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Towards Integrating Visual Analytics in Multi-Perspective Conformance Checking: A Call to Action

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Abstract

The research fields of Process Mining (PM) and Visual Analytics (VA) can mutually benefit from each other by combining their strengths. PM tasks include process discovery, enhancement, and conformance checking. This paper focuses on conformance checking, where the event log is compared against a reference model to identify potential deviations in process behavior. Conformance checking is often limited to analyzing the control flow (i.e., sequences of activities), while other relevant perspectives present in the data, such as resources and time, are frequently overlooked. These additional perspectives are crucial to form a holistic understanding of deviations and their underlying causes. To address these limitations, we propose a conceptual framework and explore future opportunities for integrating VA with PM to support conformance checking from multiple perspectives. Our contribution emphasizes interactive visualization and analysis for a more flexible and iterative conformance checking process by, for example, allowing to dynamically refine and define additional constraints based on insights from multiple perspectives and making all deviations explainable and understandable.

CCS Concepts

• ***Human-centered computing*** → ***Visualization;***

1. Introduction

From road fines [MDLR15] to healthcare [BPG*15], event sequence data plays a crucial role across various domains. Visual Analytics (VA) and Process Mining (PM) are two prominent fields dedicated to exploring and analyzing such data [YM24]. While historically disconnected [YM24, MDCSW25], VA and PM offer synergies that could potentially enhance both fields. Event sequence data (event logs) frequently contains complex behavior [MDCSW25] and obscures both higher- and lower-level structures. By employing interactive visualizations, VA can facilitate a better analysis and understanding [MDCSW25]. In contrast, PM provides powerful automated algorithms to extract information about system behavior from the data [VDAADM*12]. When combined, the quantitative data coming from PM algorithms can inform and enhance interactive human-centered VA approaches, resulting in a deeper understanding of the underlying processes.

Events are discrete occurrences over time that represent lifecycle changes of activities within a process [Wes24]. Events contain a timestamp, activity label, and associated entity. They are grouped by entity (case) and ordered chronologically to form sequences (traces). In addition to the event's type often additional attributes are included. In PM, these are referred to as perspectives and provide information about organizations, resources, cases, temporal [VDAADM*12], and spatial information [AAB*23], as well as domain-specific attributes [VDAADM*12]. In VA these are data classes: time, space, relationships, and attributes [TS20]. The idea of these classes significantly overlaps with that of perspectives within PM. In essence, each perspective is an additional view describing an additional dimension of the data or relation between events, event types, cases, sequences, or other attributes. We observed that these perspectives are underutilized and not used to their full potential in the PM analysts' workflow. The main tasks in PM are: **discovery** (i.e., identifying a model from an event log), **conformance** (i.e., comparing the model and event log for deviations or compliance), and **enhancement** (i.e., improving the model) [VDAADM*12]. The focus of this paper is on conformance checking, which allows to compare the intended behavior (i.e., as outlined by guidelines, standards, or regulations) with real-world behavior, represented by event logs. Research focused on intertwining conformance checking with VA remains limited and presents an unexplored area [MDCSW25, RPGK23]. In conformance checking, the primary focus is on the control flow (i.e., order of activities) [DSMB19]. Currently, employed techniques mainly include standard visualizations (such as bar and line charts), tables, and process model representations [KMW19]. However, presenting the deviations in trace or model visualizations or numbers is insufficient to obtain meaningful insights [RPGK23]. Furthermore, these tools fall short of conveying the seriousness of deviations and uncovering their causes. There is a necessity to consider multiple perspectives rather than relying solely on the control flow [DSMB19, CvDW22]. Moreover, there is a tendency to assume that traces shar-

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ing identical activity sequences are equivalent, ignoring other critical perspectives [vLMM*]. This limits analysts in simultaneously exploring different perspectives, relations, and deviations which is necessary to fully understand the sequences' context and implications. These opportunities motivate our position paper, outlining the following contributions.

- A systematic identification and consolidation of current opportunities and gaps in related work (Section 3);
- A conceptual framework for conformance checking integrating interactive multi-perspectives visual exploration (Section 4);
- A forward-looking vision and call to action for a closer integration of PM and VA laying a foundation for future work for multi-perspective conformance checking (Section 5).

