Behavioural Markers: Bridging the Gap between Art of Analysis and Science of Analytics in Criminal Intelligence

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***Abstract*— Studying how intelligence analysts use interaction in visualization systems is an important part of evaluating how well these interactions support analysis needs, like generating insights or performing tasks. Intelligence analysis is inherently a fluid activity involving transitions between mental and interaction states through analytic processes. A gap exists to complement these transitions at micro-analytic level during data exploration or task performance. We propose Behavioural markers (BMs) which are representatives of the action choices that analysts make during their analytical processes as the bridge between human cognition and computation through semantic interaction. A low level semantic action sequence computation technique has been proposed to extract these BMs from captured process log. Our proposed computational technique can supplement the problems of existing qualitative approaches to extract such BMs.**

***Keywords*—Behavioural Markers; Non-Technical Skills; Insight; Imagination; Fluidity and Rigour.**

I. Introduction

Visual Analytics tools in the recent years have made an impact in the criminal intelligence and analysis communities. Histories of user interactions have been used to advance our understanding of tool usage and user goals in a variety of areas. User interaction histories contain information about the sequence of choices that analysts make when exploring data or performing a task. To understand how the analyses are being made it requires support of correlating lower-level events with tasks, and tasks with goals [1]. Until recently, most of the research has focused on the techniques and methods for refining visual analytic tools, with the emphasis on empowering analysts to make discoveries faster and more accurately. Although this emphasis is relevant and necessary, we argue that the process through which an analyst arrives at the conclusion is just as important as the discoveries themselves. Understanding how an analyst performs a successful criminal investigation will finally let us correlate art of analysis with science of analytics. This contribution is part of a research work aimed to find out appropriate methods or techniques to evaluate a visual analytic tool named as Analyst's User Interface (AUI) of the project VALCRI*(Visual Analytics for Sensemaking in Criminal Intelligence Analysis). The overarching aims of this research are based on following research questions to find out–

- What are the attributes of Behavioural Markers (BMs) for criminal intelligence analysis?
- How to translate reasoning processes into Behavioural Markers (BMs) for criminal intelligence analysis?

In Section II number of existing related work, in Section III methodology overview to find out Behavioural Markers (BMs) and their constructs, in Section IV conclusion and future work have been presented.

II. Related Work

Behavioural Marker systems are generally being developed for performance measurement in a range of organizational settings, especially in high reliability industries such as air aviation, nuclear power, maritime transport, and medicine. They are usually structured into a set of categories (e.g. co-operation, decision making, and situational awareness). Recently, Behavioural Markers (BMs) concept is not only used to measure team performance in aviation or medical sectors but also their uses for evaluating visualization are noticeable. North [2] claims that the purpose of visualization is insight and to determine to what degree visualizations achieve this purpose. He listed some of the characteristics of insight such as – complex, deep, qualitative, unexpected and relevant. Saraiya, North and Duka [3] defined insight as an individual observation about the data, a unit of discovery. They presented several characteristics of insight while running a pilot study on biological and microarray data such as – observation, time, domain value, hypotheses, directed versus unexpected, breadth and depth, category. In a case study with the popular visual analytics application Jigsaw – Kang, Gorg and Stasko [4] found that analysts' interaction histories showed evidence of the high-level sensemaking processes. Reda, Johnson, Leigh and Papka [5] approached interaction and sensemaking by combining interaction logs and user-reported mental processes

*VALCRI - http://valcri.org/

into an extended log and modeling the log using transition diagrams to better understand the transition between mental and interaction states.

III. Behavioural Markers And Analytical Reasoning Process

The analytical reasoning process is viewed as a cognitive process allowing individuals to interpret information in context so as to derive knowledge to initiate specific actions [6]. The actions of reasoning process lead to ask different questions and to focus on understanding underlying cognitive processes.

