence of learning. Through the collection and analysis of 'trace data' (e.g. comments and search profiles) evaluations are made of how learners interact with content, make sense of it, and co-construct meaning [8]. Current research on learner performance in online learning environments focuses on social network analysis, discourse, and predictive modelling methods [9].

III. METHODOLOGY

Comment data collected from a MOOC with nearly 1,850 contributors posting over 20,000 comments containing more than one million words was analysed. The MOOC was delivered via 120 'steps' (learning objects), with each step allowed instructors and learners to contribute to discussions within the steps' comment field. Qualitative analysis was undertaken using a content analysis scheme based on DiAL-e (Table 1). Because it adopts nonhierarchical strategies for learning design using digital artefacts, and supports social interaction interventions, this framework was chosen as appropriate for assessing the social and situated nature of online comments.

TABLE I. DIAL-E FRAMEWORK CATEGORIES

Learning Design	Description
Engagement	
Stimulation	Inspiring learner engagement.
Narrative	Storytelling using digital artefacts.
Authoring	Creating a digital artefact. Learning by doing.
Empathising	Understanding other perspectives.
Knowledge construction	
Collaboration	Supportive interaction.
Conceptualisation	Consolidate learning about concepts & procedures.
Inquiry	Attempting to solve a real world issue.
Reflection	
Research	Searching for and researching materials.
Representations	Developing skills in media-literacy.
Figurative	Using content as a metaphor for other purposes.
Non-DiAL-e categories	
Technical	Related to course management.
Non-relevant	Off-topic.

DiAL-e consists of ten learning design categories. In this study the 'stimulation' category was omitted as all contributors were assumed to have been inspired to engage. Additional categories were adopted to measure incidence of 'non-learning' comments. Thus eleven dimensions were used by a human expert to code interactions, and measure the extent to which engagement, knowledge construction and reflection could be inferred from comments.

Initial analysis identified 'typical' engagement with learning objects. Three different comment streams were selected based on their closeness to average word and comment count, and where less than 5% of comments were made by the most active contributor.

The first 100 comments of each of these streams were coded in alignment with DiAL-e categories. It was observed that most categories could be applied more than once to some comments, whereas the 'collaborative' category was applicable only once to comments that indicated collaborative activity. For example an single comment presenting three distinct questions would be given three 'Inquiry' points, but all comments that made positive contributions were scored as 'Collaborative' only once.

A further nine comment streams were selected for coding: 3 containing the most number of comments, 3 with average comment profiles and 3 with the least number of comments. The first 25 comments of each of these streams were coded, resulting in a total of 525 coded comments. The Pedagogic Value (PV) of each LO was derived from average DiAL-e coding scores in each comment stream.

The linguistic properties of the comment corpus were analysed using Linguistic Inquiry and Word Count (LIWC) text analysis software [10] - a common method used to identify sentiment [11], as well as the prevalence of word categories which indicate cognitive processes [12]. In addition, another Learning Analytics method, graph density [13], was used to measure the level of engagement within each comment stream.

Graph density is measured by the proportion of actual connections between nodes to the maximum possible connections, with a complete graph consisting of a network in which all points are directly connected to every other point [14]. The 'social capital' of students, when explored through their engagement in learning communities, and as indicated by their relative position in a network graph is commonly seen as having a significant impact on the students' learning outcomes [13]. Social network graphs were extracted as follows: whenever a contributor (A) responded to a message from another contributor (B) we created directed edges between the two of them (A,B). The graph density for each graph was calculated using NodeXL [15].

Analysing this data enabled us to compare correlations between inferred pedagogical activity (PV scores) with methods used in Learning Analytics (sentiment, learner engagement) and Language Analysis (sentiment, significant word categories).

