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Object-Centric Process Mining: Unraveling the Fabric of Real Processes

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Abstract: Traditional approaches for process modeling and process analysis tend to focus on one type of object (also referred to as cases or instances), and each event refers to precisely one such object. This simplifies modeling and analysis, e.g., a process model merely describes the lifecycle of one object (e.g., a production order or an insurance claim) in terms of its activities (i.e., event types). However, in reality, there are often multiple objects of different types involved in an event. Think about filling out an electronic form referring to one order, one customer, ten items, three shipments, and one invoice. Object-centric process mining (OCPM) takes a more holistic and more comprehensive approach to process analysis and improvement by considering multiple object types and events that involve any number of objects. This paper introduces object-centric event data (OCED) and shows how these can be used to discover, analyze, and improve the fabric of real-life, highly intertwined processes. This tutorial-style paper presents the basic concepts, object-centric process-mining techniques, examples, and formalizes OCED. Fully embracing object centricity provides organizations with a "three-dimensional" view of their processes, showing how they interact with each other, and where the root causes of performance and compliance problems lie.

Keywords: process mining; object-centric process mining; object-centric event data; process discovery; business process management; process science

MSC: 68T99

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1. Introduction

As the field of *process mining* [1] is maturing and better software tools are becoming available, also more complex non-standard processes can be analyzed and improved in an evidence-based manner. Using process mining, we can (1) discover processes models based on event data, (2) check the conformance of processes by comparing a process model with event data, (3) analyze performance by replaying event data on models, (4) predict the evolution of the whole process or individual process instances, and (5) automatically perform actions to address performance and compliance problems. Process mining techniques and tools have proven to be valuable in a wide range of domains (finance, logistics, production, customer service, healthcare, energy, education, etc.). However, traditional process-mining approaches also tend to make a few *simplifying assumptions*:

- It is assumed that a process model describes the lifecycle of a *single* object.
- It is assumed that each event refers to *precisely one* object (often called case) of a given type.

These assumptions are reasonable because most process-model notations do the same, and most end-users are familiar with these simplified notations. The widely used *business process model and notation* (BPMN) standard [2] uses models composed of activities, gateways, and sequence flows describing individual process instances. Consider, for example, Figure 1, showing a BPMN model describing the handling of job applications. Process

instances (also called cases) flow through the model from the left (source node *start*) to the right (sink node *end*). Next to *activities*, there are six *exclusive gateways* (diamond shapes with a $\times$) and two *parallel gateways* (diamond shapes with a $+$). Applications may be rejected after the first screening, after checking references and consulting the responsible manager, and after the interview. Following a successful interview, the applicant may receive a job offer that can be accepted or declined. Note that the check references and consult manager activities can be performed in any order (i.e., these are concurrent).

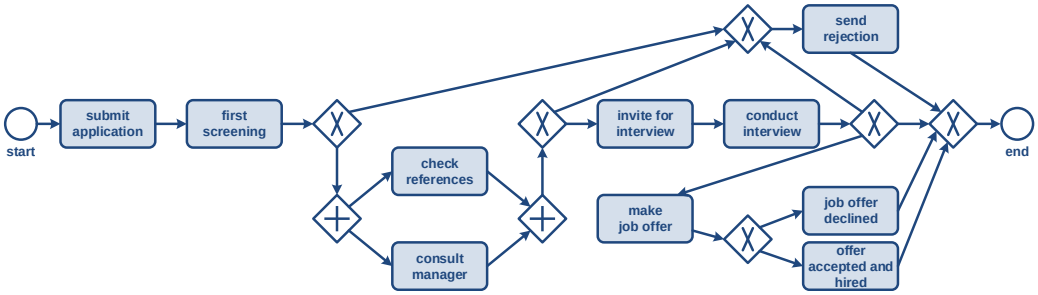


Figure 1. A BPMN model describing the lifecycle of an application. Each activity is executed for one application. The underlying assumption of such process models is that each event refers to precisely one object (often called case) of a given fixed type.

In a BPMN model, activities are always executed for one process instance. It is impossible to describe that an activity refers to multiple process instances of different types. Figure 1 only shows the flow of applications. However, this is *not* the only *object type* involved in the process. Next to *applications*, there are *applicants*, *vacancies*, *offers*, *recruiters*, and *managers*. The same applicant may apply for different vacancies, and for one vacancy there may be many applications. For an interview, one applicant, a recruiter, and the responsible manager may be involved. Applications are also not mutually independent. Hiring one applicant for a vacant position may imply the rejection of all other applications for the same position. The example shows the following:

- Real-life activities may involve *multiple objects* of *different types*.
- Objects are *not* mutually independent and *cannot* be fully understood by looking at them in isolation.
- Objects may be *related*, e.g., an order has items and refers to a customer.

These observations apply to most operational processes. Consider, for example, the handling of sales orders. One sales order may involve multiple items. Items belonging to one order may be split over multiple shipments, and shipments may contain items originating from different orders. In many processes, resources are shared, and batching is used to improve efficiency. In batched processes, the same operation is performed for many objects (e.g., products) in a single activity. These examples show that we need to consider multiple object types that are mutually dependent. Therefore, we need to drop the simplifying assumptions made by traditional process-mining approaches.

The goal of process mining is to analyze and improve processes using event data [1,3]. One can think of traditional event data as a table where each row corresponds to an *event*. (This is a simplification of actual event data stored, for example, in an XES file or a Celonis data model. Additionally, cases can have attributes, but this simplified view helps to understand the basic concepts). An event can have many different attributes. However, for traditional process mining, we need to have three mandatory attributes: *case* (refers to a process instance), *activity* (refers to the operation, action, or task), and *timestamp* (when did the event happen). These three attributes are enough to discover and check the control-flow perspective. An event may have many more attributes (e.g., costs, location, and resource), and also cases may have attributes that are invariant during the lifetime of a case. We refer to such data as *traditional event data* and these may be stored in classic *event logs* (e.g., in XES format [4]).

We use the term *object-centric event data* (OCED) for event data, where each event may refer to any number of objects, possibly of different types, instead of a single case identifier. *Object-centric process mining* (OCPM) techniques take such data as input and allow for *multi-perspective* process models [5]. This helps to address the following three limitations of *traditional* process mining:

- Data extraction is *time consuming* and needs to be *repeated* when new questions emerge. This is inflexible and prevents reuse. Additionally, logging is *not system agnostic*, i.e., the same business process creates different event data depending on the system used (e.g., SAP versus Oracle).
- *Interactions* between objects are not captured, and objects are analyzed in *isolation*.
- A 3D reality needs to be *squeezed* into 2D event logs and models. It is impossible to create views "on demand" when data are stored in 2D rather than 3D format.

Fortunately, most of the existing process-mining techniques can be lifted to multiple object types, e.g., *process discovery*, *conformance checking*, *performance analysis*, *process prediction*, etc. However, this requires a different mindset and willingness to embrace object centricity.

According to Gartner, there are now over 40 process-mining vendors, e.g., Celonis, Signavio (now part of SAP), ProcessGold (now part of UiPath), Fluxicon, Minit, LanaLabs (now part of Appian), MyInvenio (now part of IBM), and Q [6]. The recently released "Gartner Magic Quadrant for Process Mining" [7] illustrates the significance of this new category of tools. For an up-to-date overview, see the website www.processmining.org (accessed on 1 April 2023). Additionally, see [8] for example applications. All tools support the discovery of directly follows graphs (DFGs) with frequencies and times, and most of them (but not all) support some form of conformance checking and BPMN visualization. However, very few support object-centric process mining. Celonis was the first commercial vendor fully supporting object-centric process mining with the release of *Process Sphere* in 2022 [9]. Before, there were several non-commercial open-source tools supporting object centricity, e.g., the "OCELStandard" package in ProM (promtools.org), the OC-PM tool (ocpm.info), and Object-Centric Process Insights (ocpi.ai) (all accessed on 1 April 2023).

Despite the limited number of tools supporting object-centric process mining, most large-scale process-mining users and researchers acknowledge that the "one case notion" limits the application of process mining [10]. Therefore, this tutorial-style paper can be seen as a call to action. It is expected that object-centric process mining will become the "new normal" in the next decade and widely adopted in industry. Moreover, object-centric process mining provides many exciting research challenges that are highly relevant for progressing process management and automation. Things such as filtering, clustering, prediction, etc., become more challenging when considering object-centric event data. Although we will not present specific algorithms, the general principles presented in this paper can be used for object-centric process discovery, conformance checking, and most other process-mining tasks.