2. Background: Conformance Checking Workflow

Process models are often visualized as Petri nets (in academia), and Directly Follows Graphs (DFGs, in commercial tools), and Business Process Model Notation [LPW19] (BPMNs, in both academia [LPW19] and industry [DSMB19]). Unique traces in event logs (also known as "event sequence data" in VA) are typically visualized using sequence-based variant timeline visualizations [SZvZvdA24]. Differences between the log and model can happen due to: 1) data quality issues in the log (needs a log repair), 2) missing allowed behavior not captured in the model (needs a model repair), or 3) unintended deviating behavior in the real-world that is possible but might be a compliance risk (needs changes in the real-world execution). In PM, alignments are considered the most common technique for conformance checking [CvDW22]. Complete process models are not always available, therefore, some business scenarios only define a set of compliance constraints that a process must adhere to. Through conformance checking it is identified when these are violated or remain unfulfilled [CvDW22].

Two approaches model conformance checking and VA. First, Klessascheck et al. [KKP24] describe a structural model to support visualizations for conformance checking. Their abstract visualizations are of the following type; numeric, support, event log, model, sequence, and helicopter. Second, Rehse et al. [RPGK23] identify four stages in the conformance checking workflow through an analysis of the visualizations employed in various PM tools:

I. **Quantification.** Results are measures [KKP24], where conformance is quantified with a metric for a high-level impression of the conformance [RPGK23, KKP24]. Fitness is often used as metric [CvDW22,RPGK23,DSMB19] and explains how well the model explains the event log behavior [CvDW22]. Additional information, e.g., the number of conforming cases, is sometimes provided by academic and commercial tools, mostly using (colored) numbers [RPGK23].

II. **Comparison.** Several commercial tools use additional visualizations to further break down and compare the information from I., i.e., show distributions from multiple angles, e.g., over time, space, or per variant [RPGK23], or look for outliers [KKP24].

III. **Localization.** Results are also diagnostics, low-level insights to understand the details, such as, analyzing deviations [KKP24]. Tools offer the possibility to inspect deviations locally. Academic and commercial tools use process models, variant visualizations, and generic flowcharts. They use color to visualize the conformance results, such as marking deviating edges and nodes within a BPMN in red [RPGK23].

IV. **Explanation.** Tools give explanations, such as, descriptions, case attribute correlations, and occurrence frequencies, of the deviations mainly using text, numbers, and tables. Commercial tools sometimes have the option to manually exclude deviations [RPGK23]. Additionally, diagnostics visuals can include the raw event log with conformance results as a table and extra information of different perspectives (helicopter visualizations) in two-dimensional visuals [KKP24]. Next, users could use these as input for enhancement [VDA12], i.e., improving the model.

3. Related Work

This section reviews related work bridging PM and VA and methods for incorporating multiple perspectives. They establish the foundation for our conceptual framework and opportunities.

Challenges: PM Meets VA: Miksch et al. [MDCSW25] outline eleven open challenges in integrating PM and VA. Among them, key challenges relevant to conformance checking include: providing guidance, incorporating domain knowledge, data quality and uncertainties, making sense of multiple perspectives, and explaining results. Similarly, Gschwandtner [Gsc17] highlights similar challenges and further discusses scalability concerns. Specifically to conformance checking, Carmona et al. [CvDW22] identify PM (not visualization) challenges such as handling conformance uncertainty and bias, ensuring computational scalability, and supporting conformance for online data.

Including Multiple Data Perspectives: Conformance checking often involves constraints from different perspectives, e.g., how the control flow and resources should behave, and rules should be specified as input for conformance checking. These constraints are visualized using, for example, network representations. Gall and Rinderle-Ma [GRM17] visualize constraints by extending BPMNs (a network) with color, icons, and shapes. Moreover, Knuplesch et al. [KRK17] use an extended Compliance Rule Graphs language [KR17] to visualize multiple perspectives–including, resources, data, time, control flow, and interactions with partner processes–within a single model. Their approach employs colors, text, and icons to enable run-time compliance monitoring. Several studies have explored VA for conformance checking in domain-specific contexts, particularly clinical guidelines and their compliance in healthcare [Gsc17, RPGK23]. However, these solutions are often tailored to clinical guidelines [BPG*15, BFM13] or addressing one individual sequence [BFM13, RPGK23].