A. *The Problem*

As real-time and retrospective interviews of analysts sometime produce inaccurate characterizations of the analytic process, other means of collecting information on the methods and steps that comprise the analysis process e.g. logging of user interactions, has already been introduced in many systems. Endert, Chang, North and Zhou [7] argue that these user interaction data may present significant usability issues because they force them out of user's cognitive flow or zone and may place fundamental limitations on reasoning activities. Reasoning about data is an inherently cognitive activity, where the mental artifacts that we leverage to reason can manifest themselves at different semantic and symbolic levels of detail. Thus, a gap exists between the cognitive constructs and manipulations or interactions humans employ to think and reason about data [7].

B. *Detection Approach*

From a quantitative behavioural developmental theory perspective [8], behavioural constructs are events that have the potential to be directly observed. We have identified set of BMs through a Systematic Literature Review (SLR) as shown in Table I, and mainly look for their occurrence into recorded analytic process data by considering the context of the situations that these behaviours were observed (i.e. before and after actions and conditions). Within such task environment in criminal intelligence, process data from the task interface allows for the collection of information that may be indicative of observable behaviours. So, the challenges underlie of converting such analytic process related data into BMs. Such as - Fluency, specifically during the data-finding process, can be defined as the ability to generate many different pieces of data. Fluency in data finding is the indicative of a BM known as "Creativity". To detect them we aim to follow a compositionally reductive framework for the contextual information of complex analytical process that leads complex constructs being broken down or reduced into simpler, more quantitatively manageable constructs. Ideally, these smaller components have a more directly observable set of markers for a certain analytic behaviour. To illustrate this concept of applying compositional reductionism to complex tasks, suppose we need to measure "imagination". Imagination can be considered in terms of creativity, and creativity in the literature can be approximated as 'divergent thinking', and researchers have attempted to measure divergent thinking through concepts such as 'fluency in data finding' or 'flexibility unshifting between approach' [9].

TABLE I. Constructs For Behavioural Markers (BMs)

Categories	**Behavioural Markers**	**Description**
Imagination	Curiosity	• A strong desire to know or learn something.
	Creative Play/ Playfulness	• Playfulness Cognitive spontaneity, joy, and a sense of humor in approach. • Play involving make-believe, an 'as if' stance, fantasy, and symbol substitution. (Play, p. 238).
	Idea Generation	• Ideational flexibility - The number of themes or categories within an examinee's or respondent's ideation. • Ideational fluency - The total number of ideas given on any one divergent thinking exercise. •Ideational Originality - The unusualness or uniqueness of an examinee's or respondent's ideas. (Divergent Thinking, p. 400).
	Creative Problem Solving	• Fluency in data finding or information retrieving (the number of different data or information generated). • Fluency in problem finding (the number of alternate problem statements produced); • Flexibility in problem finding (the number of categories created by the generated alternate problem statements).

This concept of reducing complex construct into simpler, easier to measure constituent cognitive components can be conceivably applied to problem solving tasks. The reductionist approach gives an overview of BMs and their role for the scientists to recognize them when certain behaviours have occurred into analytic process data stream.

C. *Action Sequence Computation*

For recognizing BMs within an automated framework, the streams of actions during analytic process can be meaningful markers for complex behaviours. Current approaches such as – finite state systems for fixed manipulable elements, a priori establishment of fixed sequences for clearly defined tasks, exhausting all possible sequences for tasks with unpredictable human elements, are available for information computation about behavioural and cognitive processes and their implications for large scale complex analysis. A priori approach is suitable for large scale data, but not suitable for complex tasks with human elements. In exhaustive approach,

