Visual Analytics and Medical Discourse*

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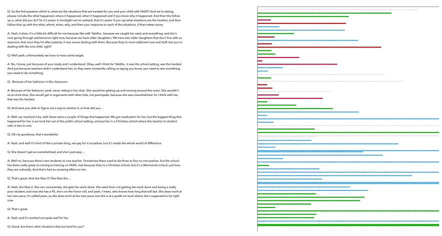
Abstract

We present a novel visualization system that summarizes interviews between clinicians and caregivers of children with Fetal Alcohol Spectrum Disorder (FASD), allowing analysts to identify common behaviors and effectiveness of caregiver strategies. The analysis workflow is streamlined by reducing document processing time while aiding in identifying significant patterns and relationships by automatically identifying the situations, behaviors, and strategies experienced by caregivers via discourse analysis, sentiment analysis, and keyword extraction.

1 Introduction

Medical document collections are examined to understand patient behaviors, the situations surrounding the behavior, and strategies associated with patient care. However, the creation of interview scripts and the manual processing and analysis of interview content to identify situations, behaviors and strategies can be a time consuming process. Using a collection of semi-structured medical interviews concerning the care and challenging behaviors of children with FASD, we provide an analysis that detects patterns across the study population and can be used to identify new relationships. Analyzing the text of a conversational dialogue can be cognitively demanding due to the difficulties in viewing the entire conversation (Tat and Carpendale, 2002). Clinical interviews can be segmented into sections such as *Opening*, *Problem*, *Cause*, *Consideration of patient's condition*, *Solution*, and *Closing* (Byrne and Long, 1976).

*This work was partially supported by a grant from Canada's GRAND Network of Centres of Excellence, and by a Discovery Grant from the Natural Sciences and Engineering Research Council of Canada.



(a) (b)

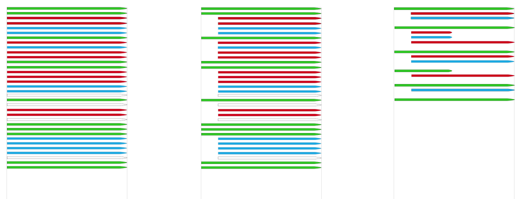
Figure 1: (a) Original interview text. (b) Discourse zones segmented by color.

2 Implementation

Using the interview discourse structure to segment the text, a quick, high-level overview of the interview's contents is constructed. The states and transitions are modeled using HMMs and CRFs (Tepper et al., 2012). Model features include word-level as well as discourse-level aspects. Lexical semantic keyword sets identify entities and discourse zones, as well as being used in the visualization (i.e., icons). Keywords were extracted from the interview questionnaire and annotation manual. Sentiment was computed by SO-CAL (Taboada et al., 2011). The dataset consists of 60 interviews between healthcare workers and caregivers. Ten documents were annotated with one of the four zone labels, with the discourse unit being the speaker's entire conversational *turn*. We reduce Byrne and Long's six zones to four: *Behavior*, *Situation*, *Strategy*, and *None* for off-topic passages.

2.1 Visually Compressing A Document

The implementation visually compresses both at the document level (as a mini-map) as well as the multi-document level (each document is a glyph). Fig. 1a shows the original medical interview text. The document is then automatically annotated, identifying segments relating to either the child's behavior, circumstance which led to the behavior, and the caregiver's response. Color is applied to the segments (Fig. 1b): Behavior (red), Situation (green), and Strategy (blue). Sentence bar lines are next normalized (Fig. 2a) with red Behaviors and blue Strategies indented so that Situations (green) are easily visible. Contiguous sections are merged to compress the text (Fig. 2c). A further vertical compression (Fig. 3) positions subsections orthogonal to segments that signal new sections.



(a) (b) (c)

Figure 2: (a) Normalizing sentence lengths. (b) Indentation marks where Situations begin and end. (c) Contiguous sections are combined for vertical compression.

2.2 Visualization of Multiple Documents

Fig. 2c's mini-map is extended to provide a visual overview of the document's content through *glyphs*, enabling analysis between documents (Fig. 3). Four key features allow for multi-document visualization.

Document Overviews Via Mini-maps The entire document can be viewed and navigated by the segmented structure of the mini-map.

Icons Provide Content Overview Icons from nounproject.com are used to summarize a document's content, allowing quick identification of patterns between documents.

Visually Comparing Documents Mini-maps and glyphs in Fig. 3 allow viewing many documents simultaneously, enabling document comparisons as well as identifying patterns.

Semantically-Motivated Colors Colors for discourse zones and icons were based on semantic intent (Lin et al., 2013). Green Situations signal the beginning of incidents, red Behaviors the child's concerning behavior, and blue Strategies the defusing of a situation (i.e., "cooling down"). Red icons convey aggression (anger, theft, etc.).

3 Discussion

Our visualization reduces an analyst's cognitive workload and improves workflow efficiency, enabling faster processing of a large document set.

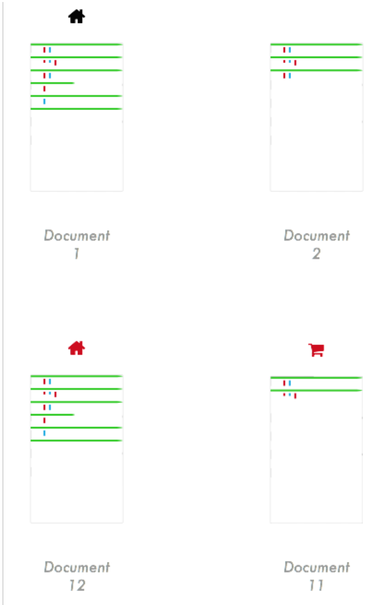


Figure 3: Multi-document visualization using glyphs. An aggressive home incident is seen in Document 11's red icon, while Document 1 has a non-aggressive incident.

Analysis can immediately begin rather than be bottlenecked by the tedious preparation and annotation process. Future work will evaluate the visualization on different genres of clinical texts (marital conflict data, etc.). Also to be explored are multi-class labelling, where two or three of the zone labels may be applied to a single utterance. We rank discourse zones (in priority of Behavior, Situation, and Strategy) and select the higher ranking zone as the true label.

References

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