IV. RESULTS AND ANALYSIS

The goal of the analyses was to find predictors that closely align with learning activity in online comments. All comparisons produced graphs that indicated approximate linear association between the PV dependent variable and 6 explanatory variables (Table II). The most striking outcome is the clear, statistically significant, negative correlation between words identified in the literature as being associated with the affective domain (e.g. expressions of empathy or "involved" writing [12,16]) and learning objects with low PV scores (Figs. 1 and 2). While the affective domain plays an important part in knowledge acquisition, through keywords in context (KWIC) analysis these words were seen to be more connected with course 'housekeeping' issues and expressions of gratitude, than with pedagogical activity.

On the other hand, the high correlation between prepositions and high PV scores (Fig. 3), suggest that the DiAL-e coding schema identified comments that reveal depth of thinking, as Language Analysis literature reports a high incidence of prepositions associated with attention to reflective behaviour [12].

Because of the association between graph density and learning outcomes, the lack of correlation between this measure and PV was unexpected (Fig. 4). This is significant as it indicates a distinct difference between interaction measures and alignment to our pedagogical framework. Some studies speculate that lower density networks are indicative of learners engaging in distinct, regular study patterns [17], and KWIC analysis suggests that connections tend to occur in distinct patterns that are unrelated to our measure of pedagogical activity.

V. CONCLUSIONS

We set out to compare Learning Analytics and Language Analysis measures with alignment to a pedagogical framework. Results show that our approach produces results that are distinct from typical interactional measures. We have identified approximately negative and statistically insignificant correlations with established Learning Analytic methods, but have found strong correlation with linguistic indicators of pedagogical activity. While our approach indicates the usefulness of close attention to the variety of pedagogic activity that occurs online, we do not claim that it represents a full account of learners' activity, rather it adds nuance to established measures. Although we demonstrate a consistent approach, decisions on how data are categorised are highly subjective, and whereas our schema has a reasonable level of clarity there are some areas of ambiguity. Some of the richness of interactions has been lost in the coding process, the study of word use as an indicator of learning attention is at an early stage, and measurement of word meaning cannot be relied upon to accurately detect people's true behaviour or intentions [12]. However, we believe our findings demonstrate that analysing online discussion in terms of pedagogical activity produces results more closely aligned with active involvement in learning than interaction methods.

TABLE II. CORRELATIONS AND RESULTS

Variable	Adj. R^2	P-value	Corr. with PV	Citations
2nd person pronoun	0.721	<0.001	Negative	[12]
+ve emotion	0.601	0.002	Negative	[12, 11]
Preps	0.463	0.009	Positive	[12]
Graph Density	0.068	0.21	Negative	[13]

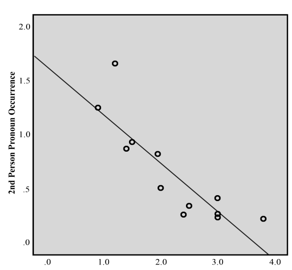

Figure 1: Correlation between 2nd person pronoun and PV

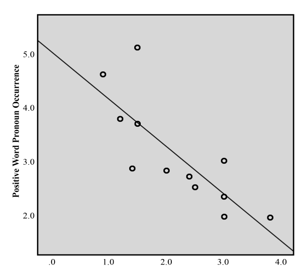

Figure 2: Correlation between positive emotion words and PV

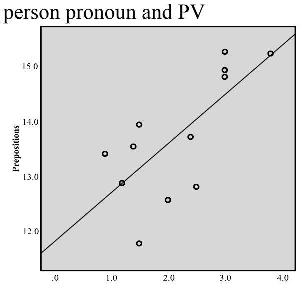

Figure 3: Correlation between prepositions and PV

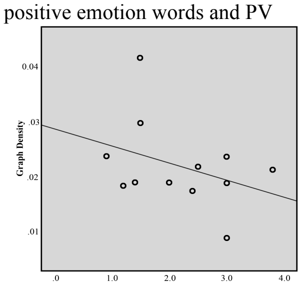

Figure 4: Corrrelation between graph density and PV

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