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Towards Multi-Faceted Visual Process Analytics☆

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ABSTRACT

Both the fields of Process Mining (PM) and Visual Analytics (VA) aim to make complex phenomena understandable. In PM, the goal is to gain insights into the execution of complex processes by analyzing the event data that is captured in event logs. This data is inherently multi-faceted, meaning that it covers various data facets, including spatial and temporal dependencies, relations between data entities (such as cases/events), and multivariate data attributes per entity. However, the multi-faceted nature of the data has not received much attention in PM. Conversely, VA research has investigated interactive visual methods for making multi-faceted data understandable for about two decades. In this study, we bring together PM and VA with the goal of advancing towards Visual Process Analytics (VPA) of multi-faceted processes. To this end, we present a systematic view of relevant (VA) data facets in the context of PM and assess to what extent existing PM visualizations address the data facets' characteristics, making use of VA guidelines. In addition to visualizations, we look at how PM can benefit from analytical abstraction and interaction techniques known in the VA realm. Based on this, we discuss open challenges and opportunities for future research towards multi-faceted VPA.

1. Introduction

Processes play an important role in business, industry, and science. *Process Mining* (PM) [1], a subfield of *Business Process Management* [2], aims to support the understanding and optimization of processes through the structured analysis of *event logs* containing data that these processes emit during their execution. This encompasses a variety of analysis goals such as understanding the most frequent execution variants (i.e., the happy path), identifying and removing anomalous process executions, as well as detecting and mitigating process bottlenecks. Yet, the analysis is typically challenging because the data analyzed in PM are usually large and complex, containing semantically rich information about many process artifacts. As deriving actionable insights from many complex process artifacts requires human expertise and reasoning [3], Visual Analytics appears to be a particularly useful approach to support PM analyses [4].

Visual Analytics (VA), defined as "the science of analytical reasoning facilitated by interactive visual interfaces" [5], aims to support the understanding of large and complex data by combining the advantages of interactive visualization, automatic computation, and human domain knowledge [6]. Tackling analysis complexity, VA differentiates fundamental *data facets*, including time (T), space (S), relationships (R), and attributes (A) [7]. By considering data facets, VA can provide dedicated visualizations to analyze multi-faceted data through (a combination of) lenses, each focusing on the characteristics of an individual data facet [8,9]. In this way, complex analyses can be broken down into simpler analytical tasks regarding temporal and spatial dependencies, connectivity between data entities, and their associated multivariate attributes, which together support a comprehensive understanding.

In PM, it is common to visualize event logs and the underlying processes they represent to facilitate interactive exploration, analysis, and presentation [10–12], often using visualizations such as Directly-Follows Graphs (DFGs) [13] that show the control flow. However, these visual representations are frequently developed without considering

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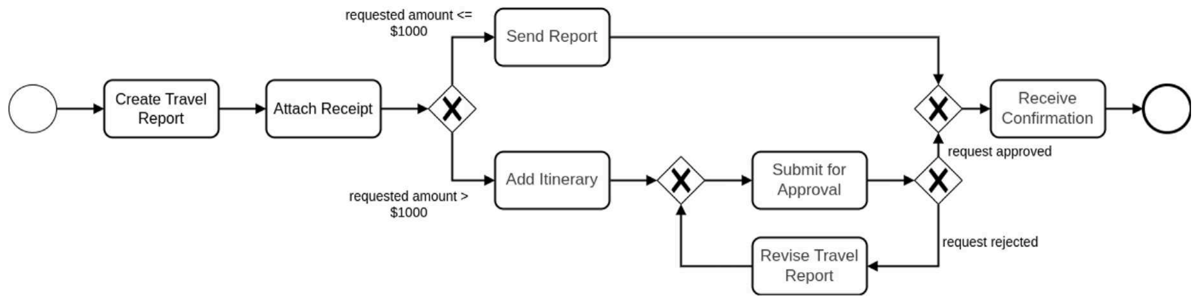


Fig. 1. Process model describing the normative behavior of the running example process using the Business Process Model and Notation (BPMN) formalism.

established design principles, guidelines, and best practices from VA. Instead, proven visualization workhorses, such as node-link diagrams, scatter plots, or histograms, are being used without adapting them to the different process artifacts and their associated data facets. As a result, the way VA is currently applied in PM contexts often fails to realize its full potential and, hence, much of VA's solution space remains under-explored for PM purposes [14].

Therefore, we propose moving towards *Visual Process Analytics* (VPA) of multi-faceted processes. The goal of this paper is to investigate how PM practice can benefit from integrating established research on multi-faceted VA, resulting in *multi-faceted* VPA. To this end, we explore how to obtain VPA solutions that are tailored to the data facets that are or can be of importance in process analyses.

We approach this by first reviewing the fundamental data facets that are commonly addressed in VA and which mechanisms VA typically uses to support multi-faceted visualizations. Then, we systematically identify current PM visualizations and compare them with VA guidelines and principles.

Our work makes the following contributions:

- it provides a systematic overview of VA data facets and their relevance in PM;
- it identifies and systematically reviews existing visualizations of practical relevance in PM;
- it categorizes popular PM visualizations in terms of VA concepts;
- it discusses research challenges and opportunities – such as abstractions and interactivity – to further enhance PM.

The remainder of this paper is structured as follows. The paper starts with providing relevant background information on PM and VA in Section 2 and discusses their common ground in terms of their input data. In Section 3, a systematic view focusing on the visual part of VA is discussed. Based on identified VA data facets that are relevant to PM, we review and categorize existing PM visualizations and identify which marks, visual channels, and tasks are involved with each. Next, we identify potential shortcomings, blind spots, and under-explored designs in Section 4. Subsequently, we provide opportunities to further enhance PM visualizations through additional analytical and interactive means from the VA realm. Section 5 positions our work in relation to other studies on this topic. A summary concludes this work in Section 6.

2. Background

In this section, we provide background information on PM, describe the relevant data (i.e. the event log), and introduce and discuss the use of VA.

2.1. Process mining

Process mining (PM) is concerned with the development of tools and techniques that generate insights into the execution of business processes based on event data [1]. As such, common artifacts used in PM are the *event data* on one hand and *process models* on the other hand. The latter refers to models of the possible executions of the process, presented in some modeling notation.

Consider, for example, Fig. 1, which depicts a process model describing an expense reporting process. The process model describes that the *Create Travel Report* activity needs to be executed first, followed by the *Attach Receipts* activity. After this, either the report is directly sent to the travel administration (*Send Report*, for amounts below or equal to $1000), or a detailed itinerary is added to the report (*Add Itinerary*, for amounts above $1000). After the itinerary is added, the report is submitted for approval. When the travel report gets rejected, it should be revised. The example process always ends with a confirmation.

A wide variety of PM techniques has been developed, all acting on the interplay of event data and process models, but serving different tasks. Traditionally, three main PM tasks are distinguished: *process discovery, conformance checking,* and *process enhancement* [1]. Recently, van der Aalst [15] introduced three additional tasks: *comparative, predictive,* and *action-oriented* PM, which we group into the task *analytics* for brevity and genericity.

Process Discovery. In process discovery, the main goal is to *discover* a process model based on (noisy) recorded event data. As such, a process discovery algorithm typically takes an event log as input and yields a process model as output. As a consequence, all theoretically possible orderings of the activities are not part of the event log, and, therefore, the process discovery algorithm needs to be able to generalize over the input data seen. The main challenge of process discovery is to model the presence of concurrency, interchangeability of activities, and activity loops, all from imperfect possibly noisy data.

Conformance Checking. In conformance checking, the main goal is to assess whether the real-world process (as reflected by the event data) conforms or deviates from a reference process model describing the intended process behavior. Both event data and a process model typically serve as input for conformance checking techniques; the output can vary, i.e., ranging from a single number indicating the conformance value to a more diagnostic-oriented conformance checking artifact.

Process Enhancement. In process enhancement, the overall goal is to enhance existing process models with information captured in event data. A typical example is to extend the process model with information on measures such as throughput time. This can be done to, for example, highlight bottlenecks in the process. As such, the typical input of process enhancement techniques is similar to conformance checking, i.e., event data and a process model. The output is a (visually) enhanced version of the process model containing additional information.

Analytics. Analytics groups the more detailed tasks of *performance analysis, comparison, prediction*, and *action-oriented* PM. Performance analysis uses event data to evaluate process performance, for instance, in terms of frequencies, time or costs. Comparison

Table 1
Simple event log describing recorded process behavior for an expense report process. The event log captures at what point in time an activity was executed for a specific case.