The remainder is organized as follows. Section 2 discusses the limitations of process-mining techniques using events that need to refer to a single object (i.e., case) rather than a set of objects. Section 3 presents object-centric event data as a means to overcome these limitations. The object-centric event data meta-model (OCED-MM) is used to introduce the core concepts. Moreover, we explain the convergence and divergence problems in detail by relating OCED-MM to traditional event logs. Section 4 formalizes the core concepts introduced in Section 3. Section 5 introduces the basics of object-centric process mining and demonstrates that many of the existing techniques can be lifted from 2D to 3D. Finally, Section 6 concludes the paper.

2. The Need for Object Centricity

To explain the need for object centricity, we first introduce some of the process-mining basics. Figure 2 introduces the different process-mining tasks.

Task *exact* (0) transforms data in the source systems to event data ready for process mining. Often, multiple source systems are involved (e.g., software systems from SAP, Salesforce, Microsoft, and Oracle), and one system may store data scattered over thousands of database tables. This is a key step and, when organizations start with process mining, this may take up 80% of all efforts. Traditional event logs focus on a single process centering around one type of object (i.e., the so-called cases). Hence, next to finding and transforming raw input data, it is important to scope and correlate these input data such that meaningful process events are generated.

Task *discover* (1) turns event data into process models using process discovery techniques. These discovered models aim to describe the underlying process. The discovered process models may focus on the frequent mainstream behavior in the event data or also include infrequent behavior. A range of process discovery techniques is available [1,11–14]. The discovered process models show what is really going on, thus providing transparency. Moreover, discovered process models can be modified from "as is" models into "to be" models. It is also possible to model the expected or normative model from scratch.

Task *check* (2) takes as input event data and process models. The latter may be produced using process discovery or created manually (or a combination of both). Event data are replayed on these models. This reveals all discrepancies between the data and model [1,15]. Moreover, process models can be further annotated with frequency and time information. Doing this may reveal important "execution gaps", i.e., differences between the reality and model. Note that deviations are not limited to control flow (i.e., the ordering of activities). These may also include deviations related to time, resources, or data. For example, parts of the process may take too long, resources may violate the four-eyes principle, or decisions may conflict with business rules (e.g., claims above EUR 10,000 need to be checked by the manager).

Task *predict* (3) is forward looking, aiming to make statements about the future based on event data and the models learned. This may involve modern machine learning (ML) techniques using neural networks or classical data mining (DM) and statistical methods, such as decision trees and regression. Task predict (3) builds on process-discovery and conformance-checking results. Based on a combination of event data and a process model connected through alignments, so-called *situation tables* are created [1,16,17]. Each situation table focuses on a specific problem often called an *execution gap* (i.e., a specific performance or compliance problem). This corresponds to a standard ML/DM problem, and existing techniques can be applied. Each row in the situation table is an instance (e.g., a case, a resource, a choice, or a time period). Predictions may refer to individual cases or the process as a whole. Typical examples include predicting the remaining processing times of running cases, predicting outcomes of cases, predicting workloads, and predicting compliance levels. In [16], we focus on extracting a wide range of process-related features from event data. These can be used to create causal models, create decision trees [1], or train a range of neural networks [17]. It should be noted that the core process-mining algorithms for the earlier tasks (e.g., process discovery and conformance checking) are very different from mainstream ML/DM techniques.

Task *act* (4) intervenes in the running process to improve it based on process-mining diagnostics. So-called action flows aim to influence the process by taking actions in the source systems or triggering stakeholders. Both automatic and human interventions are possible. Input may come from all previous tasks. It is not necessary to perform all tasks to improve processes (e.g., make predictions); also, process discovery results and conformance checking diagnostics provide valuable input for taking actions (automatic or not). For example, "execution gaps" detected using conformance checking may trigger automatic actions, such as blocking suppliers, adding resources, removing duplicate cases, and temporarily blocking requests.

As shown in Figure 2, the combination of all tasks mentioned helps to close the loop and continuously improve the process.

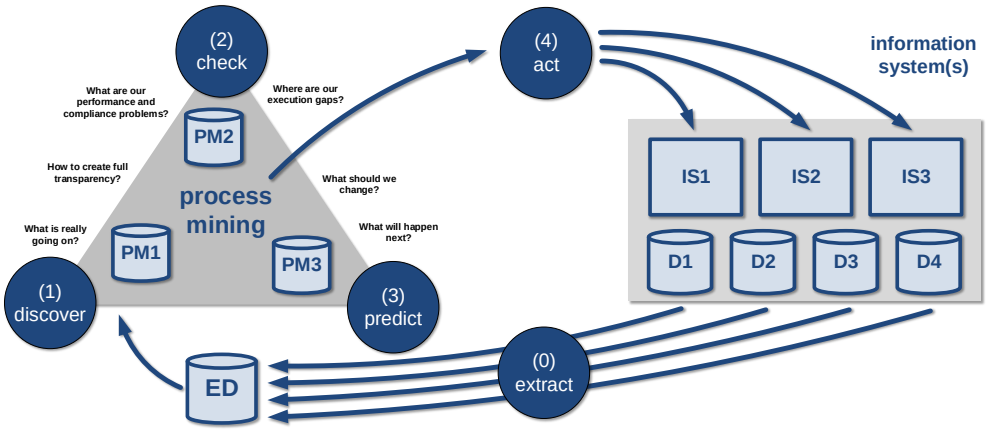


Figure 2. High-level overview of the different process-mining tasks: (0) exact, (1) discover, (2) check, (3) predict, and (4) act. Note that these tasks need to be "reinvented" for OCPM because, traditionally, they assume a single case notion and cases that are non-interacting (see Section 5).

At the minimum, events should have a timestamp and an activity label. Moreover, process models should describe the ordering of these activities. In traditional event logs and process models, it is also assumed that each event refers to *precisely one case*. This assumption leads to the following problems:

- *Data extraction is time consuming and needs to be repeated when new questions emerge.* Traditional event logs view event data from one particular angle, i.e., the case notion selected. However, different questions may require different viewpoints. Consider an order-handling process involving customers, suppliers, orders, items, shipments, payments, employees, etc. Each of these object types can be used as a case notion depending on the question. It is very inefficient to extract event data repeatedly using different case notions. Moreover, new questions may require new data extractions and the involvement of IT specialists.
- *Interactions between objects are not captured, and objects are analyzed in isolation.* Real-life events tend to involve multiple objects. These objects may be of the same type, e.g., multiple items are ordered in one transaction. Moreover, also different types of objects may be involved, e.g., delivering a package to a customer involving items from different orders. When events are only related through a case identifier, interactions between objects get lost. Moreover, it leads to distortions, such as convergence and divergence problems (see Section 3.6).
- *A 3D reality needs to be squeezed into 2D event logs and models.* Traditional approaches use two-dimensional (2D) event logs and models. The first two dimensions are the activity dimension and the time dimension. The third dimension is the object dimension covering multiple object types. In 2D event logs and models, one focuses on one object (type) at a time. However, to capture reality better, one needs three-dimensional (3D) event logs and models. One needs to add the third dimension considering multiple object types, where one event may refer to any number of objects.

Object-centric process mining (OCPM) aims to tackle these challenges. There have been several other proposals using artifact-centric models [18,19], object-centric behavioral constraint models [20,21], multi-perspective models [22], multi-event logs (Celonis), extensible object-centric (XOC) event logs [23], graph databases tailored toward event data [24], catalog and object-aware nets [25], etc. However, none of these approaches were adopted in industry due to complexity. Good analysis techniques were missing, there were scalability problems, and it was hard to extract such data. This is in stark contrast with the current uptake and attention for OCPM as presented in this paper. This is illustrated by the Celonis Process Sphere implementation [9] that is already used in a dozen larger organizations and will become the standard Celonis platform to be used in thousands of organizations. It is expected that many vendors will follow and adopt OCPM [7].

To appreciate the practical relevance of these problems, it is good to understand that most events involve multiple objects. Consider, for example, an assembly process, where intermediate products and final products are composed of different parts. Another example is a project meeting for a project involving multiple participants. Additionally, think of the shipping of a container containing different pallets stacked with products for different customers, or the hiring decision for a vacant position with dozens of applications. In summary, the above-mentioned challenges are omnipresent.

3. Object-Centric Event Data

Object-centric process mining starts from object-centric event data leveraging the insight that events may relate to any number of objects. The *object-centric event data meta-model* (OCED-MM) shown in Figure 3 introduces the main concepts detailed in the reminder. OCED-MM can be viewed as an extension of the meta-model used for the OCEL (object-centric event log) format (cf. www.ocel-standard.org, accessed 1 April 2023, and [26]) defined in 2020 and is also related to the standardization discussions in the context of the IEEE Task Force on Process Mining [10]. Here, we focus on the core concepts and considerations instead of technical details, such as the storage format.