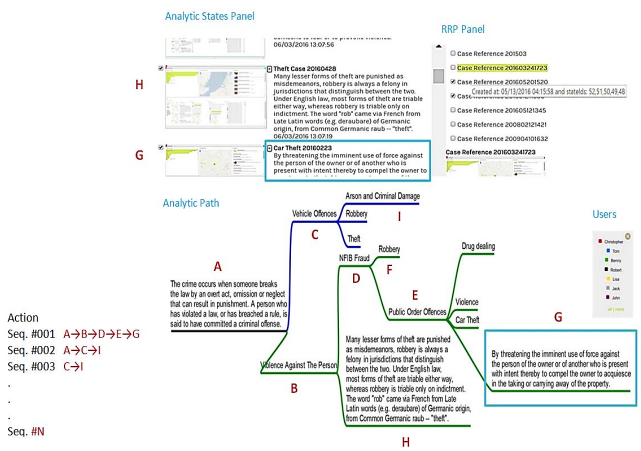

Fig. 1. Analytic Path showing annotations set by analysts with captured states & their relationships based on interactions with colour coded users (analysts) information. States can be selected from States Panel & RRP (Repetitive Replicating Playback) list of Analyst's User Interface (AUI) of the project VALCRI* to load analytic path for understanding intersections of analytical states captured by different analysts during their analysis process [11].

number of sequences increase exponentially and very rapidly reaches infeasible levels. Bakeman and Gottman [10] suggested that exploratory aspects of sequential analysis can provide empirical data which can ground later interpretations of observed behaviours because "*as we gain experience with the phenomena we are investigating, we learn which variables are important to us*". The use of network graph visualization in this context can be a useful exploratory process, rather than exhaustive, to observe and gain understanding which empirical action combinations may provide meaningful sequence for targeted BM. To determine which sequences are more valid measures of BMs, we consider our identified constructs of Table I and this would entail some form of network analysis; so each low level actions (representing an analytic state) can be defined as a 'node' and the links that make up a sequence across the nodes, can be defined as 'edges'. To test this idea we developed a visual analytic provenance visualization prototype by using which an analytic state can be captured, restored and retraced back [11]. The "Analytic States Panel" into prototype (Fig. 1) shows captured analytic states with inserted annotations which are representatives of analyst's reasoning provenance. The RRP (Repetitive Replicating Playback) panel into prototype (Fig. 1) supports creating compositions of captured analytic states that can be reapplied on different datasets. We collected these analytic provenance data during our prototype evaluation session and visualized them as colour coded user actions network known as "Analytic Path" (Fig. 1). Such analytic path networks are representatives of analyst's higher level subtasks (Gotz et. al., 2008) through lower level action sequences. To determine which sequence paths are more valid measures of BMs, we adopted eigenvector centrality computation technique for the network graph. For better demonstration of the idea, we consider a denser network graph as shown in Fig. 2 where the weight of each edge has been considered as 1 for this computation. The adjacency matrix has been determined and the centrality or approximate importance of each node for the action sequence graph has been computed. The eigenvector of the adjacency matrix has also been computed such that all of its elements are positive and to identify the prevalent nodes for pathways of actions. As found from computation, node F (Fig. 2) shows higher importance and associated edges, which indicates that it has been taken more often and therefore may imply that the analysts are finding more sensible choices for shifting from one approach to another *(Flexibility)* or generating more alternative approaches *(Fluency).* For better explaining about how shifting occurs through an "Analytic Path" as shown in Fig. 1, we consider Seq**.#001** A→B→D→E→G, Seq**.#002** A→C→I, …., Seq**.#N.** The incidence nodes of this network path are considered as composite of it's adherent nodes. We propose a compositional reduction technique for the contextual information of complex analysis which demonstrates shifting among analytic states. To illustrate the technique, we assume P(S) as a semantic state composition function P(S), where *S* is an analytic state.

So,

$$P(S) = S \qquad (1)$$

For different sequences up to Seq**. #N,** it can expressed as –

$$P(S_A) = S_A \qquad (2)$$
$$P(S_B) = S_B \qquad (3)$$
$$P(S_D) = S_D \qquad (4)$$
….. ….. ….. …..

$$P(S_n) = S_{n,} \qquad (5)$$

where *n* is the number of nodes.