Event ID	*Case ID*	*Activity*	*Timestamp*
1	1	Create Travel Report	26-04-2024 9:40 AM
2	1	Attach Receipt	26-04-2024 9:42 AM
3	1	Send Report	26-04-2024 9:43 AM
4	2	Create Travel Report	26-04-2024 10:21 AM
5	2	Attach Receipt	26-04-2024 10:27 AM
6	2	Add Itinerary	26-04-2024 10:35 AM
7	2	Send Report	26-04-2024 10:42 AM
8	2	Revise Travel Report	26-04-2024 5:25 PM
9	2	Add Itinerary	27-04-2024 9:45 AM
10	2	Send Report	27-04-2024 9:53 AM
11	1	Receive Confirmation	27-04-2024 11:13 AM
12	1	Close Report	27-04-2024 11:14 AM
13	2	Receive Confirmation	28-04-2024 11:18 AM
14	3	Create Travel Report	29-04-2024 11:22 AM
15	3	Attach Receipt	29-04-2024 11:28 AM
⋮	⋮	⋮	⋮

leverages multiple event logs to enable the identification of differences in the process flow, performance, etc. between, for example, time periods, customer segments or organizational branches. Prediction encompasses techniques to make process-related predictions, e.g., the next activity that will be performed for an ongoing case, based on historical event data. Finally, action-oriented PM uses event data to trigger immediate actions within a process. A common PM task is the *exploration* of different aspects not directly related to one of the three main tasks above (e.g. data exploration, what-if scenarios, resource utilization, etc.). We group these *exploration*-oriented tasks in the *analytics* category.

2.2. Data description

Event data used in PM are typically recorded by modern *information systems* such as SAP ERP.[1] They accurately record the different actions performed by users interacting with the system in their underlying databases. The recorded event data is then transformed into an event log. Note that the creation of an event log takes up a significant amount of time and typically involves an iterative process where recorded actions are added, fine-tuned, and abstracted, to come to a final set that enables analysis [16].

Consider, for example, Table 1, which depicts a (simplified) event log related to the expense reporting process introduced earlier. Every row in the table refers to an *event*, i.e., the recording of an execution of some activity relevant to a specific *business process* supported by the information system. The identifier of the event is stored in the ***Event ID***-column, whereas the identifier of the instance of the corresponding business process is stored in the ***Case ID***-column.

The first event (i.e., with identifier 1), describes the execution of the business activity *Create Travel Report*, relevant to an instance of the process, i.e., an expense report with identifier 1. The event was executed on April 26th of 2024, at 9:40 AM. Observe that the events with identifiers 2, 3, 11, and 12 took place later in time and are tied to the same expense report with identifier 1. This relates to the temporal order data facet. Typically, events store many additional data attributes (e.g., resource information, cost information, etc.), which relate to the attributes data facet. Similarly, the database may also store additional data attributes for the instances of the business process at hand (e.g., in this case, the amount of the expense report). For simplicity, we omitted these details from the example dataset.

[1] https://www.sap.com/products/erp.html

2.3. Visual analytics

Visualization involves transforming data into images using graphical elements that amplify users' cognitive capabilities and enable them to observe, explore, and interact with their data for visual knowledge discovery [17].

In general, visualization is concerned with creating interactive visualizations for both physical and non-physical data. This paper focuses on visualizations for non-physical, abstract data (such as event sequence data and process models). At the core, two main elements play a role: *representation* and *interaction*. Many design models [18] and interaction techniques [7] for the creation of effective interactive visualizations exist. Section 4.2 further elaborates on how the interaction techniques from VA can additionally enhance multi-faceted PM.

The field of VA expands interactive visualizations. The focus is less on developing novel representations and interaction techniques, but rather on supporting users in the analytical sense-making process. As such, VA is a multi-disciplinary field of research that is defined as the science of analytical reasoning facilitated by interactive visual interfaces [5]. VA combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision-making based on large and complex datasets [6]. It is important to note that VA focuses on the integration of human decision-making with automated data analysis methods, perfectly coinciding with the process analyst who performs, for example, process discovery or conformance checking analyses to better understand the process, or make decisions regarding how and where to optimize. By exploiting a *human-in-the-loop* approach, VA enables the incorporation of domain knowledge to steer the automated methods and the analytical process [19], e.g., a combination of domain knowledge and automated process discovery might result in a better process map compared to a fully automated one.

In this paper, we mainly focus on the analysis and categorization of existing PM visualizations (i.e., *representations*) according to different *data facets*. A *visual representation* (also referred to as idiom) can be described by four elements: *data*, *marks*, *visual channels*, and *tasks* [18].

Data. The data behind the chart. For example, are the data attributes categorical or quantitative, and how many of them are used in the chart? Additionally, the data element describes what the *main* data facet is (e.g., temporal, spatial, relationships, or other) and what the *supporting* facets are. We define the data facets relevant to PM and elaborate on them in Section 3.1.

Marks. The visual elements that are used to represent a data item (e.g., points, lines, glyphs).

Visual channels. The channels encode different data values on the marks (e.g., position, size, color). They are also related to the *effectiveness* principle, where different visual channels are interpreted and perceived with different levels of accuracy. Therefore, it is important that the most important attribute (the main data facet) is encoded with the most effective visual channel [18]. Decreasingly important facets can then be matched with less effective channels. For an analysis of the effectiveness ranking of visual channels, the reader is referred to Cleveland & McGill [20] and Heer & Bostock [21].

Tasks. The tasks to be supported by the visualization (e.g., discover trends, outliers, understand distribution). In this paper, we classify the main PM tasks at a high level as *discovery, conformance checking, enhancement*, and *analytics* (cf. Section 2).

With these four elements, a visual representation can be described such that visual designers can reason about the effectiveness of a visualization and the encodings that are used. For example, the process model shown in Fig. 1 can be described as follows. *Discovery,* *conformance checking, enhancement* and *analytics* are PM tasks that are commonly supported by a BPMN process model. The data represented are categorical event sequences (the event log), with time (temporal order) as the primary data facet and relationships as the secondary facet; the marks are rectangles to represent activities, a diamond to represent operators, circles to represent begin and end states, and lines to represent relationships. Here, the visual channel shape is used to encode the semantic meaning of the visual elements. The main visual channels used are horizontal and vertical positions to encode the relationships (topologically sorted from left to right). As the primary data facet, temporal order, is encoded with the most effective visual channel (position), resulting in what can be considered an effective visualization. The next section elaborates on the data facets.

3. Systematic view for integrating PM and VA

In this section, we present a systematic view of the integration of PM and VA. Section 3.1 discusses data facets that are known in VA and are or can be relevant in PM. Section 3.2 explores the combination of multiple facets in visualizations. Section 3.3 presents an overview of commonly used PM visualizations, which we classify in terms of data facets, marks, channels, and tasks in Section 3.4.

3.1. Data facets

Data can be multivariate, come from multiple sources, and involve multiple modalities. In VA, the terms multi-faceted data or data facets have been used to refer to the representation of heterogeneous data [8, 9]. A data facet relates to a particular interpretation or perspective of the data. Similar to how data types in programming languages decide about the interpretation of bits and bytes, data facets give semantic meaning to the quantitative and qualitative data values under investigation. VA generally distinguishes four fundamental data facets [7], of which some are prevalent in PM, while others remain less frequently used:

Time (T) is an intricate dimension [22] and an omnipresent data facet in PM. Event data and process models typically include this facet. As shown earlier, event logs are commonly used to capture processes that comprise activities that take place in a certain chronological order. These processes are represented as sequences of events that occur over a period of time. The example in Table 1 relates events to timestamps, which enable a *quantitative* interpretation of time. For example, temporal distances can be calculated, as is typically done when inspecting arrival rates. In other scenarios, time might be of *qualitative* nature, meaning that only temporal ordering of events is defined but not distances.

Space (S) can be associated with processes or process artifacts. This data facet would represent the 2D or 3D location where an event occurs, typically in geo-space. For instance, the location at which events occur in a production process can indicate potential areas to improve the process as long distances between stations at which subsequent activities are performed can cause delays. Also, in domains such as healthcare and warehousing, this facet can be of interest. Although space is highly relevant as a data facet in VA, it is not (yet) often seen in current PM practice.

Relationships (R) describe link structures between data entities, where the links may span networks (graphs) or hierarchies (trees). While time and space describe the when and the where of data entities, relationships capture their logical or physical connectivity. Fig. 1 provides an example of a process model where the activities, such as *Attach Receipt* and *Send report*, are entities, and the directed arcs are relationships between these entities spanning a graph. Fig. 2 provides more examples about what can constitute an entity. Note that our relationships data facet is not to be confused with the formal mathematical definition of relations.