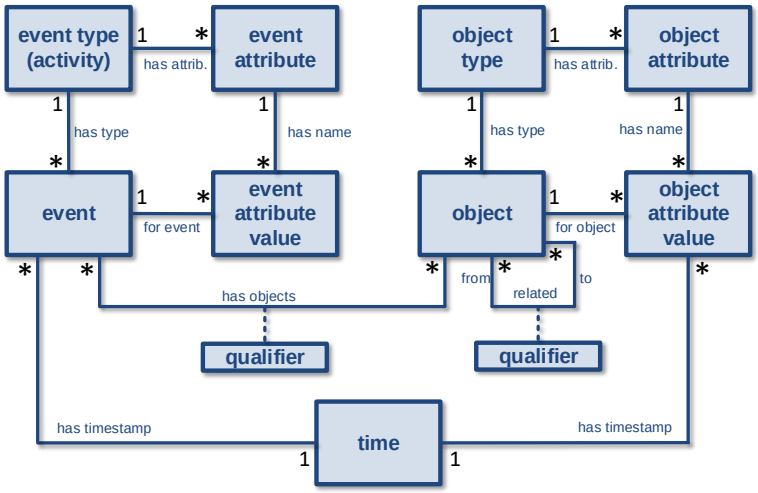


Figure 3. The object-centric event data meta-model (OCED-MM). The classes (rectangles) introduce the main concepts (events, objects, attributes, etc.). The relationships are annotated with cardinalities ($*$ denotes zero or more), e.g., an event may refer to any number of objects, an object may be involved in any number of events, an event has precisely one timestamp, and an event has precisely one event type.

3.1. Objects and Object Types

As Figure 3 shows, each *object* has precisely one *object type*, but many objects may have the same type. This is denoted by the 1 and $*$ on the association *has type* connecting the classes *object* and *object type*. Note that we use a "UML-like notation" just using classes (the rectangles) and associations (the connections). The $*$ denotes zero or more. Example object types are patient, customer, supplier, machine, order, treatment, product, container, claim, payment, complaint, request, etc. Objects are *instances* of these types, for example, a particular patient or a specific order.

3.2. Events and Event Types

Each *event* has an *event type*, also called *activity*. Many events can have the same type, but each event has precisely one type. We will use the terms event type and activity interchangeably. Example event types are approve request, cancel order, send payment, take blood test, skip container, activate account, etc. Events are instances of these types. We assume that events are *atomic*. Therefore, each event has one timestamp as indicated in

Figure 3. Since time is an important notion in process mining, *time* is added as a separate class in the meta-model. To model activity instances that take time, one can use a start and complete event, or add duration as an attribute. However, for simplicity, it is best to view events as atomic and having just one timestamp.

3.3. Event-to-Object (E2O) Relations

In traditional process mining, each event needs to refer to precisely one case. Object-centric process mining generalizes this, allowing an event to refer to *any number of objects*. The association *has object* is a many-to-many relationship (see the two $*$'s) and may have a *qualifier*. The *qualifier* class connected to the association *has object* is also called an association class as is used to label the relationship. Consider an event of the type meeting; there may be five participants, of which one is the chair or a product presentation with ten attendees and two presenters. In such situations, an event is connected to objects of the type person, but we would like to distinguish between a normal participant and the chair, or distinguish between an attendee and a presenter. Note that the same person may be a presenter for one presentation and an attendee for two other presentations. Therefore, it is possible to qualify the relation between an event and an object, i.e., add an additional label.

In traditional process mining, there would be just one object type *case*, and each event would refer to precisely one object of that type. *Event-to-object* (E2O) relations generalize the concept into a *qualified many-to-many* relationship.

3.4. Object-to-Object (O2O) Relations

Objects can be related using *object-to-object* (O2O) relationships. Figure 3 shows that the association *related* is also qualified using an association class. This qualified many-to-many relationship is *static* for reasons of simplicity. Just like an object does not change type over time, the O2O relationships do not change. An order object can be related to a customer object. A diagnosis object can be related to a patient object. A payment object can be related to a claim object. O2O relationships may also represent bill-of-materials (BOM) structures. A BOM typically has a hierarchical structure with the finished end product at the root. The qualified many-to-many relationship may represent a labeled directed hypergraph. Sometimes, such relationships are restricted to one-to-many relations or even the more restricted structures found in a snowflake or star database schema.

It is important to note that objects can be related *directly* via O2O relations or *indirectly* via two E2O relations. Objects o_1 and o_2 can be related via some O2O relation (e.g., a "part of" relation) or via an event e, where o_1 and o_2 are involved (i.e., two E2O relations). Note that the O2O relations are *static* and the E2O relations are *dynamic*. For example, there may be events where both o_1 and o_2 are involved, and other events where just o_1 or o_2 is involved. Moreover, these events are timestamped.

It is important to note the foundational differences between O2O and E2O relations. O2O relations are *static*. E2O relations are *dynamic* and may also indicate *active* participation in the event (e.g., a resource involved in the execution of an activity).

3.5. Event and Object Attributes

Both objects and events can have any number of *attributes* with corresponding *values*. An *event attribute value* refers to precisely one *event* and one *event attribute*. This is the assignment of a concrete value (e.g., €10) to an attribute (e.g., transaction costs) for a specific event (e.g., a bank transfer event). Similarly, an *object attribute value* refers to precisely one *object* and one *object attribute*. As Figure 3 shows, each event type may refer to any number of event attributes, and each object type may refer to any number of object attributes (see the two *has attrib* associations). These can be interpreted as the expected attributes for the events or objects of the corresponding type. For an event, one can navigate the *has type* and *has attrib* associations to find the set of expected event attributes. Moreover, for the same event, one can navigate the *for event* and *has name* associations to find the set of actual event attributes. One can impose consistency constraints to ensure that both are the same, or one

is a subset of the other. Using OCL (object constraint language), it is possible to define such constraints [27]. We leave this open to ensure flexibility. For an object, one can navigate the *has type* and *has attrib* associations to find the set of expected object attributes, and one can navigate the *for object* and *has name* associations to find the set of actual object attributes. Additionally, here, one could impose consistency constraints to ensure that both sets of object attributes are the same, or one is a subset of the other.

Please note the deliberate asymmetry in the OCED-MM when it comes to timed attributes (cf. Figure 3). Object attribute values have a timestamp, and event attribute values do *not* have a timestamp. The reason is that event attribute values refer to events that already have a timestamp. Hence, event attribute values have an implicit timestamp. Although not explicitly visible in Figure 3, there is at most one event attribute value per event and event attribute combination. It would not make any sense to assign multiple values to the same attribute in one event. There may be multiple object attribute values per object and object attribute combinations because the value may change over time. For example, the price or weight of an object can change. Therefore, any object attribute value has a timestamp. There is, at most, one object attribute value per object, time and object attribute combination. By default, one can assign time "zero" to an object attribute value, i.e., the earliest point in time. The first object attribute value for an object and an object attribute combination can be seen as the initial setting and all later object attribute values as updates of this value. At time t, the value of an attribute for an object is the value of the latest object attribute value for the object and object attribute combination.

3.6. Convergence and Divergence

The object-centric event data meta-model (OCED-MM) in Figure 3 provides a clear conceptual basis for reasoning about object-centric process mining. Moreover, we can now better explain the limitations of traditional process mining. In traditional process mining, we only consider one object type called "case", and events refer to just one object. Figure 4 shows a meta-model for such traditional event logs, e.g., event logs using the XES standard [4]. This is merely a representation of the main concepts and does not aim to be complete. For example, XES has extensions supporting classifiers, lifecycle information, activity instances, resources, and cost information [4]. Here, we abstract from these extensions and focus on the core concepts. Comparing Figures 3 and 4 reveals the main differences. There is no object type class, because there is only one object type case. The association connecting events and objects is a many-to-one relation instead of a many-to-many relation. Therefore, a qualifier does not make sense. Since only one case is involved in an event, there is no need to distinguish objects having different roles. Figure 4 also does not show object-to-object (O2O) relations and case attribute values do not have a timestamp. These concepts are not supported by XES and other exchange formats. Meaningful O2O relations tend to relate objects of different types; therefore, this was not considered in XES. Additionally, case-level attributes cannot be changed in XES.

If we make the assumption that the actual reality is closer to the OCED-MM in Figure 3 but process-mining tools require traditional event logs described by Figure 4, then we need to map the data from the former to the latter representation. An obvious approach is the following:

- Pick an *object type* to serve as the *case notion*.
- Remove all *objects* of a *different type*. The remaining objects are called *cases*.
- Only keep *object attribute values* corresponding to cases, and, if there are multiple case attribute values for a case and case attribute combination, keep only the last one. Remove the timestamps of the remaining case attribute values.
- Remove all *events* that do not have an O2E relation to at least one case (i.e., object of the selected type). Therefore, the remaining events refer to one or more cases.
- If an event refers to multiple cases, then *replicate the event once for each case*. By replicating events for each case, we can ensure that each resulting event refers to a *single* case.