Research has proposed conformance checking techniques that accommodate multi-perspective inputs. For example, alignment algorithms can integrate multiple perspectives, such as resources and data [CvDW22]. Mannhardt et al. [MDLRVDA16,CvDW22] introduce a data-aware alignment method, where they compute alignments by balancing data dependencies, resources, and time restrictions rather than aligning the control flow first and considering the perspectives afterwards. Another approach is decision point analysis, which includes additional data and identifies decision points in process models based on event logs and related data. These points can be abstracted as decision trees, incorporating the decision point

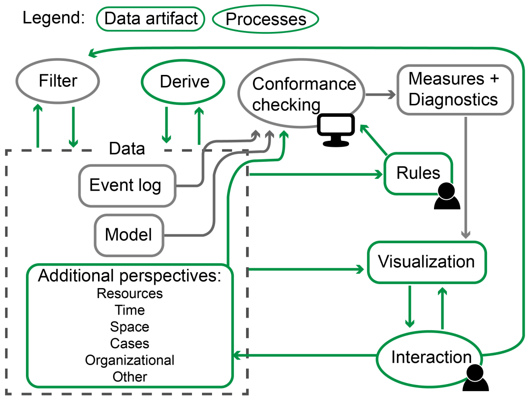

Figure 1: *Overview of opportunities within our conceptual framework. Gray arrows indicate existing processes and green arrows new or existing processes we are extending in the opportunities. Icons indicate where humans or automated methods are involved.*

split information into the models and alignments [CvDW22]. Alizadeh et al. [ALF*18] visualize their alignments as variant timelines with colored glyphs indicating the deviations in the data perspective between the event logs and the process model. Similarly, the multi-perspective process explorer from Mannhardt et al. [MDLR15] displays the process model together with a panel providing further information, such as fitness metrics and configuration options for data-aware methods. Their approach integrates decision points and data constraints directly into process models while visualizing misalignments and data distributions through variant timelines and basic charts like histograms. Beyond conformance checking, Alman et al. [AAB*23] combine VA and PM in a multi-layered method merging typical PM visual representations and additional context-aware visualizations.

Closest to our work are event knowledge graphs, which represent log data from multiple entity (cases) types and perspectives in one single connected graph structure [Fah22]. These graphs encode both directly-follows and correlation (to which entities events belong) relationships and can be queried and aggregated. While not explicitly designed with conformance checking in mind, event knowledge graphs represent a unified multi-perspective structure. Overall, related work underscores the interest and need to include multiple perspectives in conformance checking. In our paper, we take a stance on combining VA and PM to enhance the explainability and adaptability of deviations from multiple perspectives.

4. Conceptual Framework

This section presents our vision for VA in conformance checking, emphasizing the integration of multiple perspectives. Derived from discussions among the authors and related frameworks [KKP24, RPGK23], we specify key data perspectives, consisting of event logs, models, and additional perspectives (see Fig. 1–“Data”). The event logs and models typically serve as input to the conformance checking. We explicitly mention the additional perspectives because conformance checking of event logs often focuses only on the control flow and our vision is extending this to include additional perspectives. While conformance checking typically prioritizes the control flow, it is beneficial to include other commonly occurring perspectives from the VA and PM domains [VDAADM*12, TS20], e.g., resources, time, space, cases, organizational aspects, and other domain-specific data attributes. The model can be derived from a set of process constraints as defined by Klessascheck et al. [KKP24], e.g., the control flow is derived from the data as well as the users’ expectations of how the process should be or a set of domain constraints. When constructing a model, e.g., a DFG, the event log is often filtered to include the most frequent directly-follow relations. Filtering during the interactive analysis process helps to reduce the data visualized on the screen in a straightforward manner [Mun14]. Filtering is a key interaction in VA and part of the VA mantra [KMSZ06, p.6]. Therefore, our opportunities, see Section 5, discuss how we can apply filtering in different ways (see green arrows in Fig. 1–“Filter”).

Conformance checking is an automated method and results in a set of measures and diagnostics [KKP24] often based explicitly on the event log and model (see Fig. 1–“Measures + Diagnostics”). These results are then visualized (see Fig. 1-“Visualization”) and present the data both as high-level measures [KKP24] (I. and II. from Rehse et al. [RPGK23]) as well as low-level diagnostics [KKP24] (III. and IV. from Rehse et al. [RPGK23]). In our opportunities, we extend mainly the diagnostics to include the multiple perspectives in, e.g., explaining deviations interactively (see Fig. 1–“Interaction”), leveraging VA approaches in combination with automated PM methods. Furthermore, rather than treating conformance checking as a static linear process, we discuss how additional data can be iteratively and interactively derived (see Fig. 1–“Derive”) during the analysis process based on multiple perspectives to refine process constraints (see Fig. 1–“Rules”).