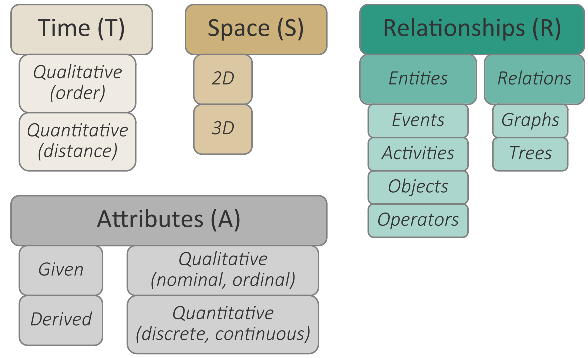


Fig. 2. Data facets and their relevant characteristics.

Attributes (A) add context or provide further information about events and process artifacts. Attributes can be either given or derived via computational analysis methods. The domain of attributes is relevant, and they can be qualitative (nominal or ordinal) or quantitative (discrete or continuous). For example, the customer ranking (given, ordinal), country of destination (given, nominal), ordered items count (derived, discrete), or total order volume (derived, continuous) can all be attributes in a goods delivery process.

Fig. 2 outlines the individual data facets as discussed before, and Fig. 3 shows a Venn diagram of all possible combinations of data facets that may be relevant in the context of VPA. The individual combinations are typically associated with distinct categories of data, such as temporal data, spatio-temporal data, or multi-faceted graphs, which play an important role in VA research.

3.2. VA for multiple data facets

In VA, dedicated subfields exist that focus on the visual representation and analysis of particular data facets: time-oriented visualization for T [23], geo-visualization for S [24], graph visualization for R [25], and multivariate data visualization for A [26]. The more facets a dataset has, in general, the more complicated the visualization becomes (see, for example, Hadlak et al. [9] for multi-faceted graphs).

The challenge of visualizing multi-faceted data lies in finding a visual encoding (marks and channels) that effectively communicates the relevant data facets (given the task). As there is only a limited set of visual channels, not all relevant data can usually be encoded in a single representation. Instead, multi-faceted visualizations need to make a compromise: particular data facets can be encoded in full detail, while others can only be indicated or hinted at. This also implies that different visual representations are required, each highlighting a particular data facet while only hinting at selected remaining facets.

To obtain well-balanced visual representations of multi-faceted data, a two-step approach design procedure can be followed [7]:

1. First, a base representation is defined for the primary data facet whose depiction will govern the overall display. Using the *effectiveness* principle [18], the most important data element should be selected as the primary facet, and will often be visually represented with position as highest ranked visual channel.
2. Second, additional data facet(s) will be incorporated into the base representation with other (less accurate) visual channels, such as color, size, orientation, or shape.

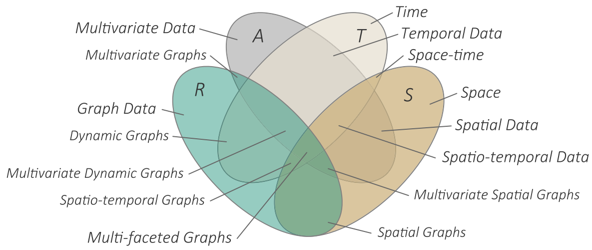


Fig. 3. Overview of data facets and how their combinations lead to different categories of data.
Source: Adapted from [7].

This general VA design process can also be used in the context of PM. In what follows, we look at typical PM visualizations, first through the lens of PM and then through the lens of multi-faceted VA.

3.3. Inventory of popular PM visualizations

The PM literature describes a wide variety of visualizations that are created or used as a part of a PM analysis. To identify the most commonly used PM visualizations, a set of recently published PM case studies has been reviewed. This subsection outlines the methodology used to identify and select case studies, followed by an overview of the identified visual representations.

3.3.1. PM case study selection

To inventorize the most commonly used PM visualizations, we identify published PM case studies from three sources. Firstly, publicly available *Business Process Intelligence Challenge*[2] (BPIC) reports were collected. In these reports, academics and practitioners present the result of a PM analysis on real-life data. We selected 21 BPIC reports for further analysis, distributed over 2015 – 2020, i.e. the most recent BPIC editions. The selection process followed three steps: only reports that were publicly accessible were considered, submissions from academic and professional teams were prioritized, and a subset was chosen with a focus on the use of visualizations in the report. Secondly, PM case study papers that discuss real-life PM applications were collected. To identify such papers, we queried Web of Science to select papers with *"case study" and "process mining"* in the abstract. To complement the timeline of the BPIC reports and ensure coverage of recent visualizations, we focused on papers published in the last 5 years (2020 – 2024). All identified articles (122) were screened. When a paper met at least one exclusion criterion, the paper was excluded from our subsequent analysis. The following criteria were used:

- the article does not contain PM visualizations;
- the article focuses on the development of a new PM (related) computational method;
- the article focuses on the optimization of a new PM algorithm.

Finally, we used Reinkemeyer's textbook [27] on PM applications as a third source, as it provides a collection of PM case studies from various businesses. All case studies in the book were screened using the previously described exclusion criteria.

In sum, we used 21 BPI challenge reports, 48 PM case study papers and 5 case studies from Reinkemeyer [27] to analyze the most commonly used PM visualizations from the last decade. This resulted in 74 papers in total. A complete list of the selected case studies can be consulted in Appendix.

[2] https://www.tf-pm.org/competitions-awards/bpi-challenge

Table 2
Visual representation (sub-)categories and associated occurrence frequencies as identified in the screening of 74 PM case studies. Relative frequencies at the category level represent the distribution across categories, while relative frequencies within a category represent the frequency distribution of the subcategories within a single category. Process-mining-specific visualizations are italicized.

Visual representation	*Absolute freq.*	*Relative freq.*
Chart-based	**201**	**47.07%**
Bar-chart	100	49.75%
Line-graph	48	23.88%
Dotted chart	*27*	*13.43%*
Box-plot	8	3.98%
Pie-chart	8	3.98%
Area chart	4	1.99%
Bubble chart	1	0.50%
Heatmap	4	1.99%
XmR-chart	1	0.50%
Network-based	**190**	**44.50%**
Process map	*134*	*70.53%*
Node-link	31	16.32%
Petri net	*13*	*6.84%*
BPMN	*11*	*5.79%*
Sankey diagram	*1*	*0.53%*
Matrix-based	**14**	**3.28%**
Process matrix	*14*	*100%*
Hierarchy-based	**14**	**3.28%**
Decision tree	4	28.57%
Process tree	*3*	*21.43%*
Classification tree	2	14.29%
Dendrogram	2	14.29%
Organizational chart	2	14.29%
Treemap	1	7.14%
Timeline-based	**8**	**1.87%**
Variant diagram	6	75%
Process time-line	2	25%
Map-based	**0**	**0.00%**

3.3.2. Visualization categorization

The 74 selected case studies contained 427 PM visualizations that were coded using ATLAS.ti. In this visualization categorization, we focus on the visualization techniques themselves rather than the specific content these visualizations may represent. The categories that were used to code the visualizations stem from the survey paper of Guo et al. [28], which categorize and survey visualization techniques for event sequence analysis. We slightly adapted the categorization to the PM context. Due to the strict focus of Guo et al. on event sequences, model-based process representations were not present in their proposed classification; therefore, we replace the specific 'Sankey' category with a more generic *network-based* category allowing for the inclusion of visualizations of *process models* (including Sankey diagrams).

We further added the main category of 'map-based' visualizations as this category maps to our *space* (S) data facet which was missing in the categorization of Guo et al. [28]. This results in the following categorization: chart-based, network-based, matrix-based, hierarchy-based, timeline-based, and map-based. Open coding was used to identify the subcategories within each main category. When a new visualization occurred, we added a code (subcategory) that described the visualization. This iterative approach allowed us to refine our classification framework as we progressed.

Table 2 summarizes the results of coding as it lists the visualization categories and subcategories, along with their absolute and relative frequencies in the 74 investigated case studies.