The above approach turns OCED into classic event logs in a deterministic manner and only parameterized by the selected object type. Note that we are forced to replicate events because of the requirement that an event can refer to only one case in the traditional setting. The resulting event data are called *flattened event data*.

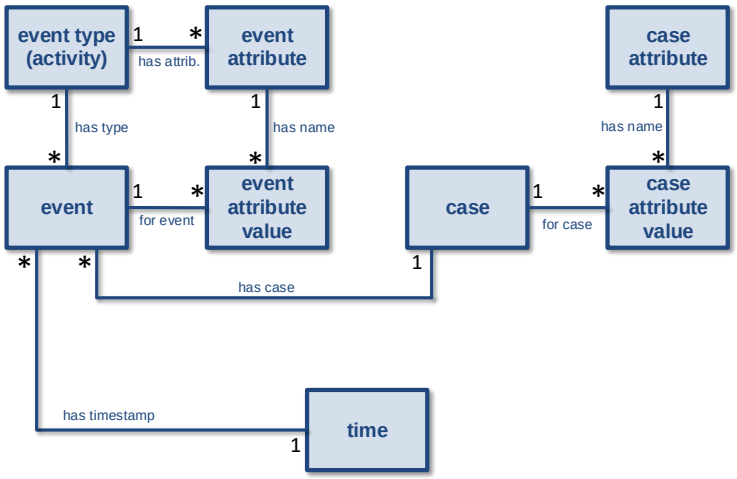


Figure 4. A meta-model describing traditional event logs. There are no object types, and each event can refer to only one object (called a "case").

Obviously, events in the original event log that have no corresponding events in the flattened event log disappear from the input data. This is called *deficiency*. However, more interesting are the *convergence* and *divergence* problems:

- *The convergence problem*: Events referring to multiple objects of the selected type are replicated, possibly leading to unintentional duplication. The replication of events can lead to misleading diagnostics.
- *The divergence problem*: There are multiple events that refer to the same case and activity; however, they differ with respect to one of the not-selected object types. In other words, events referring to different objects of a type not selected as the case notion become *indistinguishable*, looking only at the case and activity (i.e., event type).

Consider an order o consisting of ten items $i_1, i_2, \ldots, i_{10}$ and the activities *place_order*, *pick_item*, and *pack_item*. The corresponding event *place_order* refers to objects $o, i_1, i_2, \ldots, i_{10}$ and can be denoted as $place\_order(o, i_1, i_2, \ldots, i_{10})$. There are ten *pick_item* events each referring to o and one of the items. These can be denoted as $pick\_item(o, i_k)$ with $1 \leq k \leq 10$. Similarly, there are ten *pack_item* events denoted as $pack\_item(o, i_k)$ with $1 \leq k \leq 10$.

If we choose *item* as a case notion, then event $place\_order(o, i_1, i_2, \ldots, i_{10})$ needs to be replicated. The event $place\_order(o, i_1, i_2, \ldots, i_{10})$ is converted into ten events: $place\_order(i_1)$, $place\_order(i_2), \ldots, place\_order(i_{10})$. Although the *place_order* happens only once, the flattened event log will show that it happened ten times. This is the convergence problem influencing statistics related to frequency, time, costs, etc.

If we choose *order* as a case notion, then the number of events does not change, i.e., there are no convergence problems. However, there is a divergence problem. There is one *place_order* event, ten *pick_item* events, and ten *pack_item* events. Sorted by timestamp, we could see the following sequence of events for case o: $place\_order(o)$, $pick\_item(o)$, $pick\_item(o)$, $pack\_item(o)$, $pick\_item(o)$, $pick\_item(o)$, $pack\_item(o)$, $pick\_item(o)$, $pick\_item(o)$, $pick\_item(o)$, $pack\_item(o)$, $pick\_item(o)$, $pick\_item(o)$, $pick\_item(o)$, $pack\_item(o)$, $pack\_item(o)$, $pack\_item(o)$, $pack\_item(o)$, $pack\_item(o)$, and $pack\_item(o)$. Note that for the same case o, *pick_item* is followed by *pick_item*, *pick_item* is followed by *pack_item*, *pack_item* is followed by *pick_item*, and *pack_item* is followed by *pack_item*. This suggests that there is not clear ordering among the activities *pick_item* and *pack_item*. However, for each item i_k, $pick\_item(o, i_k)$ is always followed by $pack\_item(o, i_k)$. The causal relation between $pick\_item(o, i_k)$ and $pack\_item(o, i_k)$ is lost when using o as the only identifier. Due to the

divergence problem, the ten *pick_item*(o) events and ten *pack_item*(o) events become indistinguishable. As a result, the clear causal relation between *pick_item* and *pack_item* is lost.

The above convergence and divergence examples show the limitations of traditional two-dimensional (2D) event logs and models. By focusing on items only, one can no longer see the correct activity frequencies resulting in a distorted view. By focusing on orders only, one can no longer see the causal relations. One needs the third dimension showing all object types. This illustrates that, to capture reality better, one needs three-dimensional (3D) event logs and models.

3.7. Example Illustrating Convergence and Divergence

Let us now consider a larger, more realistic, example. Consider an order handling process involving orders, items, packages, and routes. An *order* may refer to multiple items, but each item refers to one order. A *package* may contain multiple items, but each item ends up in one package. A *route* may involve many packages to be delivered. If a package cannot be delivered on a route because the customer is not at home, then the package is added to a later route. The right-hand side of Figure 5 shows the relations between the four object types: *order*, *item*, *package*, and *route*. The left-hand side shows the event types (i.e., activities). Note that all elements of Figure 5 are at the type level and not the instance level, i.e., no events and objects are depicted (only event types and object types). As before, we use a UML-like notation using classes, associations, and cardinalities.

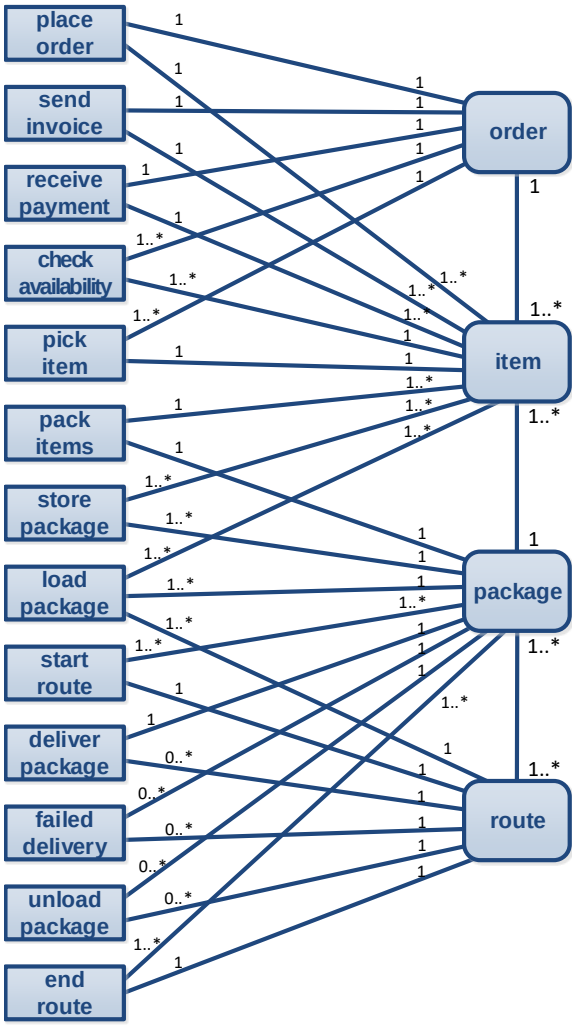


Figure 5. Larger example illustrating convergence and divergence problems. The left-hand side shows event types (i.e., activities) and the right-hand side shows object types.

Figure 5 shows the cardinalities of object-to-object (O2O) relations (right-hand side) and event-to-object (E2O) relations (middle). To illustrate the E2O relations, consider activity *place order* which refers to one order and one or more items. Activity *place order* occurs once for each order and once for each item. Activity *pack items* refers to one package and one or more items, and *pack items* occurs once for each package and each item. The E2O relations in the middle of Figure 5 show the cardinality constraints between events of the given type on the left and objects of the given type on the right. The range on the left-hand side of the association closest to the event type shows how often the activity happens for objects of the type on the right-hand side. The range on the right-hand side of the association closest to the object type shows how many objects of the type are involved in events of the type on the left.