5. A Call to Action: Opportunities

We identified opportunities and a forward-looking vision of how these can be addressed by integrating VA based on discussions among the authors who are experienced in the VA and PM fields.

Data Characteristics, Quality, and Uncertainties: Conformance checking begins with input data: event logs and a process model. Before applying PM algorithms, it is important to determine the input data characteristics (e.g., whether it is online or offline data), the data quality (e.g., the extent of missing data), and the level of uncertainty. Event logs can grow rapidly, reaching up to a million events per hour [CvDW22]. In some cases, users need to detect and understand deviations immediately to steer the process in the correct direction, rather than analyzing the data post hoc. Online data introduces additional challenges, as events arrive unpredictably at different frequencies. Storing these events in their raw form is impractical due to the volume of the data. Therefore, the data needs to be aggregated or selectively discarded. Moreover, recent deviations are typically more relevant than older ones [CvDW22]. As process behavior evolves, the process model and constraints might need to be adjusted over time. Considering the multiple perspectives alongside the control flow increases the complexity. Within PM there is research on conformance algorithms for online data [Bur22], however from a VA perspective, despite the existence of visualization techniques for this data type [DAF*18], these do not focus on conformance checking problems in PM. When combining PM and VA,

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the data characteristics and quality can be interactively explored with the help of machine learning techniques, possibly leading to edits or adaptations of the chosen methods.

PM algorithms need input data with reasonable quality, however, this is often not the reality [MDCSW25, Gsc17]. Uncertainty may be introduced at any stage of a process, from data collection to processing, to analysis. For example, time-related uncertainties in event data may affect the accuracy of conformance checking [MDCSW25, Gsc17]. Additionally, when an observed behavior within the event logs represents a sample of the entire process, conformance checking algorithms can only provide an estimate of the conformance [CvDW22]. Expanding conformance checking to include additional perspectives, will introduce further uncertainties or quality issues that need to be addressed. Current VA methods for data quality exist but these do not take the PM needs, e.g., case heterogeneity, into account [MDCSW25, Gsc17].

Determining Deviations: After determining the data characteristics and uncertainties, the next step is to run the conformance checking algorithm to identify deviations, an example technique of how PM can help VA. Conformance checking selects the optimal alignment based on a cost function that quantifies the severity of a misalignment [CvDW22]. However, when multiple perspectives are involved (i.e., control flow, resources, and time) users might want to change the weight of certain attributes or event categories according to domain-specific knowledge to investigate the impact it has on the output. For example, users might want to prioritize control flow and time in certain situations, providing some flexibility in resource constraints. In such cases, a non-optimal alignment may be more meaningful. A key opportunity for VA is to provide interactive methods to tweak parameters in real-time or beforehand, e.g., assign weights to different attributes and allow adapting the cost function to specific use cases. Moreover, visual representations of different alignments could help to explore trade-offs and refine the definitions of deviations based on domain knowledge and tasks.

Presenting Deviations: Per our conceptual framework, once deviations are computed, they must be effectively communicated to users. However, presenting these deviations is not straightforward. For example, activity *A* in the process is flagged as a deviation because it occurs earlier than expected in some variants. Later in the process that same activity *A* appears, but now it conforms to the expected control flow. While both instances represent the same activity *A*, the deviation is detected in some variants because it happens earlier. Simply highlighting and providing textual descriptions of these deviations in such cases is not sufficient for users to quickly grasp these, especially when multiple perspectives are involved. To fully describe a deviation, it is necessary to communicate *where* it occurs, *how* it differs from conforming cases, *when* or under *what* circumstances it occurs, and *which* perspectives are affected. A possible solution can be seen in Fig. 2. Deviations are presented in a list (Fig. 2-D), with statistics (e.g., occurrence frequency) and details about attribute categories from different perspectives (Fig. 2-D.1). Alternatively, deviations can be represented as networks providing a quick overview (Fig. 2-D.2). The data perspectives can display the similarities of deviations (Fig. 2-E), highlighting clusters of similar conforming or non-conforming traces (Fig. 2-E.1-2). Each point represents all perspectives of one deviation or conform trace. Linked interactions can further highlight a specific deviation across the views upon selection (Fig. 2-C.1-2, E.4, B.4-7).