Interestingly, generic *chart-based* visualizations are most often used. In particular bar charts, line graphs, and dotted charts (scatter-plots) are observed relatively frequently. The *network-based* visualizations, i.e. visualizations intended to represent process models, are the second most frequently used type of visualization. Within this category,

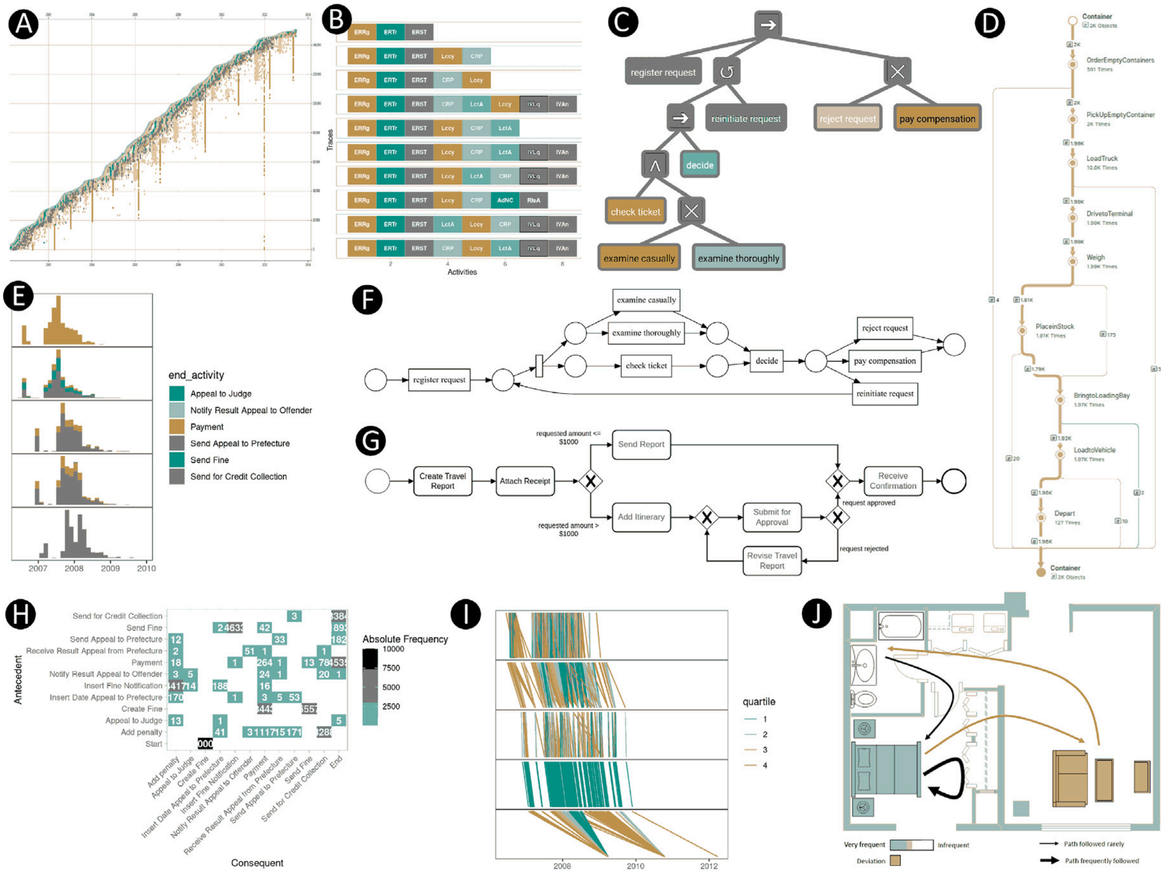


Fig. 4. Identified popular PM visualizations: (A) Dotted chart, (B) Variant diagram, (C) Process Tree, (D) Process Map, (E) Frequency diagrams, (F) Petri Net, (G) BPMN, (H) Process Matrix, (I) Performance Spectrum, (J) Spatial Map [14]. Images created using the PMTK process mining tool [29] (A); Cortado [30] (C), PRoM [31] (F), bupaR [32] (B, E, H, I), and Celonis (D).

process maps (e.g. DFGs) are most frequently used. We further observe that node-link diagrams are often used to represent various types of relationships next to control-flow (e.g., resource relationships such as the handover-of-work or social networks can be visualized). Perhaps unexpectedly, visualizations of process modeling formalisms such as Petri nets and BPMN (see Fig. 1) are used relatively infrequently. Note that our sample might be biased due to the relatively large space consumption of process model visualizations, whereas space is typically expensive in academic publications and, hence, less used. Other less frequently used visualization categories are the *matrix-based*, *hierarchy-based*, *time-line based*, and *map-based* categories, where the latter did not appear at all. Similar to the network-based control-flow models – i.e., Petri nets and BPMN –, the hierarchy-based control-flow models – i.e., process trees – are relatively infrequently visualized.

3.4. Categorization of popular PM visualizations in terms of VA concepts

Starting from the popular PM visualizations identified in Section 3.3, we present a categorization of these visualizations in terms of *data facets*, *mark(s)*, *visual channel(s)*, and *tasks*, as described in Section 2.3 and 3.1. We limit ourselves to the visualizations considered as *typical* PM visualizations, i.e., the ones italicized in Table 2: *Dotted Chart*, *Process Map*, *Petri net*, *BPMN*, *(Process) Matrices*, *Process trees*, and *Variant diagram*. All non-PM-specific representations categorized in the *chart-based* category are considered *Frequency diagrams* and are also characterized, as these visualizations are often utilized in PM analyses.

Next to the most popular PM visualizations – as identified in reported case studies – we expand the list with visualizations that are more recently introduced in academic studies. Despite their absence in the screened case studies, we postulate that these visualizations might be of great potential in the future of VPA. To this end, we screened the conference proceedings of all editions of the International Conference on Process Mining (ICPM 2019–2024) and the proceedings of the last five editions of the annual conference on Business Process Management (BPM 2020–2024). In the first phase, titles were screened for newly introduced visualizations. When an indication of a visualization was present in the title, the full paper was screened in the second phase to assess whether a new visualization was introduced.

The examination of these proceedings led to one additional visualization, the *Performance Spectrum* [33]. Aside from this, the space annotation was mentioned [34]. Annotations were not considered new visualizations to be included. However, annotations link explicitly to one of the VA data facets. Additionally, it is tied to a new visualization, the *Spatial Map*, that was presented at a workshop in the margin of ICPM 2023 [14]. Therefore, we added both the *Performance Spectrum* and *Spatial Maps* to the list of PM visualizations that are of interest to examine from a VA point of view.

In the following, we introduce the visualizations in detail and indicate their primary and secondary facet as well as the marks, visual channels, and tasks used.

To determine *time* or *relationship* as the primary data facet (e.g., in process maps), we consider if the semantics of a relationship include any notion of time (either absolute or temporal order). If so, e.g., the *direct succession* between activities in a DFG, time is considered the primary facet. If a relationship is more abstract or generic (i.e., no time, no space) and we are concerned with the overall structural properties of all relationships (e.g., resource usage) we consider relationship to be the primary facet.

The task categorization was informed by the contextual relevance of each visualization within its respective case study and by a broader understanding of its typical applications in the field, derived from the collective author's domain expertise and experience. We leveraged our domain expertise to minimize any misalignment between the tasks we inferred from publicly available visualizations in case studies and the actual tasks analysts perform to draw conclusions. While visualizations suggest certain interactions and insights, the way analysts use them in practice may differ. To account for this, we carefully examined both the visual representations, the supporting text, and the reasoning process analysts typically follow. However, some discrepancies may still exist between the tasks we identified and the actual tasks performed, as these might not be directly observable from the visualization and supporting text alone.

Dotted chart. A dotted chart visualization is a scatterplot-like visualization of event data [10]. Consider Fig. 4-A, in which we depict an exemplary dotted chart visualization. Whereas the visualization is highly customizable, time is most commonly plotted on the x-axis. As each event in the event data relates to a case, we can consider the case identifier as an event attribute. Given some ordering specified over the case identifiers, the y-axis represents the case identifier value of the events. As such, all events (represented as a dot) related to the same case are plotted on the same y-axis value. Event colors are mostly based on the corresponding activity. A dotted chart is often used to spot interesting patterns at a glance. For example, the emergence of "vertically stacked dots" in a dotted chart indicates the presence of *cross-case batching behavior*, where events of the same type but from different cases happen at the same time.

We identify *time* (x-axis) as the primary facet of the dotted chart. *Attributes* (dot color) are considered an additional facet. The main visual mark is identified as being a *dot*. As visual channels, *position* and *color* are identified. Finally, dotted charts are primarily used for *analytics* tasks.

Variant diagrams. Variant diagrams [35] are a summarizing event log visualization that group all traces that record equal control-flow behavior. For example, reconsider the example event log depicted in Table 1. Assume that multiple cases all describe the sequence of activities *Create Travel Report*, *Attach Receipt*, *Send Report*, and finally *Receive Confirmation*. We refer to the aforementioned sequence of activities as a *trace variant*, i.e., a sequence of activities described by one or multiple cases. Consider Fig. 4-B which provides an example visualization of a variant diagram. Typically, the activities are represented by a shape, and given a specific color.

As a primary facet for the variant diagrams, we identify *time* (temporal order). Additional facets identified comprise *relationships* and *attributes*. Visual marks are *rectangles* and *points*, while visual channels are *position on a common scale* and *color hue*. Variant diagrams are primarily used for *conformance*, *enhancement*, and *analytics* tasks.