All E2O associations having a cardinality constraint different from 1 on the *right-hand side* lead to convergence problems when the corresponding object type is taken as the case notion. Based on Figure 5, there are convergence problems when picking *item* or *package* as a case notion (see the "1..$*$" entries on the right). For example, events of type *place order* are replicated for each item when *item* is the selected case notion, and events of type *start route* are replicated for each route when *package* is the selected case notion.

All E2O associations having a cardinality constraint different from 1 on the *left-hand side* may lead to divergence problems when the corresponding object type is taken as the case notion and there are other E2O associations starting from the same event type that may contain causal information. The "1..$*$" entries on the left that are combined with a "1" for the same event type, but another E2O association, entail possible divergence problems. For example, event type *pick item* has E2O relations to *order* and *item* with cardinalities "1..$*$" and "1", respectively. Therefore, picking *order* as a case notion may lead to divergence problems because causalities between events involving specific items get lost. Event type *start route* has E2O relations to *package* and *route* with cardinalities "1..$*$" and "1", respectively. Therefore, picking *package* as a case notion may lead to divergence problems because causalities between events involving specific routes get lost.

Figure 5 shows many E2O relations. The question is whether all of these are needed. Some E2O relations are derivable from O2O relations, e.g., given an item involved in an event, we can determine the corresponding order. Sometimes E2O relations can be derived from O2O relations and sometimes E2O relations can be derived from O2O relations. In principle, one can consider such derivable relations as redundant. However, the roles of O2O and E2O relations are different. An E2O relation may express the *active participation* in an event. Organizations need to establish conventions to determine how information is distributed over O2O and E2O relations.

To summarize, convergence and divergence problems are omnipresent. This also applies to the example introduced in the introduction (cf. Figure 1) involving applications, applicants, vacancies, offers, recruiters, and managers.

4. Formalizing Object-Centric Event Data

The object-centric event data meta-model (OCED-MM) shown in Figure 3 can be formalized in a fairly direct manner. Note that the formalization says nothing about the actual technical storage or exchange format (e.g., whether it is a relational database, a graph database, XML, or JSON). It also does not type attribute values (e.g., strings and timestamp formats). One can create a database schema based on OCED-MM and fill it with data using a view automatically generated by annotating a regular database schema. However, this is out of scope and under development as part of the revision of the OCEL standard. Here, we focus on the concepts to precisely define the core elements that need to be present. Instead of providing a syntax, we *formalize* object-centric event data (OCED). We start with defining a collection of universes.

Definition 1 (Universes)**.** *We define the following pairwise disjoint universes:*

- $\mathcal{U}_{ev}$ *is the universe of events;*

- $\mathcal{U}_{etype}$ *is the universe of event types (i.e., activities);*
- $\mathcal{U}_{obj}$ *is the universe of objects;*
- $\mathcal{U}_{otype}$ *is the universe of object types;*
- $\mathcal{U}_{attr}$ *is the universe of attribute names;*
- $\mathcal{U}_{val}$ *is the universe of attribute values;*
- $\mathcal{U}_{time}$ *is the universe of timestamps (with* $0 \in \mathcal{U}_{time}$ *as the smallest element and* $\infty \in \mathcal{U}_{time}$ *as the largest element);*
- $\mathcal{U}_{qual}$ *is the universe of qualifiers.*

Note that the universes are assumed to be pairwise disjoint, i.e., objects cannot be used as events, $e \in \mathcal{U}_{ev}$ will be used to denote an event, $et \in \mathcal{U}_{etype}$ will be used to denote an event type, $o \in \mathcal{U}_{obj}$ will be used to denote an object, $ot \in \mathcal{U}_{otype}$ will be used to denote an object type, $ea \in \mathcal{U}_{attr}$ will be used to denote an event attribute, $oa \in \mathcal{U}_{attr}$ will be used to denote an object attribute, $v \in \mathcal{U}_{val}$ will be used to denote an attribute value, $t \in \mathcal{U}_{time}$ will be used to denote a timestamp, and $q \in \mathcal{U}_{qual}$ will be used to denote a qualifier. We assume a total ordering on timestamps, with $0 \in \mathcal{U}_{time}$ as the earliest timestamp and $\infty \in \mathcal{U}_{time}$ the latest timestamp (i.e., for any $t \in \mathcal{U}_{time}$: $0 \leq t \leq \infty$. These artificial timestamps are added for notational convenience, e.g., we can use 0 for missing timestamps and the start of the process, and ∞ as the end time.

Based on Figure 3 and the universes, object-centric event data (OCED) can be formalized in a fairly straightforward manner.

Definition 2 (OCED). *Object-centric event data (OCED) are described by a tuple* $L = (E, O, EA, OA, evtype, time, objtype, eatype, oatype, eaval, oaval, E2O, O2O)$ *with the following:*

- $E \subseteq \mathcal{U}_{ev}$ *is the set of events;*
- $O \subseteq \mathcal{U}_{obj}$ *is the set of objects;*
- $evtype \in E \to \mathcal{U}_{etype}$ *assigns types to events;*
- $time \in E \to \mathcal{U}_{time}$ *assigns timestamps to events;*
- $EA \subseteq \mathcal{U}_{attr}$ *is the set of event attributes;*
- $eatype \in EA \to \mathcal{U}_{etype}$ *assigns event attributes to event types;*
- $eaval \in (E \times EA) \not\to \mathcal{U}_{val}$ *assigns event attributes to values at specific times;*
- $objtype \in O \to \mathcal{U}_{otype}$ *assigns types to objects;*
- $OA \subseteq \mathcal{U}_{attr}$ *is the set of object attributes;*
- $oatype \in OA \to \mathcal{U}_{otype}$ *assigns object attributes to object types;*
- $oaval \in (O \times OA \times \mathcal{U}_{time}) \not\to \mathcal{U}_{val}$ *assigns object attributes to values;*
- $E2O \subseteq E \times \mathcal{U}_{qual} \times O$ *are the qualified event-to-object relations;*
- $O2O \subseteq O \times \mathcal{U}_{qual} \times O$ *are the qualified object-to-object relations.*

As such,

- $dom(eaval) \subseteq \{(e, ea) \in E \times EA \mid evtype(e) = eatype(ea)\}$ *to ensure that only existing event attributes can have values;*
- $dom(oaval) \subseteq \{(o, oa, t) \in O \times OA \times \mathcal{U}_{time} \mid objtype(o) = oatype(oa)\}$ *to ensure that only existing object attributes can have values.*

The last two requirements in the definition ensure that events and objects can only have attribute values for attributes belonging to the corresponding event or object type. Note that event attributes are assigned to event types and object attributes are assigned to object types, i.e., attributes are distinguishable between different types. This does not imply that they cannot have the same name. The formalization only says that the can be distinguished, even when names are shared.

We use the following notations given an OCED L: $ET(L) = \{evtype(e) \mid e \in E\}$ is the set of event types, and $OT(L) = \{objtype(o) \mid o \in O\}$ is the set of object types. $ET2OT(L) = \{(evtype(e), objtype(o)) \mid (e, q, o) \in E2O\}$ describes E2O relations at the type level. If $(et, ot) \in ET2OT(L)$, then objects of type ot are involved in activity

et. $OT2OT(L) = \{(objtype(o_1), objtype(o_2)) \mid (o_1, q, o_2) \in O2O\}$ describes O2O relations at the type level. These notations will be used later and help to interpret Definition 2.

For clarification, we also provide some notations for attribute values. For any event $e \in E$ and event attribute $ea \in \mathcal{U}_{attr}$: $eaval_{ea}(e) = eaval(e, ea)$ if $(e, ea) \in dom(eaval)$, and $eaval_{ea}(e) = \bot$ if $(e, ea) \notin dom(eaval)$. For any object $o \in O$, object attribute $oa \in \mathcal{U}_{attr}$, and time $t \in \mathcal{U}_{time}$, $oaval^t_{oa}(o) = oaval(o, oa, t')$ if there exists a $t' \in \mathcal{U}_{time}$ such that $t' \leq t$ and $(o, oa, t') \in dom(oaval)$ such that there is no $t'' \in \mathcal{U}_{time}$ such that $t' < t'' \leq t$ and $(o, oa, t'') \in dom(oaval)$. If no such t' exists, then $oaval^t_{oa}(o) = \bot$. Hence, $oaval^t_{oa}(o)$ provides us with the latest object attribute value at time t. $oaval_{oa}(o) = oaval^{\infty}_{oa}(o)$ is the final value for the object attribute in the event log. These notations show how to interpret event and object attributes. Note that there is a close correspondence between Definition 2 and Figure 3.

