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What BPM Researchers Should Know About Visual Analytics

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Abstract. Visual Process Analytics (VPA) is an emerging discipline at the intersection of Process Mining (PM) and Visual Analytics (VA), aiming to facilitate the analysis and enhance the understanding of complex processes. In this keynote, the speaker reflected on her research journey in the visual analysis of temporal event sequences, commonly referred to as cases or traces within the PM community, and situated this work within the broader context of process mining and VPA. To illustrate this trajectory, she used two systems developed in her VA research group, Sequen-C Explorer and EventBox, as case studies for examining both the benefits and challenges of applying visual analytics to process data, while also pointing to future opportunities for advancing the field.

Keywords: Visual process analytics · Visual analytics · Process mining.

1 Introduction

Process Mining (PM) seeks to generate insights into the execution of complex processes by analyzing event data recorded in event logs [1]. Visual Analytics (VA), more broadly, develops interactive visual methods to support human understanding of multifaceted data. At their intersection, Visual Process Analytics (VPA) has emerged as a research opportunity that unites the goals of both communities: advancing methods to make complex processes and phenomena more comprehensible [7,12]. This convergence has been further stimulated by dedicated forums such as the Schloss Dagstuhl seminars 23271 Human in the (Process) Mines and 25152 Multi-Faceted Visual Process Mining.

Traditionally, PM has focused on discovering, analyzing, and improving process models derived from event logs, with particular attention on temporal aspects and contextual attributes [1]. Its methods are largely algorithmic and strongly oriented toward delivering actionable insights for organizations. In contrast, VA is grounded in the integration of data, analytical tasks, and the characteristics of the end-users posing those tasks. VA systems combine visualization, computation, and interactivity to support human sense-making across diverse types of data (see Figure 1). Authors such as Munzner [9] have highlighted the

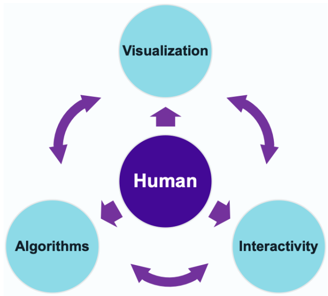

Fig. 1: Human-centered VA.

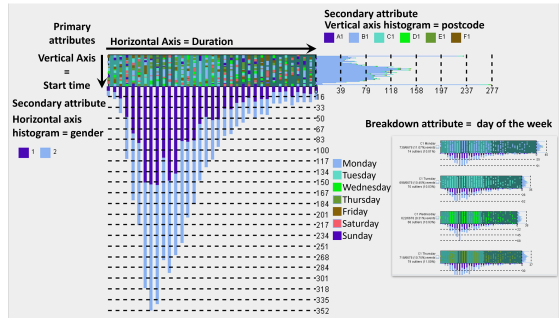

Fig. 2: Example of VA comparisons [8].

foundational dimensions of data, representation, and interaction design, while Tominski et al. [11] have stressed the pivotal role of interactivity.

Despite clear synergies, the two fields retain distinct emphases: PM tools have a focus on established visualizations and user-driven exploration strategies, while VA research, although methodologically rich, lacks the strong links to companies interested in improving their internal operations. As noted by Yeshchenko et al. [14], PM tends to prioritize algorithmic discovery, whereas VA emphasizes exploration, interpretation and evaluation of the proposed visualizations.

This disciplinary gap exists in the use of terminology. Concepts central to PM have direct analogues in VA, albeit under different names. Activities in PM correspond to event types in VA; individual events (activity instances with a timestamp and case ID) to event occurrences; traces or cases to individual sequences; variants to unique sequences; and process models to sequential patterns.

The VA community has already developed extensive resources on time-oriented data visualization [2], visual data analytics [3], and interactive techniques [11], alongside the formalization proposed by Munzner in terms of data abstractions, tasks abstraction, visual representations and validation [9]. Recent work has also identified open challenges in the analysis of event sequences [5,13,14], which includes the development of a multilevel task framework [15]. Interactive online tools such as the Event Sequences Viz Browser [4] and the TimeVis Browser 2.0 [10] provide valuable entry points for exploring this body of knowledge.

2 Risks and benefits of VA for PM

The use of VA in PM applications offers substantial benefits. However, each benefit entails potential risks, especially when data quality, uncertainty, heterogeneity and scalability challenges are not adequately addressed. Some of these are illustrated below.