Importance of Deviations: In conformance checking, it is not uncommon to discover thousand of deviations, making it challenging to effectively visualize relevant ones [CvDW22]. VA can support users in comparing and clustering deviations and conforming traces. For example, applying dimensionality reduction techniques to deviations with multiple perspectives can highlight potential clusters and similarities between the deviations or conforming traces (Fig. 2-E). Users can inspect representative deviations from each cluster to gain insights about similar and diverging behavior. Additionally, glyphs could be incorporated to encode information about the different perspectives (Fig. 2-B.8-9 and E.3). Guidance can be used to assist users in finding interesting deviations based on particular perspectives or their current task. Such guidance could incorporate, e.g., domain knowledge and past interactions, to find interesting data through visual cues [MDCSW25].

Explaining Deviations: Once users find deviations of interest it is important that those deviations are explained (related to step IV. from Rehse et al. [RPGK23]) alongside the semantic context in which the deviation occurred (related to step III. [RPGK23]). Explaining behavioral characteristics where the event log and model differ remains an open challenge [MDCSW25]. These explanations must integrate multiple perspectives, comprised not only of the event log and process model but further additional perspectives and the relations and correlations between them (see Fig. 1). Currently, analysts mainly look at the control-flow PM models, flowcharts and variant visualizations occasionally supported by supplementary visualizations [RPGK23]. Constraints are often visualized using small models or networks [GRM17, KRK17]. VA can enhance the explainability of the detected deviations by incorporating multiple perspectives, interactions, and multiple levels of detail. Given that PM models are inherently based on network structures, techniques from diverse network visualization disciplines can be leveraged as outlined by Filipov et al. [FAM23]. Building on our mockup, we visualize the process model and event log as a variant visualization (see Fig. 2-B.1-2) as these are familiar representations for users. From the VA side, this is an example of how PM techniques help to summarize event data from different levels of detail. We also integrate additional perspectives through small multiples [vdEvW13] where each perspective can be visualized in an appropriate visualization (see Fig. 2-B.3). These views are juxtaposed in a grid (see Fig. 2-B) and users can add or delete perspectives dynamically. When selecting a deviation, all related data across the perspectives is highlighted in the corresponding small multiple (see Fig. 2-B.4-7, C.1-2, E.4). If multiple resources belong to a single deviation they can be highlighted using varying visual cues, such as different border widths proportional to their occurrences. Alternatively, glyphs-based encodings can encode these details directly within the model or variant visualization, following established guidelines [MRSS*12] (see Fig. 2-B.8-9). In combination, these approaches can effectively communicate the semantic context of the identified deviations from multiple perspectives.

Interactively Incorporating Domain Knowledge: Based on findings and exploration of the deviations and their explanations, users need to incorporate their domain knowledge to refine the results and