As mentioned, it is deliberate that object attribute values are not connected to events. The definition allows for events without objects or objects without events. Events should correspond to relevant activities, and therefore, there should not be the need to promote individual object attribute changes to events. Additionally, the object-to-object relations may exist independent of events. The only explicit connections between events and objects are the event-to-object relations (i.e., *E2O*). However, for an event e happening at time t involving object o with attribute oa, we can look up the corresponding value at the time of the event via $oaval^t_{oa}(o)$.

Of course, these are, in essence, design choices, and it is possible to make other decisions. Things are kept simple deliberately, and there are many things that can be added, e.g., O2O relations that are created by events, object attribute values set by events, event-to-event (E2E) relations, etc. However, increasing complexity increases the barrier to start using it. Moreover, it does not make much sense to standardize things for which there are no analysis techniques.

5. Object-Centric Process Mining

Figure 2 already showed the main process-mining tasks: (0) extract, (1) discover, (2) check, (3) predict, and (4) act. These can all be extended to handle OCED, but it requires "reinventing" the tasks shown in Figure 2. One should realize that, unlike traditional event logs, the scope of OCED could be an entire organization and is not limited to a single process. In principle, all objects and events of an organization could be captured using the formalization in Definition 2 and the meta-model in Figure 3. It does not make sense to try to discover a model for the whole organization. This is technically possible, but the complexity would be overwhelming.

Given an OCED $L = (E, O, EA, OA, evtype, time, objtype, eatype, oatype, eaval, oaval, E2O, O2O)$, we introduced $ET(L)$ as the set of event types, $OT(L)$ as the set of object types, and $ET2OT(L)$ as the relation between event types and object types. One can think of this as a *contingency table* where the rows correspond to the activities in $ET(L)$, the columns correspond to the object types in $OT(L)$, and the correspondence between rows and columns is described by $ET2OT(L)$. Table 1 shows the contingency table for the example involving orders, items, packages, and routes introduced using Figure 5.

There could be dozens, hundreds, or even thousands of object types and event types. This makes it pointless to look at the whole. One still needs to pick an angle to view processes. However, one can change the angle *without* extracting new data. All events and objects have been captured already, and one just needs to scope the event data. Scoping OCED requires selecting rows and columns. A *profile* $P_{sel} = (ET_{sel}, OT_{sel})$ (also called *perspective*) is a selection rows $ET_{sel} \subseteq ET(L)$ and columns $OT_{sel} \subseteq OT(L)$. Such profiles can be reused to create useful views on the event data. It is also possible to use a more fine-grained profile notion that allows for selecting individual cells in the contingency table. In this case, $P_{sel} \subseteq ET2OT(L)$. For example, $P_{sel} = \{(place\ order, order), (send\ invoice, order), (receive\ payment, order), (place\ order, item), (pick\ item, item), (pack\ items, item), (pack\ items, package), (deliver\ package, package)\}$ selectively picks combinations of event types and object types that should remain. After applying these more refined P_{sel} six event

types (i.e., six rows in the contingency table), three object types (i.e., three columns in the contingency table) remain. Moreover, also individual cells in the contingency table are suppressed, e.g., the send invoice and receive payment activities no longer refer to the items involved.

Table 1. Contingency table relating activities $ET(L)$ (rows) to object types $OT(L)$ (columns) based on Figure 5. The checkmarks (✓) describe $ET2OT(L)$. Instead of checkmarks, one can also show the cardinalities. To scope OCED for analysis, one needs to select the relevant rows and columns.

	Order	**Item**	**Package**	**Route**
place order	✓	✓		
send invoice	✓	✓		
receive payment	✓	✓		
check availability	✓	✓		
pick item	✓	✓		
pack items		✓	✓	
store package		✓	✓	
load package		✓	✓	✓
start route			✓	✓
deliver package			✓	✓
failed delivery			✓	✓
unload package			✓	✓
end route			✓	✓

Note that after applying a profile to OCED L, we obtain another OCED L' satisfying Definition 2. Hence, using a profile to view one OCED yields another OCED.

In the remainder of this section, we briefly discuss how we can leverage existing process-mining techniques for OCPM. We focus on the tasks *discover* and *check* in Figure 2 because these are the most essential for process mining. Of course, also the output of task *extract* and the input of the tasks *predict* and *act* changes. However, this is beyond the scope of this paper.

5.1. Object-Centric Process Discovery

There exists a plethora of process discovery techniques that can be applied to flattened event logs [1,11–14]. Here, we discuss how these can be used to discover object-centric process models.

It is possible to pick a profile $P_{sel} = (ET_{sel}, OT_{sel})$ such that OT_{sel} is a singleton, i.e., there is one ot_{sel} such that $OT_{sel} = \{ot_{sel}\}$, and $ET_{sel} = \{et \mid (et, ot_{sel}) \in ET2OT(L)\}$. This corresponds to the first four steps in the flattening of OCED described in Section 3.6. To apply existing process discovery techniques, we also need to apply the fifth step and replicate each event for all objects it refers to.

Now assume that we did this for every object type, i.e., we created one flattened event log for each object type. This means that we can obtain a process model for each object type. Now, we need to merge these. To do this, we face two problems. First of all, the frequencies are no longer correct due to the convergence problem explained in Section 3.6. Second, we need to merge the models in such a way that the semantics are preserved (the handling of different objects is synchronized properly). How this can be done is explained in [5] using Petri nets. The convergence problem leading to incorrect frequencies can be resolved using variable arcs, i.e., arcs that can be used to consume or produce multiple tokens in one step. This is a concept already present in colored Petri nets (CPNs) [28,29] and supported by, for example, CPN Tools (cf. cpntools.org, accessed on 1 April 2023). In CPNs, transitions can consume and produce multisets of tokens having arbitrary values (colors). The result is a Petri net *per object type* with variable arcs to indicate that multiple objects of the *same type* can be involved in the occurrence of an activity. This way, we can create one Petri

net with variable arcs per object type. Next, these Petri nets need to be merged. This is straightforward if the discovery technique does *not* generate multiple transitions with the same activity label. Very few discovery techniques are able to discover such duplicate transitions. This is not limited to Petri nets and also applies to discovery techniques that produce DFGs or BPMN models. Therefore, this is not a practical limitation. While folding, all places belong to just one type and are not merged. Only transitions representing visible activities can be shared among different object types. Silent transitions, i.e., transition not describing visible activities, are never merged and correspond to one object type. Moreover, it is also possible to extend transitions with cardinality constraints, e.g., not more than 10 objects are involved of a given type. These constraints may also involve multiple object types, e.g., the number of resource objects is smaller than the number of operation objects. The resulting merged Petri net is an *object-centric Petri net* (OCPN) [5].

To illustrate the discovery of OCPNs, assume that we applied the profile $P_{sel} = \{(place\ order, order), (send\ invoice, order), (receive\ payment, order), (place\ order, item), (pick\ item, item), (pack\ items, item), (pack\ items, package), (deliver\ package, package)\}$ to simplify the input. This is the view we pick, and after applying the profile, we obtain a much smaller OCED. Using this view, we discover the OCPN shown in Figure 6. Due to the selected profile, we have only three object types and six activities. The double-headed arcs indicate that a variable number of objects of the corresponding type are involved in the event. For example, each execution of activity *placeorder* involves one *order* object (normal arrow) and a variable number of *item* objects (double arrow). It is possible to add more precise cardinality constraints, e.g., *placeorder* involves at least 1 *item* object and at most 10 *item* objects (next to the *order* object). The two "1..*" annotations in Figure 6 show that at least one item is involved on both *placeorder* and *packitems*. The four red places contain *order* objects. The four green places contain *item* objects. The three purple places contain *package* objects. In this small example, only the activities *placeorder* and *packitems* have a variable number of objects involved. Events of type *pack items* have one *package* and one or more *item* objects.

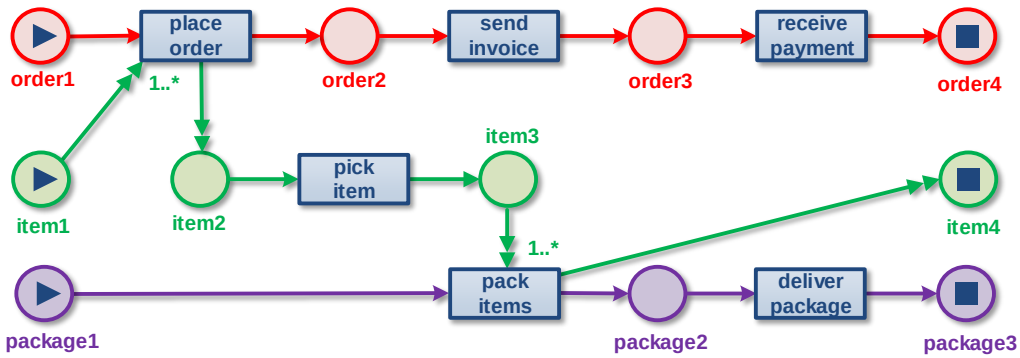


Figure 6. An object-centric Petri net (OCPN) discovered after applying profile P_{sel}. The places and arcs colored red refer to orders. The places and arcs colored green refer to items. The places and arcs colored purple refer to packages.