Process tree. Process trees [36] are used to model the control-flow of processes. As the name suggests, they are an extension of the graph-theoretical notion of a tree. Consider Fig. 4-C, in which we visualize an example process tree. The internal vertices of the tree (i.e., the non-leaf vertices) are referred to as *operators*. Operator vertices specify the control-flow of their children. For example, a *sequence operator*, typically visualized with the →-symbol, specifies sequential behavior, i.e., the left-most child should be fully executed first, followed by the second child (from left to right), etc. Other operators include the *exclusive choice* (×), *concurrency* (∧) and *loop* (↺) operator. The hierarchical nature of process trees allows to easily spot groups of (sub-)process behavior, which is arguably harder to achieve from other modeling formalisms such as Petri nets and BPMN models. As a primary data facet, *relations* are visualized by process tree visualizations. *Time* and *attributes* are considered as additional facets, e.g., computing any activity-based KPI (time, costs, etc.) and use a relative color scale to overlay on top of the model leaf nodes. The identified marks are *points*, *lines*, and *rectangles*. As visual channels, we identify *position on an unaligned scale*, and *spatial region*. Finally, process trees are generally used in the three core PM tasks, i.e., *process discovery*, *conformance checking*, and *process enhancement*.

Process map. Fig. 4-D presents an example visualization of a process map. The nodes in the process map represent *process activities*, and the arcs connect two activities that are (in)directly following each other as recorded in the event data. Typical interactions with process maps include zooming in/out, gradually adding more behavior, and inspecting activity information. Compared to the *dotted chart* visualization, a process map applies more aggregation. That is, events are not explicitly visualized but rather the activities they represent.

As a primary facet, we identify that *time (temporal order)* among process artifacts (i.e., activities) are visualized. Additional facets are *relationships* and *attributes*, i.e., typically time and attribute-derived values can be overlaid on the process maps.

The marks used are *points, lines* and *rectangles*; the visual channels are *positioning on an unaligned scale*, and (tool-dependent) *color hue and saturation*. Note that for all process map visualizations (DFG, BPMN, Petri Net) also object-centric counterparts exist that encode the different objects by using color hue.

Frequency diagrams. As indicated, *frequency diagrams* entail all non-PM-specific visualizations in the *chart-based* category, i.e., bar-charts, line-graphs, etc. (see e.g., Fig. 4-E). Generally, we observe *attributes* to be the primary facet of this type of visualization. All facets can also act as an additional facet. Marks such as points, lines, and areas are predominantly used in frequency diagrams. The visual channels adopted are primarily length and color hue. Finally, the frequency diagrams, such as the dotted chart in the same category, are predominantly used in *analytics*.

BPMN. Business Process Model and Notation (BPMN) is a process modeling notation that is designed for (but not limited to) use in industry [37]. Reconsider Fig. 1, in which an example BPMN model is depicted. In addition to what is seen in Fig. 1, the BPMN standard describes many more modeling constructs that can be used to model a business process. However, notably, in the context of PM, the modeling elements shown in Fig. 1, i.e. tasks/activities, routing operators, and start/end points are most commonly used. This is due to the fact that most PM algorithms internally use Petri nets. Hence, Petri nets, having less support for "advanced modeling constructs", are often converted to BPMN models.

The facets identified for BPMN are equal to process maps (primary: *time*, secondary: *relationships, attributes*). As marks we identify *points*, *lines* and *rectangles*. Visual channels represent *position on an unaligned scale* and *area*. BPMN models are typically used for all tasks.

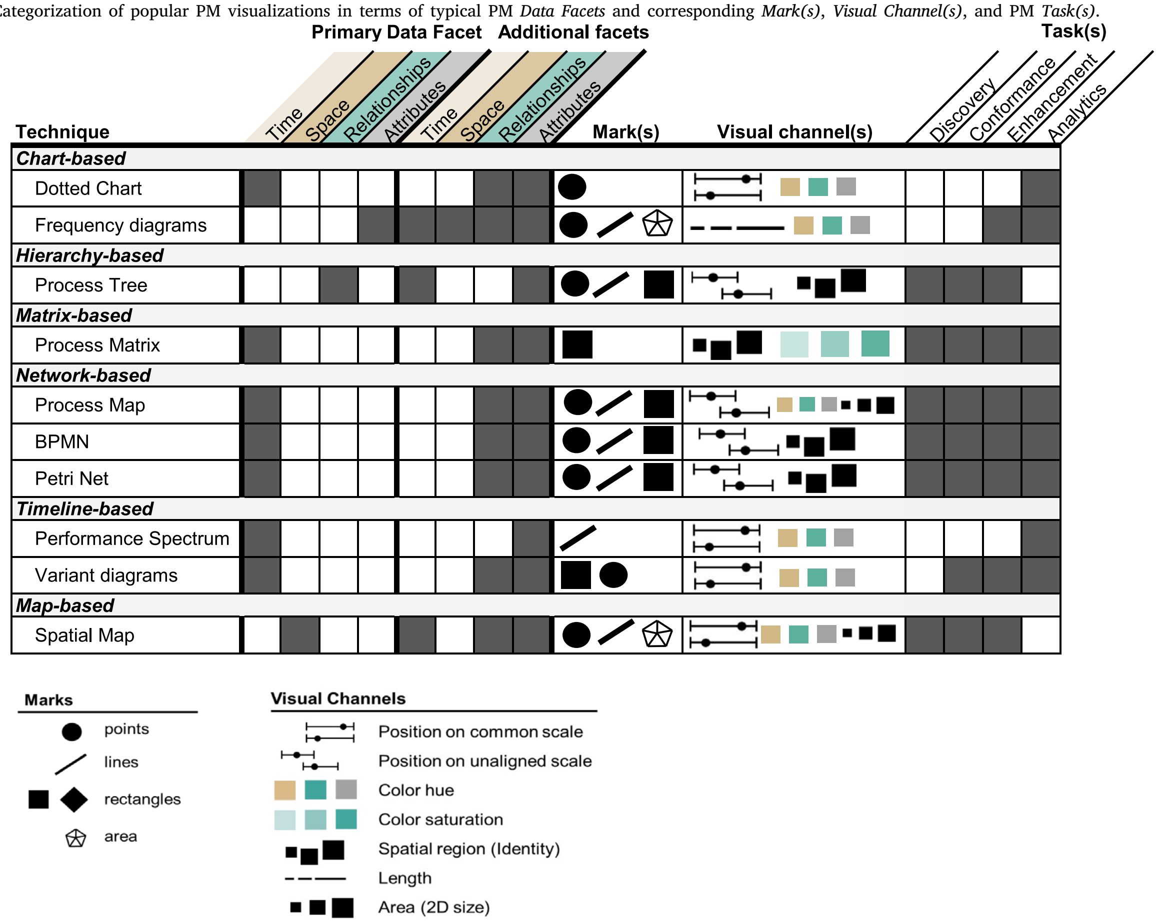
Petri nets. A Petri net [38] (see Fig. 4-F) is a graph-based mathematical modeling notation that allows for modeling the behavior of complex systems that exhibit concurrency. In the context of PM, a subclass of Petri nets is often considered, i.e., *Workflow nets* [39], which assumes that the system modeled (i.e., the process) has an explicit single start and end point.

We classify Petri nets similar to BPMN models (see Fig. 4-G) on all aspects of our categorization.

Process matrix. Process matrices visualize typical process properties in an $n \times m$ table. Consider Fig. 4-H, in which we depict an example process matrix. On both axes, activity names are plotted. The value depicted in a cell at position (i, j) refers to the number of times the activity at position i of the x-axis was followed directly by the activity at position j at the y-axis.[3] The color intensity (saturation) is based on the relative frequency of the cell values. Alternative matrix-like representations exist as well. For example, one axis could show activities and the other axis could represent resources, and values in the cells record the (relative) frequency of a resource executing the activity.

[3] In some cases, the process matrix can be seen as the matrix representation of a process map.

Table 3
Categorization of popular PM visualizations in terms of typical PM *Data Facets* and corresponding *Mark(s)*, *Visual Channel(s)*, and PM *Task(s)*.



As a primary facet, the process matrix visualizes the *time (temporal order)* between process entities. Typically, *relationships* and *attributes* can potentially be additionally visualized using color or glyphs in each matrix cell, i.e., acting as additional facets. This has, to the best of our knowledge, not been done and provides a simple and effective manner to increase further use of the Process Matrix. *Rectangles* are used as marks, the visual channels entail *areas* and *color saturation*. All tasks can be supported by process matrices.

Performance spectrum. The *Performance Spectrum* [33] visualization is a specific instantiation of a Marey chart, tailored to event data. Consider Fig. 4-I which depicts an example of the performance spectrum. As in any Marey chart, the x-axis represents time. The different values on the y-axis represent the occurrence of a specific activity. For example, assume the two activities *Create Travel Report* and *Attach Receipt* are part of a performance spectrum visualization. Whenever two such events directly follow each other for some case in the process, we draw a line from one activity to the other in the spectrum. The color of the line is based on the relative duration of the segment it represents.