Thus we computed *n*th state S_n as $P{:}\ S_{A,B,D,\ \ldots\ldots,\ n-1} \rightarrow S_n$.

Composition function of different analytic states can be expressed as –

$$P(S_A) \circ P(S_B) = P \circ P(S_A,S_B) = \{S_A,S_B\} = S_{A,B} \qquad P{:}S_A \rightarrow S_B$$
$$P(S_B) \circ P(S_D) = P \circ P(S_B,S_D) = \{S_B,S_D\} = S_{B,D} \qquad P{:}S_B \rightarrow S_D$$

… … … … … … …

$$P \circ P(S_{A,B,D,\ \ldots\ldots,\ n-1}, S_n) = \{S_A, S_B, \ldots\ldots, S_n\}$$
$$P{:}\ S_{A,B,D,\ \ldots\ldots,\ n-1} \rightarrow S_n = S_{ST}$$

where S_{ST} is a Sub-Task State (Gotz et. al., 2008) through low level actions or events.

Creativity is manifested through the flexibility, fluency and originality of responses to a task [12] which can be approximated as "Divergent Thinking" or alternately "*Imagination*". Such compositional reduction can help to find out such cognitive constructs computationally. The main challenge of recognizing such cognitive constructs within an automated framework include the limitation that a computer has no ability to make an expert judgement in the same way that a human can. However such technique still helps to validate the outcome of qualitative measure.

IV. Conclusion

Recovering cognitive reflection on analytic reasoning processes from extended log data or only by observing is a difficult task. Throughout this research work we have showed that analyst's cognitive and adopted analysis steps can be bridged by using their captured analytic reasoning data. For this, we have considered markers of analyst's cognitive behaviours (known as Behavioural Markers) as attributes for bridging human cognition and analytic computation through interactions. To detect these Behavioural Markers (BMs) from captured analytic data, we have proposed a computational technique known as "Compositional Reductionism". We have detected BMs by computing adjacency matrix of an analytic path as shown in Fig. 1. Such technique provides a simple solution to overcome tedious effort of qualitative approach for detecting analyst's cognitive aspects from sequential actions into log data. Although computational technique is an automatic approach, it still lacks ability of making an expert judgement in the same way that a human can.

As for our future work we aim to carry on further research to investigate how transitions among BMs can be detected as well as their influences on analytical activities. This will help us to understand how human cognition leads to interactions and vice versa to achieve certain goals. Analysis of combinations of BMs that occur during large complex task also introduces research challenges of predictive analytic goal oriented recommendation for action sequences. The inverse compositional reductionist approach can unfold the process of analysis being carried out to reach a goal. But how can such approach be applied on actual working environment, still requires more research on this.

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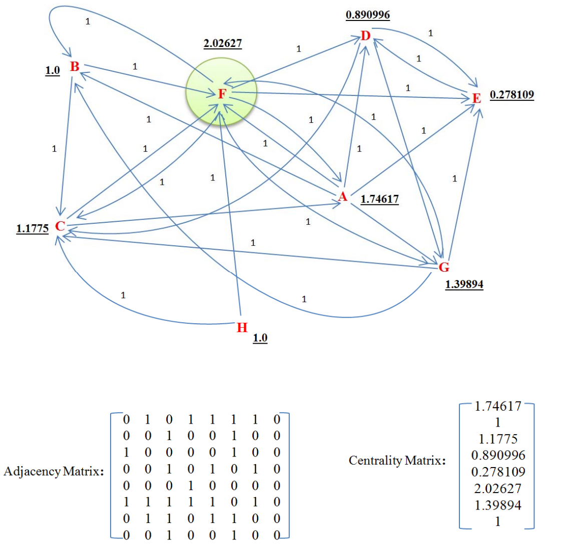

Fig. 2. Calculating approximate importance of an action sequence network graph.

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