To illustrate the semantics of OCPNs, we add some artificial frequency information in Figure 7. All arcs and transition now have a frequency. We also change the cardinalities of the variable arcs. *place order* now involves at most 10 *item* objects ("1..10") and *pack items* involves at most 5 *item* objects ("1..5"). It is also possible to show a frequency distribution of the number of objects involved in activities. In this toy example, there are 100 orders, 500 items, and 250 packages. Events of type *place order* refer to one order and on average five items. Events of type *pack items* refer to one package and on average two items. Figure 7 shows the flow of objects and the correct frequencies. Note that if we used *item* as a case notion, *place order* would have happened 500 times and *pack items* would have happened 250 times (i.e., we would have the convergence problems mentioned before). Figure 7 only shows frequencies. However, it is also possible to show object-involvement distributions,

routing probabilities, and time information (e.g., minimum, maximum, and average time between two activities). Using O2O relations, it is also possible to answer such questions as the following:

- What is the average time between placing an order and delivering all the packages that contain items of the order?
- Do people typically pay the order before or after they receive all the items?
- Does the size of an order influence the time until delivery?

Note that all of these questions involve multiple object types.

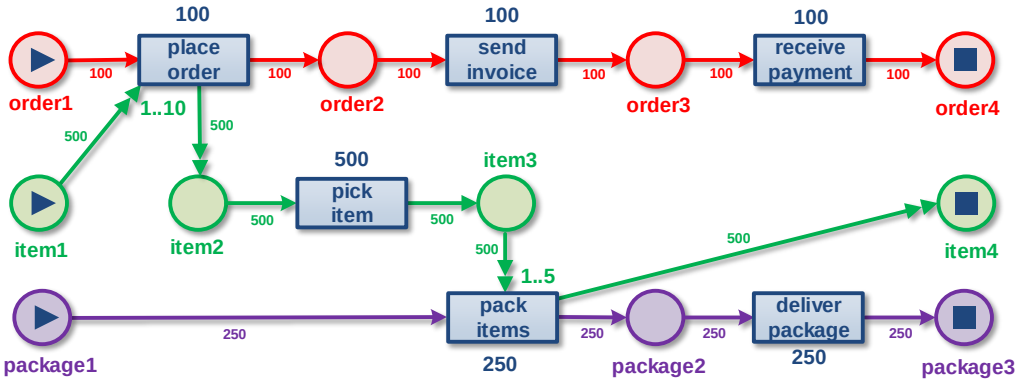


Figure 7. An OCPN showing the true frequencies of activities and object flows. Next to showing frequencies, it is also possible to show routing probabilities and time information (e.g., bottlenecks).

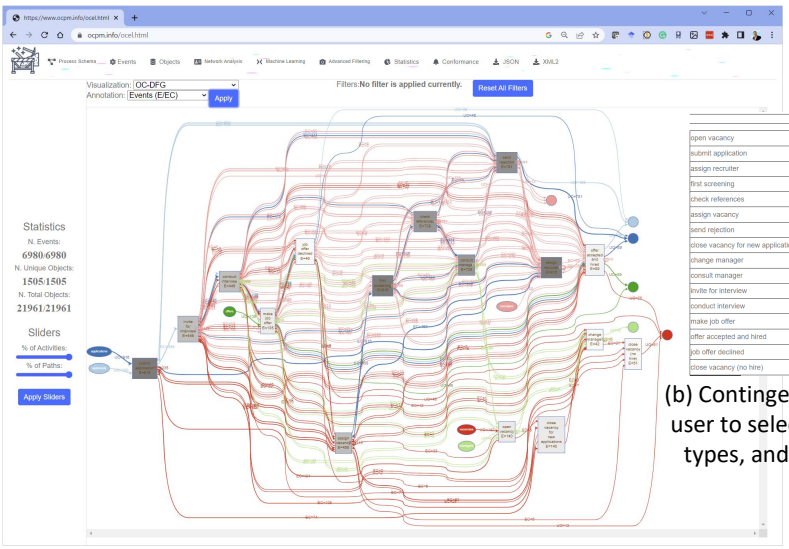
In [5], the above approach is fully formalized. The approach was also implemented in the open-source tools mentioned before, i.e., the "OCELStandard" package in ProM (promtools.org), the OC-PM tool (ocpm.info), and Object-Centric Process Insights (ocpi.ai) (all accessed on 1 April 2023). The same general approach is used in Celonis Process Sphere [9].

For OCED, it is also possible to use mechanisms other than first creating a model for each object type and then merging and correcting the models. It is possible to *reintroduce cases* (also called process instances) on top of objects. One can pick a so-called *leading object type* as the case notion and flexibly decide which other objects belong to these so-called *leading objects*. It is also possible to create a so-called *event-object graph* and declare each *connected component* to be a process instance. The latter ensures that there are no convergence and divergence problems, but the process instances may be too coarse grained. A detailed discussion on these mechanisms is out of scope, but their existence allows for flexible applications of existing process-mining approaches.

5.2. Object-Centric Conformance Checking

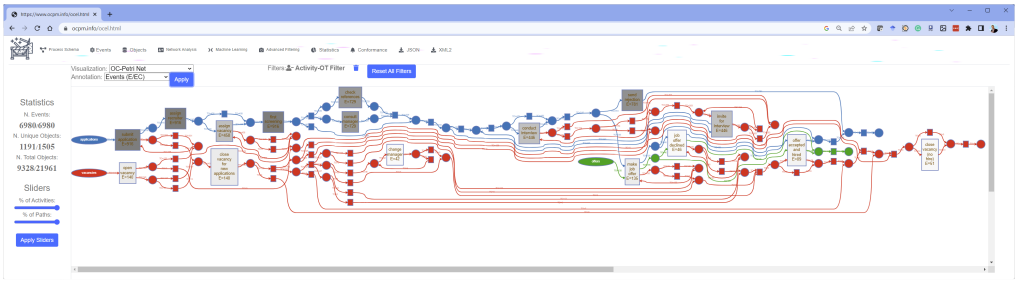
For conformance checking, we follow the reverse approach. We start from an object-centric process model. This could be an *object-centric directly follows graph* (OC-DFG), an *object-centric Petri net* (OC-PN), or an *object-centric BPMN* (OC-BPMN). A precise definition of these notations is out of scope. To check conformance, cardinality constraints in the model can be directly checked on the event log. For example, if the model indicates that the activity *place order* relates to one *order* object and at least one *item* object, then this constraint can be checked directly on the event data. For the behavioral aspects, we can again flatten the event log and process model per object type and use standard conformance checking approaches, such as *token-based replay* and *alignments* [1,15].

Again, we refer to [5] for details. It is important to note that these principles do not depend on Petri nets and are quite general. When moving to more advanced process-mining tasks building on process discovery and conformance checking, things get more tricky, for example, when extracting features related to process instances, where process instances refer to a collection of related objects.

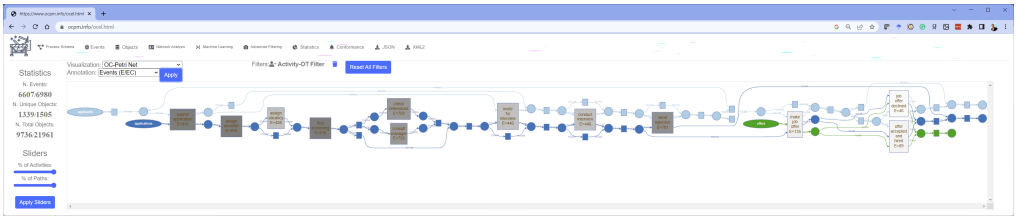


(a) Object-Centric Directly-Follows Graph (OC-DFG) showing all 6 object types and all 16 activities

(b) Contingency table allowing the user to select event types, object types, and their combinations.