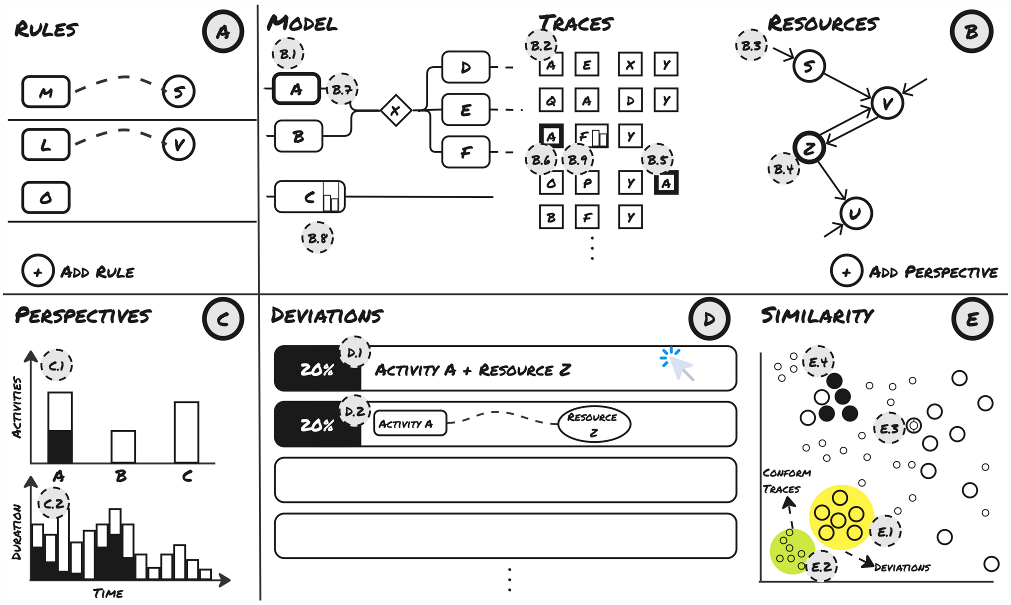

Figure 2: *Mock-up of ideas to incorporate opportunities in a VA method for illustration and as inspiration, not a complete, correct system. It contains a model (B.1), variant (B.2), and additional perspective (as separate plot, resources in this scenario, B.3, or as glyphs, B.8-9, E.3) with scented widgets [WHA07] for filtering (C). The deviations are listed (D) in textual (D.1) or network (D.2) form. A similarity plot (E) displays the similarities between deviations (E.1) and conform traces (E.2). Selected deviations (D.1) are highlighted (B.4-7, C.1-2, E.4).*

tailor constraints to the specific domain (see Fig. 1–“Rules”). This could be achieved by interactively creating new compliance rules or constraints on the fly, incorporating findings from multiple perspectives in an intuitive manner (see Fig. 2-A). These findings can be utilized to derive additional information (see Fig. 1–“Derive”). Users can add multi-perspective rules in different manners, e.g., using small network visualizations (similar to constraints) or interactive motif queries [TWC*23], natural language [WLGW22], or regular expressions [CVW17]. In our mock-up, we use small-network visualizations because they align with users’ familiarity with process models, also represented as networks. The rules the users created are listed and the user can add, edit, or remove a rule, see Fig. 2-A. The user-defined rules can be created interactively by dragging, dropping, or connecting nodes from different perspectives. Additional constraints can be assigned to the nodes or edges, similar to Vimo [TWC*23]. The idea is that once a rule is added, the deviation list and similarity plot (see Fig. 2-D, E) are recomputed based on the newly added constraint, and all other views are updated accordingly. This allows users to interactively tailor general VA solutions to the domain-specific characteristics of their data and incorporate domain knowledge.

Communicating Findings: Behavioral processes often involve multiple stakeholders and communicating findings from the conformance checking deviation analysis is not always straightforward. This opportunity extends beyond PM and applies to many domains. VA helps to communicate insights through provenance visualizations [vdEvW13] or abstract visual representations that make insights accessible to a broader audience [vdEvW14]. For conformance checking, it is important to present deviations that the users find relevant and communicate their impact on the behavioral process. These insights can serve as evidence to convince stakeholders to change a process to conform to the desired behavior.

6. Conclusion

Multi-perspective conformance checking presents unique challenges due to the complexity of integrating these dimensions. This paper describes a conceptual framework and derives future opportunities for integrating PM and VA to support conformance checking across multiple perspectives, including the logs, process models, resources, time, space, cases, and organization. A mock-up is provided to give future inspiration for VA approaches incorporating several opportunities. The opportunities do not occur in isolation but build on each other–changes in one aspect affect the others. The multiple views in the mock-up (see Fig. 2) are linked, e.g., highlighting something in one view highlights the corresponding data in other views. Their current order describes a linear process of analyzing the deviations, but the actual workflow is iterative, allowing users to go back and forth refining their analysis. For example, an insight gained while explaining deviations may trigger inspiration for adding a new rule, leading to a recomputation of the deviations and potentially changing their importance. This prompts users to revisit that opportunity. Data reduction strategies [DSP*16] or progressive VA [FFS24] provide potential solutions for scalability issues. Generally, there is a trade-off between providing standardized solutions that apply across many domains and creating domain-specific ones. Providing the necessary flexibility with solutions enables users to incorporate domain knowledge and iteratively refine their analyses. By making this process interactive and iterative users can transition from standard to specific domain solutions. Using these opportunities, future steps are laid out to improve the multi-perspective conformance checking workflow.

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