For the performance spectrum, we identify *time* as the primary facet. As an additional facet, we identify *attributes*. As visual marks, *lines* are used. The visual channels identified are *position on a common scale* and *color hue*. The performance spectrum is primarily used in *analytics* tasks.

Spatial map. In spatial maps (see Fig. 4-J), the main element is spatial position. Typically, this is related to a geographical location, but not necessarily; spatial maps can also represent (virtual) resources. The process is of secondary importance and generally represented on top of the spatial map. Consider Fig. 4-J, where a room is depicted as the main spatial element, and the arrows represent the process flow (person movement) [14].

As a primary facet for spatial maps, we identify *space*. Additional facets identified are *time, relationships* and *attributes*. Visual marks are *dots, lines*, and *area*. The visual channels are *position on a common scale, color hue*, and *area*. Spatial maps are primarily used for all three main tasks *discovery, conformance*, and *enhancement*.

An overview of the categorization of popular PM visualizations in terms of VA concepts is presented in Table 3. Starting from this overview, we discuss the challenges and opportunities of VPA.

4. Challenges and opportunities

To discuss the open challenges of bringing together VA and multi-faceted PM in more detail, we start with a gap analysis by analyzing the results of our categorization (see Table 3). Next, potential avenues for future research are posited. More specifically, we discuss how PM visualizations could further be enhanced towards true multi-faceted VPA through the use of abstraction and interaction.

4.1. Gap analysis

Observations and opportunities. From the existing PM visual representations classified according to the earlier defined data facets, marks, visual channels, and high-level PM tasks, we observe the following:

- *Time* tends to be the primary facet in multiple PM visualizations, mostly focusing on the temporal order between activities. These visualizations are typically representing the process models with variations of a node-link diagram where nodes represent the activities or operators and the links represent the relations (process tree, process matrix, process map, BPMN, and Petri Net). The

relationships are typically used to determine the layout of the node-link diagram (often through means of topological sorting). Therefore, the visual channel used to encode the relationships is *position on an unaligned scale*. As a consequence the process maps and variant diagram only show temporal order, not absolute or quantifiable time. The dotted chart and performance spectrum typically show quantifiable time. For these time is encoded with the visual channel of *position on a common scale*. As this is the highest ranked visual channel in terms of effectiveness, this is a good match.
- Only the process tree has *relationships* as the primary facet. The operators and relationships are typically positioned using standard tree-based layouts. As the visual channel that is used here is *position on an unaligned scale*, the relationships are well encoded. However, the secondary facet *time* is not explicitly encoded and can only be derived from interpreting the operators.
- *Space* is never used as a primary facet except for the spatial map (which was only encountered once in our review on PM visualizations). In a spatial map, the primary space facet would be encoded through *position on a common scale* (*e.g.,* latitude–longitude pairs). *Time* and additional *attributes* are then encoded with *color* and *size*, but *relationships* is not present. In general, this is an under-explored area that provides ample opportunities for further exploration (e.g., in a recent workshop paper, maps are used as a backdrop [14]).
- *Attributes* as a primary facet are only present in the frequency diagrams, typically encoded with *length* and *color* (e.g., bar charts, line-graphs, etc.).
- The process model visualizations (process tree, process matrix, process map, BPMN, and Petri Net) are typically used for the primary task of understanding the control-flow: discovery, conformance checking, and enhancement. Analytics on top of this is typically a secondary task that is performed with visual channels (e.g., color) enhancing the process model visualization. More advanced analytics for which perspectives need to be combined are mainly performed with different (linked) frequency visualizations that are chart-based (frequency diagrams, dotted chart) and timeline-based (performance spectrum, variant diagrams). There lies an opportunity and challenge in combining these into a single view, or enabling flexible reconfiguration by dynamically changing the primary facet for a different perspective [40].
- Most visualizations used for the PM tasks of analytics are what would be considered simple visualizations from the perspective of VA (e.g., bar-charts, line-charts, pie-charts, area-charts, heatmaps). Alternatively, analytics information is also encoded with additional visual channels such as color and size, on top of the control-flow. These direct encodings and linked visualizations are typically only capable of conveying univariate patterns (i.e., color, size, a bar or line chart only shows one variable at a time). We observe that more complex advanced multivariate visualizations are not used (e.g., scatterplot-matrix, parallel-coordinate plot, glyph-based approaches). A recommendation would be to start using these instead of the basic charts to discover more complex relationships and (inter-)dependencies. For example, there might be correlations between time, bottlenecks, and resources used, which cannot be identified and discovered by solely looking at visualizations of the individual components. A more challenging opportunity is to integrate or extend these multivariate visualizations to also show relationships to convey control-flow simultaneously.
- The process model visualizations (process tree, process matrix, process map, BPMN, Petri Net) all have the same primary and secondary facets from a data visualization point of view, but they use different semantics. This is reflected in the diverse selections of marks and visual channels used. Here, there is an opportunity to tailor the visualizations to convey the semantics, e.g., reflecting loop operators with activities positioned along a circle, or conveying concurrency by showing activities intertwined.
- Related to the opportunity of visual objects better reflecting their semantics, are object-centric process maps. Current object-centric process maps use the (arguably) most important element, *object*, and encode this with the visual channel of color. However, if color is removed, they can be considered traditional process maps. Here is an opportunity and challenge to rethink how to encode the objects with higher ranked visual channels to truly treat objects as first-class citizens.

4.2. Enhancing PM via abstractions and interactivity

So far, our focus has been on the visual aspects of integrating VA into PM. Yet, VA is only complete when visual methods work in concert with automatic computations and interactivity [5], as explained in Section 2.3.

The automatic computations mainly serve the purpose of abstraction: the analysis is focused on information that is essential to the task at hand, while less relevant information is abstracted or omitted altogether. Interactivity is key to enabling an analytic discourse between the human analyst and the machine-generated artifacts (i.e., visualizations and abstractions).

In the following sections, we briefly review typical abstraction methods and interaction techniques in VA that can be useful to further enhance multi-faceted VPA.

4.2.1. Abstractions

When the data to be analyzed become larger (more data entities, more data attributes) and more complex (more data facets, more data sources, more data types, etc.), which is regularly the case in PM, it is no longer possible to show all information on one screen [41]. This is even more true when considering multi-faceted VPA, which involves several tailored views focusing on different parts of the data and distinct data facets. This focus on essential information can be achieved through abstraction methods.

Different categories of abstraction methods exist in VA [7]. They vary in *what* is abstracted and *how* the abstraction is obtained. In terms of *what* is abstracted, one can distinguish visual abstraction and data abstraction. Visual abstraction operates in the visual domain and includes density-based representations and bundling approaches. Data abstraction works directly on the data. Typical methods for *how* abstraction can be implemented include degree-of-interest approaches, clustering, or dimensionality reduction. The remainder of this subsection will outline the aforementioned approaches, of which an overview is also provided in Fig. 5.

Density-based representations — from individual items to item density. Instead of visualizing data as discrete visual items, density-based representations, as the name suggests, show density fields. That is, individual data or visual items are abstracted to density values. One example technique is continuous scatter plots [42], which can be helpful when visualizing the associated data attributes of object-centric processes.

Bundling — from cluttered lines to bundles. Visual representations that work with many lines or paths, such as DFGs, can be abstracted by means of bundling. The visual clutter that is caused by many lines is reduced by routing the lines in bundles. Bundles can make major flows among processes more clear. Yet, individual paths can become more difficult to identify. Depending on the data and visualization requirements, different bundling techniques can be applied [43].

Sampling — from all data to sampled data. Sampling is an approach to reduce the number of data items to be visualized. Sampling creates a sampled dataset that includes a selection of the original data. The key challenge is to perform sampling such that the sampled data preserves most of the properties of the original data [44]. While event log sampling has been considered in PM [45], graph sampling [46] could be useful to sample the topological structure of relations between process entities in a PM process model.

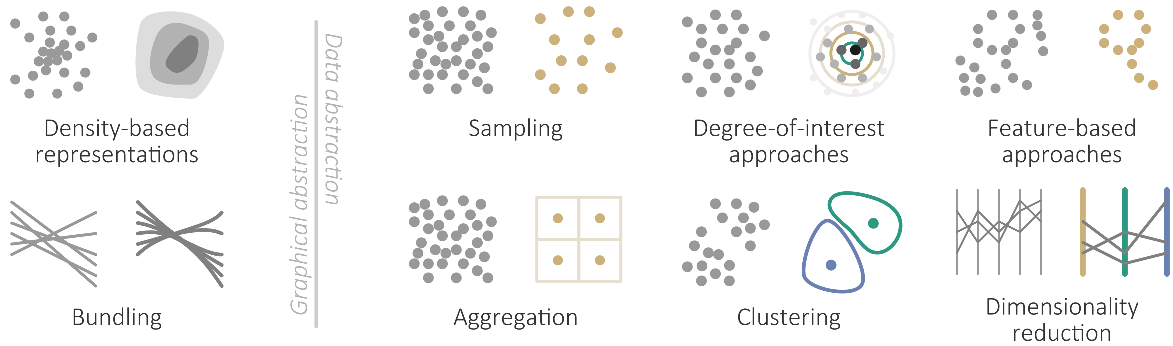


Fig. 5. Overview of graphical and data abstraction methods being used in VA.
Source: Adapted from [7].

