Creating Transparent Search and Discovery Algorithms

Chreston Miller
chmille3@vt.edu [1]

[1]Research, Learning, and Informatics, University Libraries, Virginia Tech

March 18, 2019

There is growing interested in discovering how to incorporate human expertise in the analysis process. One specific question centers on how to support an expert analyzing multimodal data of human behavior over time in a way that facilitates locating subjectively relevant behavior patterns. The process of supporting such an expert begins with a seed idea that evolves over time as one investigates and searches the data. We call this kind of analysis Interactive Relevance Search and Modeling (IRSM) [4].

Many search and discovery algorithms apply statistical analysis and machine learning to identify trends in datasets. While the effectiveness of such approaches has been shown, they can alienate the user from how trends and pattern structure are discovered. They may also hide pattern details necessary to learn and identify additional trends. A transparent understanding of the underlying patterns may aid the user in the identification and discovery of behavioral trends. This can also be used to verify the functionality and accountability of the algorithm(s). Depending on a researcher's area of expertise, the functionality and limitations of the patterns used and operations of the algorithm(s) may not be apparent. IRSM puts the expert in a position to steer the search and discovery process and open the blackbox of trend/pattern identification.

We investigate the affect of making the pattern formation visible in order for researchers to intelligently drive their own analysis and understanding of algorithm(s) operation. We aim to better understand how the user analyzes, identifies, and discovers trends in their data. This then informs how to transparently represent patterns, and supports algorithm accountability. To benefit from this, one must understand how a user thinks about their data and the structure of relevant trends.

We started with how human behavior analysts (psychologists and psycholinguists) view and identify patterns of human behavior [1, 2]. For this kind of analysis, there was an over-arching interest in the ordered and temporal relationships of behavior events. For example, a mutual gaze between Person A and B. This can be formulated as A looks at B, then B returns the gaze, or more precisely, <A gaze at B:s><within T seconds><B gaze at A:s>, where ':s' represents the start of the gaze event and T is time. In this case, the interest was in the temporal relationship between the start of the two gaze events without a concern with when they end. This sequence of human interactions was viewed as a behavior pattern, a pattern that encapsulates a relevant trend in the data. Taking a step back, we realized the behavior patterns had a general formulation of the ordered and temporal relationships between events in time, where an event is an instance in time with some labeled description, as in above.

This observation was simple, and yet powerful for the human behavior analysts as they represented their patterns of interest by situating the labeled events along a timeline – creating an intuitive visual representation. Given this visual representation, we developed a pattern search algorithm that identifies patterns based on this visual representation (Structural and Temporal Inference Search [3]). Hence, the underlying pattern representation used by the algorithm is transparent to the user. What the user actually sees is how the pattern is stored and used by the algorithm. The user can adjust the pattern as he/she searches for pattern occurrence(s) (i.e., trends) and visual adjustments to the pattern are reflected in what the algorithm uses as input and, in turn, how the algorithm operates. This is the embodiment of IRSM. Through three longitudinal case studies, we observed how intuitive and effective IRSM can be in providing a view into users' data, discovering relevant trends, and placing the user closer to the operations of the algorithm.

References

[1] L. Chen, R. Rose, Y. Qiao, I. Kimbara, F. Parrill, H. Welji, T. Han, J. Tu, Z. Huang, M. Harper, F. Quek, Y. Xiong, D. McNeill, R. Tuttle, and T. Huang. Vace multimodal meeting corpus. *MLMI*, pages 40–51, 2006.

[2] D. McNeill, S. Duncan, A. Franklin, J. Goss, I. Kimbara, F. Parrill, H. Welji, L. Chen, M. Harper, F. Quek, T. Rose, and R. Tuttle. Mind-merging. In *Expressing oneself / expressing one's self: Communication, language, cognition, and identity*, 2007.

[3] C. Miller, L.-P. Morency, and F. Quek. Structural and temporal inference search (stis): pattern identification in multimodal data. In *Proceedings of the 14th ACM international conference on Multimodal interaction*, ICMI '12, pages 101–108, New York, NY, USA, 2012. ACM.

[4] C. Miller, F. Quek, and L.-P. Morency. Interactive relevance search and modeling: Support for expert-driven analysis of multimodal data. In *Proceedings of the 15th ACM on International Conference on Multimodal Interaction*, ICMI '13, pages 149–156, New York, NY, USA, 2013. ACM.