Overviews. VA systems commonly generate visual summaries that present event logs at a high level of abstraction (see Figure 3). These overviews give analysts a valuable entry point to quickly identify dominant temporal patterns,

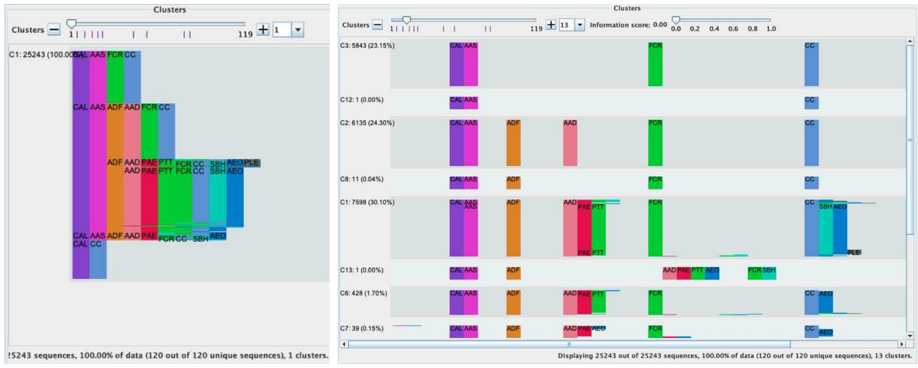

Fig. 3: Two examples of overviews (*left*) a single overview, and (*right*) an overview containing 13 clusters [6].

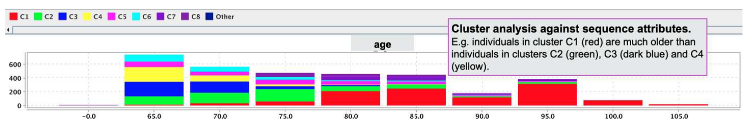

Fig. 4: Example of relationships exploration [6].

frequently occurring variants, and overall process dynamics. As such, they provide orientation and enable rapid familiarization with complex datasets. However, overviews may also obscure important details, particularly in large or noisy datasets. Rare variants, anomalies, or exceptions—which can carry high diagnostic value—are easily hidden in aggregated views. In addition, if data quality is poor (e.g., missing events or inconsistent logging), summaries may present distorted pictures of the process. The lack of mechanisms to visualize uncertainty further compounds this risk, creating a misleading sense of precision.

Relationships. Another benefit of VA lies in uncovering relationships among multiple attributes of the data (see Figure 4). Through interactivity and specialized visual encodings, analysts can investigate dependencies, correlations, or temporal interactions between activities and cases. This exploratory capability supports hypothesis generation and can point to areas where algorithmic methods should be applied more systematically. The main risk is that heterogeneous and noisy datasets often contain coincidental or weak correlations. Without explicit representation of uncertainty or rigorous statistical grounding, analysts may overinterpret patterns that are in fact artifacts of the data. Misleading relationship visualizations may thus lead to premature or unsupported conclusions.

Comparisons. VA excels in supporting side-by-side comparisons of processes, subgroups, or variants (see Figure 3(*right*). Coordinated and aligned visual views allow analysts to identify differences, and to investigate how these differences relate to multivariate attributes. Interactivity empowers analysts to choose what to compare, making the analysis flexible and user-driven. Yet comparisons can be difficult to sustain as data complexity grows. Large datasets with many cases and attributes often overwhelm visual interfaces, leading to clutter and loss of interpretability. In addition, if the provenance of analytical steps is not captured, comparisons may be difficult to reproduce or validate, raising concerns about transparency. Finally, failing to communicate uncertainty may lead to over- or underestimation of differences between subgroups.

Serendipity. VA encourages serendipitous discovery by supporting multiple perspectives and open-ended exploration. This capability is particularly valuable in PM, where rare or anomalous cases can reveal critical inefficiencies, compliance issues, or opportunities for process improvement. Analysts may identify unexpected behaviors that would remain hidden in more rigid, hypothesis-driven analyses. However, serendipity can also introduce risks. Noise in the data may be mistaken for insight, and open exploration can reinforce confirmation bias if findings are not critically validated. Without systematic provenance tracking, it may also be difficult to explain or replicate how a particular discovery was made.

Transparency and Interpretability. A key benefit of VA is its potential to enhance transparency and interpretability. By providing interactive visualizations, VA can make algorithmic analyses more accessible, empowering analysts. This human-centered approach aligns with PM's goal of actionable organizational insight. Nonetheless, transparency is not guaranteed. Complex visual encodings, scalability limitations, or poor design may reduce interpretability, especially for non-expert users. Misinterpretations of visual patterns may lead to misguided process interventions. Moreover, if user interactions are not systematically recorded, the exploration process lacks reproducibility, limiting both scientific validity and practical accountability.

3 Conclusions

VA strengthens PM by enhancing exploration, interpretation, and discovery, highlighting the promise of Visual Process Analytics (VPA) as a discipline. However, challenges remain, particularly regarding data quality, uncertainty, scalability, and heterogeneity. *Provenance* tracking and systematic *evaluation* are open research problems, complicating validation, reproducibility, and assessment of usability and insight generation. Addressing these challenges is crucial for realizing the full potential of VPA in both research and practice.

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