Degree-of-interest approaches – from all data to relevant data. When complex processes with many entities (cases/activities) need to be analyzed, indistinctly showing all entities is not feasible. Instead, the analysis should be focused on the subset of entities that are relevant to the task at hand. Degree-of-interest approaches assign relevance values to data entities and dedicate more visual resources to highly-relevant entities while using less or no resources for irrelevant entities. This can be particularly useful for large graph structures such as process hierarchies or DFGs [47,48].

Feature-based approaches — from all data to a few features. In VA research, the term feature denotes a derived characteristic of the data. By focusing the analysis on the derived features, one can achieve a substantial level of abstraction. This requires a formal description of features to be extracted from the data [49]. Once extracted, features can be visualized instead of the raw data. Features can also be tracked over time to understand their evolution, including certain events during the evolution [50]. In PM, features could, for example, be certain motifs in a DFG; we identify topological structures such as multi-activity loops, stars, or highly connected activities, and consider these features [51]. Rather than visualizing the individual activities and their relationships, we show a representation of the features for a high-level analysis.

Aggregation — from raw data to aggregated data. Aggregation is a classic means to reduce several original data values into a single aggregated value. Typical aggregates include min, max, sum, count, average, median, and mode. In addition to such value aggregations, complete data entities can also be aggregated into meta-entities. This can, for example, be useful for hiding subprocesses in meta-nodes in DFGs, as suggested by works on event abstraction in PM [52]. By visualizing aggregated data rather than raw data, the visual complexity of visual representations can be reduced [53].

Clustering — from all data to a few groups of similar data. Clustering is an unsupervised machine learning method that groups data based on their similarity. The visual analysis can then be centered around the clusters (and their properties) rather than the raw data. These have been used to allow the interactive exploration at various levels of detail of event sequence data using multiple overviews [54]. In PM, trace clustering approaches have been proposed to group similar traces in a cluster such that, e.g., a less complex DFG can be discovered for each cluster instead of for the event log as a whole [55]. An appropriate specification of the notion of similarity is very important to obtain good clustering results. For multi-faceted data, similarity can be defined, for example, with respect to multivariate attributes or the structure defined by the relationship among data items [56].

Dimensionality reduction — from many to few dimensions. When data are associated with many attributes (e.g., multidimensional sensor data in machinery processes), dimensionality reduction can reduce the number of data dimensions to be visualized. The reduction of dimensions (not data entities) focuses the analysis on major trends in the data, while neglecting less important information. A difficulty is that the reduced dimensions might not be easy to interpret with respect to the semantics of the original dimensions and that minor but maybe still interesting patterns are suppressed. Typical dimensionality reduction methods include principal component analysis, multi-dimensional scaling, UMAP, and t-SNE [57]. An example in PM would be to consider all (derived) attribute values of events and reduce these to 2D for visualization [41] such that clusters of points then indicate events with similar attribute values.

4.2.2. Interactivity

In addition to visualization and automatic computation, the third key ingredient of VA is interactivity. Interactivity is the bridge between the machine and the human analyst [58]. It is required because complex data such as multi-faceted event data about processes cannot be comprehensively understood from a single visual representation. Interactivity enables the human analyst to flexibly orchestrate a whole spectrum of computational and visual methods with the goal of satisfying constantly changing information needs during multi-faceted process analyses [59].

In the following, we first provide an overview of fundamental VA interactions, and second, we use the example of interactive lenses to illustrate how VPA can benefit from interactivity notions present in the VA domain.

Fundamental interactions. Yi et al. [60] categorize the wealth of possible interactions with data and their visual representations by means of seven interaction intents. These intents capture *why* data analysts need to interact and can be briefly summarized as follows:

Mark something as interesting. This fundamental operation allows users to temporarily (hover) or permanently (select) mark parts of the visual representation as particularly relevant for the task at hand (e.g., highlight an anomalous process instance).

Show me something else. As it is typically only possible to show parts of the data, users need to move from one partial view to the other to create an overall picture of the data (e.g., look at different subsets of the process instances included in the original event log).

Show me a different arrangement. Rearranging the marks of a visual representation can help make specific parts of the data easier to follow and understand (e.g., centrally align a path of interest in a process map).

Show me a different representation. Especially for multi-faceted data, different visual representations need to be studied. Each representation emphasizes the peculiarities of a particular facet (see Fig. 4). Taken together, they lead to comprehensive understanding (e.g., changing from a DFG to a dotted chart to study both relationships and quantitative time).

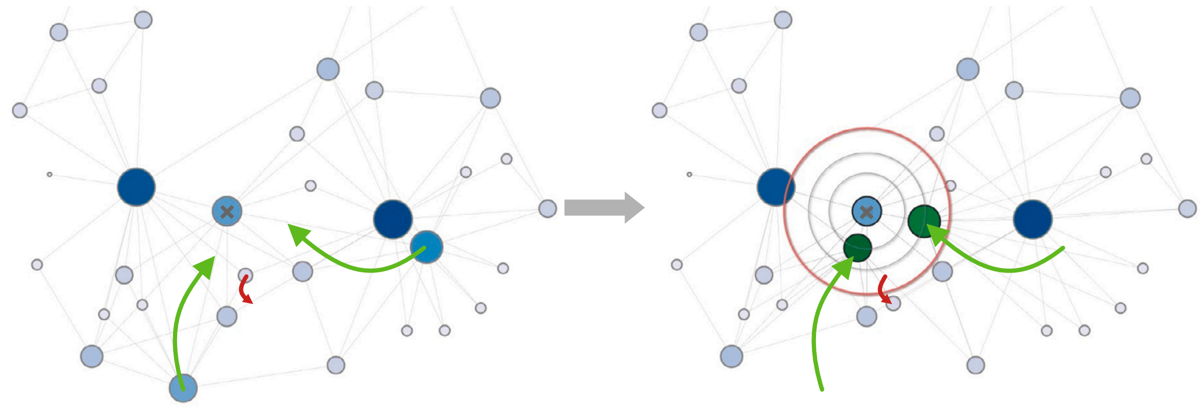


Fig. 6. The similarity lens for the "show me related things" interaction intent. Left: The situation before applying the lens. The visualization shows the graph topology. The node size and color additionally represent the node degree. The focus object is denoted by ×. While one can see how × is connected in the graph, the similarity with respect to the objects' data attributes cannot be readily accessed. Right: The similarity lens has been activated and moved on top of ×. Dissimilar objects were pushed out of the lens (red arrow), while similar ones were pulled to the lens interior (green arrows). The similar objects' distance to × and their green colors encode the degree of similarity. The analyst can now easily assess the similar objects. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Show me more or less detail. As described earlier, different kinds of abstractions offer different degrees of detail about the data. By showing more or less detail, the level of abstraction can be adjusted to the task at hand (e.g., visualizing activity clusters instead of individual events).

Show me something conditionally. By interactively specifying conditions, analysts can dynamically query or filter the data and work on a reduced subset that meets the conditions (e.g., filter based on frequency such that infrequent behavior is not shown).

Show me related things. Seeing something interesting in the data often raises the question of seeing related things. These interactions can dynamically change the visualization to bring related things to the display, as we will illustrate later in the example of interactive lenses.

Several of the aforementioned interaction intents can be implicitly connected to PM research. For instance: to cope with settings in which the process flow exhibits high variance, a process map can be discovered for subsets of process instances instead of the entire event log ("show me something else") [61,62]. To give another example: many control-flow algorithms such as heuristics miner [63], inductive miner [64] and split miner [65] have parameters that enable analysts to exclude less frequent behavior from the discovered process map ("show me something conditionally"). While these examples demonstrate that the interaction intents offer a relevant perspective for PM research, targeted research on this topic is lacking. Hence, creating and investigating effective approaches that support these interaction intents in a PM setting constitutes an avenue for further research. A promising step in that direction is Cortado, a tool that supports incremental process discovery and enables several types of interaction [30].

Current commercial PM tools also support several interaction intents by, for instance, providing different types of filters (e.g., filter out a particular subset of cases or a time period) and sliders to remove less frequent nodes and arcs in order to simplify the resulting process map [1]. From an academic perspective, the actual use of these interactive functionalities and their impact on the performed PM analysis and gathered insights has not yet been investigated, marking a valuable direction for future research.

PM often involves switching between different tools or environments when tuning algorithmic parameters (e.g., re-run an algorithm at the console) and analyzing the mined processes (e.g., create a new visualization view). VA aims to integrate these steps, for example, by bringing together different tools in a unified interface [66] and by designing techniques with direct and fluid interaction [67]. Next, we showcase how such direct and fluid interaction can look like using the example of interactive lenses.

Interactive lenses for PM. Interactive lenses are versatile, lightweight tools for directly and fluidly interacting with visualizations [68]. Despite their utility, they have not yet been applied in the context of PM.

Lenses can be moved across a visualization very much like a regular looking glass. But unlike regular looking glasses, interactive lenses can also be adjusted in size or shape to control the space where they take effect.

In the lens interior, the *lens function* creates an adapted version of the original visualization underneath the lens. The VA literature describes various lens techniques with lens functions that create manifold effects, including changing the visual encoding, altering the layout, and filtering data items [68].

To give a concrete example, let us consider the *similarity lens* whose effect is to alter the layout of a graph visualization [69]. The similarity lens has been developed to support the exploration of node similarities in multivariate graphs. In other words, the similarity lens supports the interaction intent of "show me related things" or more specifically, "show me similar nodes". In PM terms, this may translate to exploring similar objects in DFGs, where the objects are associated with several data attributes.

Applied to VPA, the similarity lens could work as follows. When it is moved across a DFG, the object that is closest to the lens center is selected as the focus object. The lens function will then locally adapt the DFG layout in two steps. First, objects that are similar to the focus object are smoothly pulled towards the lens and are positioned inside the lens such that their distance to the lens center corresponds to their similarity to the focus object. Second, any objects within the lens that are dissimilar to the focus object are pushed out of the lens. As a result, the lens creates a local view that collects all objects that are similar to the focus object and thus satisfies the "show me related things" interaction intent. Once the analyst's need for node similarity information is satisfied, the lens can be discarded and the original DFG layout is restored. Fig. 6 illustrates the effect of the similarity lens with the example of a basic node-link diagram of a simple graph. It shows how the relationship facet (nodes and links) and the data attribute facet (dynamic similarity-based rearrangement of selected nodes) can be intertwined with the help of interactivity.

In this section, we presented computed abstractions and interactivity as important ingredients of multi-faceted VPA. Here, our review of potentially useful methods could only be brief. A full survey of VA methods for PM would be a task for future work.

Table A.4
Case study references for data analyses.

Source	Year	References
BPIC reports	2015	Dixit et al. [70], Teinemaa et al. [71], Suchy and Suchy [72], Van den Spiegel and Blevi [73], Martin et al. [74], Buffett and Emond [75], Choi et al. [76], Martens and Verheul [77], van der Ham [78]
	2017	Berger [79], Scheithauer et al. [80], Smith and Day [81], Ryu et al. [82], Wangikar et al. [83], van der Ham [84], Dadashnia et al. [85], Rodrigues et al. [86], Blevi et al. [87]
	2019	Botti [88], Diba et al. [89]
	2020	Nikolayuk et al. [90]
Case studies in Web of Science	2020	Duma and Aringhieri [91], De Oliveira et al. [92], Remy et al. [93], Schuh et al. [94], Elleuch et al. [95], Arias et al. [96], Aloini et al. [97], Stefanini et al. [98], Kempa-Liehr et al. [99], Halawa [100], Stefanini et al. [101], Andrews et al. [102], Agostinelli et al. [103]
	2021	Amrou M'hand et al. [104], de Leoni and Pallettiero [105], Ito et al. [106], Tran et al. [107], Pang et al. [108], Pan and Zhang [109], Hobeck et al. [110], Bravo et al. [111], Ramires and Sampaio [112], Khaosanoi and Limpiyakorn [113], Bernthuis et al. [114]
	2022	Singh et al. [115], Benevento et al. [116], Hobeck et al. [117], Lim et al. [118], Benevento et al. [119], Roubtsova and Berk [120], Kumbhar et al. [121], Rashid and Louis [122], Friederich et al. [123]
	2023	Li et al. [124], Yari Eili et al. [125], Berti et al. [126], Butt et al. [127], Coremans et al. [128], Chinnathai and Alkan [129], Choudhary et al. [130], Lugaresi et al. [131], Wickramanayake et al. [132]
	2024	Kobialka et al. [133], Urrea-Contreras et al. [134], Krajcovic et al. [135], Nogueira and Zenha-Rela [136]
Case studies in Reinkemeyer [27]	2020	Henriques [137], Boenner [138], El-Wafi [139], Balint et al. [140], Reindler [141]

5. Related work

The basis for our study is our *Human in the (Process) Mines* Dagstuhl Seminar report [4], which has been extended with an extensive study of visualizations used in PM case studies and a systematic view of relevant (VA) data facets in this context. The presented categorization is derived from Guo et al. [28] and Yeschchenko and Mendling [12].

Guo et al. [28] provide an overview of existing VA techniques that are developed for event sequence data and formalize a design space for characterizing each VA approach and introduce analytical tasks that are frequently applied to event sequence data. Their work primarily discusses the VA techniques that are designed for each task, while we survey and identify the visualizations specific to PM and the different involved PM-focused tasks.

Yeshchenko and Mendling [12] extend the design space and propose the ESeVis framework to categorize visualizations of event sequence data. We deviate from this categorization by introducing network-based visualizations to support process maps and extend it with map-based visualizations. In contrast to the categorization of Guo et al. [28] and Yeshchenko and Mendling [12], we focus on the multi-faceted data aspects and classify each visualization according to these facets. Additionally, for each visualization, we identify the marks, visual channels, and tasks from a VA perspective. This enables us to analyze the information space and identify opportunities and challenges to enhance PM visualizations. It further enables us to reason about whether the used techniques are effective according to their task as being used in practice.

While its potential was already highlighted by Van der Aalst et al. [142] in the Process Mining Manifesto, the combination of VA and PM is still largely unexplored. Pioneering work by Gschwandtner [143] identified six challenges and opportunities for extending PM solutions with techniques from VA based on reviewing academic literature. In addition to (more recent) academic work, we also analyze PM visualizations used in practice and map these to our multi-faceted framework to derive additional challenges and opportunities. In addition to challenges and opportunities, Klinkmüller et al. [144] examine the information needs of process analysts through an extensive systematic literature review. Their focus is on analysis of the visual representations used and their contribution to PM tasks. We build on this with a multi-perspective categorization also including data facets, marks, and visual channels, enabling us to identify challenges and opportunities at different levels and perspectives.

Only few works address the novel combination of PM and VA techniques by focussing on, e.g., interactive conformance analysis [145], event data exploration and analysis [146], visual drift detection [147]. Knoblich et al. [148] review visual encodings in six common business PM tools. Our study complements this work by focusing on academic case studies rather than industry tools and extends the taxonomy to also include PM tasks. A more narrow categorization based on conformance checking is presented by Rehse et al. [11]. Related to this, a structural model for conformance checking is presented and evaluated by Klessacheck et al. [148].

Finally, Alman et al. [14] propose a novel framework to leverage VA for the interactive visualization of multi-faceted process information, aimed at easing the investigation tasks of users in their process analysis tasks. Similar to our study, they discuss facets and show how existing process models can be extended with additional facets using a layered approach utilizing backdrops. We anticipate that our systematic review of multi-faceted VPA results in more novel approaches such as theirs.

6. Conclusion

In this paper we aimed to bring together PM and VA by studying and categorizing existing PM visualizations from a VA perspective on data facets. To this end, we identified the data facets currently present in PM, being *time, space, relationships*, and *attributes*.

Next, we studied visualizations used in PM case studies from the last decade. From this, we grouped the visualizations into six categories *chart-based, networks-based, matrix-based, hierarchy-based, timeline-based*, and *map-based*. For each category, typical instances are selected and analyzed by identifying and discussing primary and secondary *data facets, marks, visual channels*, and *tasks*.

We present the categorization in an overview table, and identified gaps, opportunities, and challenges from this. Furthermore, we discuss opportunities how to enrich PM visualizations with analytical abstraction and interaction techniques from VA. This paper presents ample opportunities to adapt, enhance, and enrich PM visualizations to move towards true multi-faceted Visual Process Analytics.

CRediT authorship contribution statement

Stef van den Elzen: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Mieke Jans:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Niels Martin:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Femke Pieters:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Christian Tominski:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Maria-Cruz Villa-Uriol:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Sebastiaan J. van Zelst:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sebastiaan J. van Zelst reports financial support was provided by Celonis Labs GmbH, Germany. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Case study references

See Table A.4.

Data availability

No data was used for the research described in the article.

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