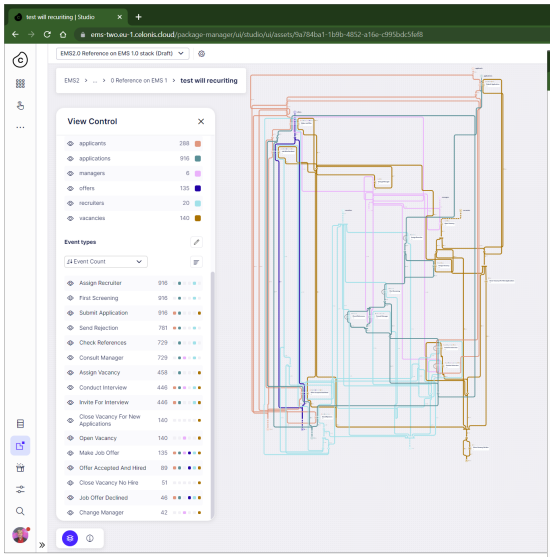


(c) Object-Centric Petri Net (OC-PN) showing three object types (applicants, applications, and offers) and all related activities

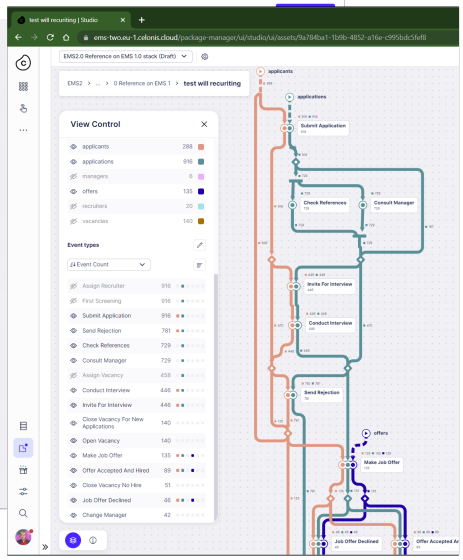


(d) Object-Centric Petri Net (OC-PN) showing the same three object types (applicants, applications, and offers), but a subset of 12 activities.

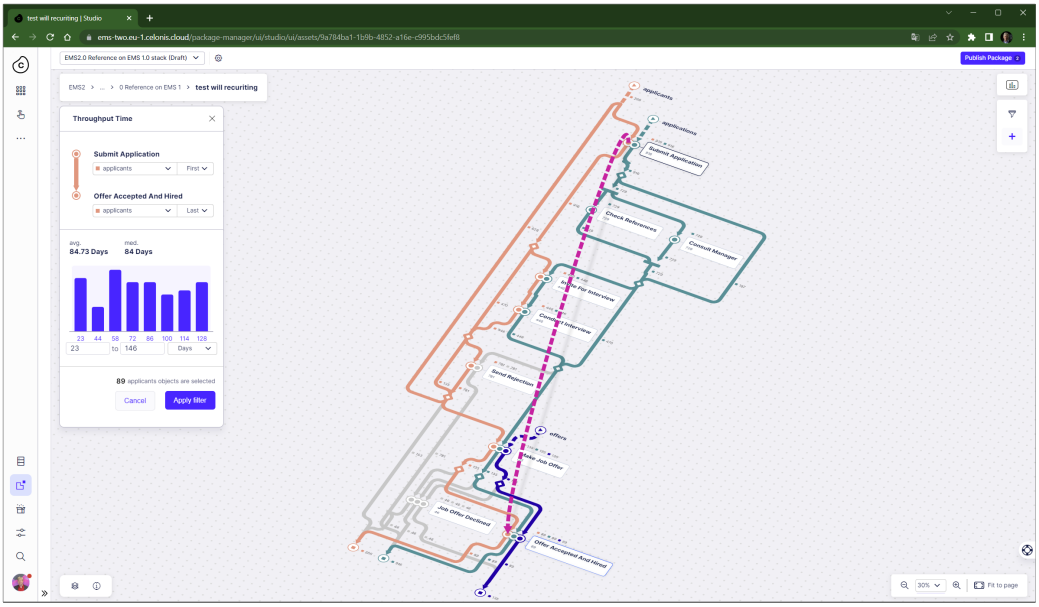
Figure 8. Example results produced using the OC-PM tool (ocpm.info, accessed on 1 April 2023). The screenshots are not intended to be readable but illustrate the capabilities of OC-PM. The different colors correspond to the six object types.



(a) Object-Centric BPMN model showing all 6 object types and all 16 activities and the interface to select subsets of objects types and activities (contingency table) on the left-hand side



(b) Object-Centric BPMN model after selecting three object types (applicants, applications, and offers)



(c) Analyzing the time between an applicant applying for a vacancy and actually being hired. In total 89 applicants were hired (of a total of 288 applicants applying 916 times). The average time between applying and accepting an offer was 84 days

Figure 9. Example results produced using Celonis Process Sphere [9]. The screenshots are not intended to be readable but illustrate the capabilities of Process Sphere. The different colors correspond to the six object types.

5.3. Example Using OC-PM and Process Sphere

To illustrate the techniques just described, we use a small example and show discovered process models in both OC-PM and Celonis Process Sphere. In this small data set, we have six object types having the following numbers of objects: 288 *applicants*, 916 *applications*, 135 *offers*, 140 *vacancies*, 20 *recruiters*, and 6 *managers*. There are 16 activities (i.e., event types): *open vacancy*, *submit application*, *assign recruiter*, *first screening*, *check references*, *assign vacancy*, *send rejection*, *close vacancy for new applications*, *change manager*, *consult manager*,

invite for interview, *conduct interview*, *make job offer*, *offer accepted and hired*, *job offer declined*, and *close vacancy (no hire)*. In total, there are 1505 objects and 6980 events.

If we flatten the OCED data set using *applications* as a case notion, we obtain a process model similar to Figure 1 using the BPMN notation.

Figure 8 shows a few screenshots using the OC-PM tool (ocpm.info, accessed on 1 April 2023). OC-PM supports Object-Centric Directly Follows Graphs (OC-DFGs), Object-Centric Petri Nets (OC-PNs), and Object-Centric BPMN models (OC-BPMNs). Figure 8a shows the OC-DFG based on the whole data set. Figure 8b shows the contingency table. The user can select the object types and events to be included. If we select *vacancies*, *applications*, and *offers* as object types (i.e., three of six) and all related activities, we obtain the OC-PN shown in Figure 8c. Places, arcs, and silent transitions related to *vacancies* are shown in red. Model elements related to *applications* are blue, and elements related to *offers* are green. It is also possible to show the OC-DFG and OC-BPMN based on this selection. The view selected shows frequencies, but it is also possible to show average durations. If we select *applicants*, *applications*, and *offers* as object types (*applicants* are shown in light blue) and a subset of activities, we obtain the OC-PN shown in Figure 8d.

Figure 9 shows a few screenshots of Celonis Process Sphere using the same data set [9]. Although the visualizations are very different, the underlying principles are the same. Figure 9a shows the OC-BPMN based on the whole data set. In the "view control" window on the left, one can see the list of object types and event types. Again, it is possible to select subsets. Figure 9b shows the OC-BPMN generated after selecting *applicants*, *applications*, and *offers* as object types. We pick the same subset of event types as in Figure 8d. Figure 9c shows a screenshot of Celonis Process Sphere while analyzing the time in between two selected activities. We selected the activities *submit application* and *offer accepted and hired* and the object type *applicant*. There are 84 applicants with activity *submit application* followed by *offer accepted and hired*, and the average time between the first application and actually being hired is 84 days. The window on the left shows the distribution of the throughput time.

Both the open-source OC-PM tool and Celonis Process Sphere provide many more capabilities that are beyond the scope of this paper. However, Figures 8 and 9 provide some insights into possibilities and the value of showing multiple object types.

5.4. Other Considerations Related to Scalability, Adoption, and New Opportunities

In principle, an organization can store all events and objects in a single OCED $L = (E, O, EA, OA, evtype, time, objtype, eatype, oatype, eaval, oaval, E2O, O2O)$. This triggers questions related to *scalability*. Today's leading process-mining engines can handle billions of events and cases, which is amazing. Summing up all the objects and events for all processes of larger organizations may lead to hundreds of billions of events and cases. However, it makes no sense to discover a process model for the whole organization involving all event and object types.

Note that state-of-the-art process-mining systems (e.g., Celonis) use a two-tier architecture. In the first tier, a cloud relational database is used (e.g., Vertica). Here, the focus is on scalability and not (process mining) speed. In the second tier, a selected part of the data is loaded into the process-mining engine (typically using an in-memory database) for analysis purposes. This allows us to leverage the so-called *profiles* (also called perspectives) introduced at the beginning of this section. These profiles correspond to typical views ideally having no more than five object types and twenty activities. Only the selected data are loaded into the process-mining engine. Process-mining computations are performed over these views and are therefore non-problematic for most applications. In general, one can even say that OCPM makes process mining more scalable. The events are typically captured at a higher level of abstraction and there is no duplication of data. Using non-object-centric process mining, event logs are often overlapping, e.g., multiple logs refer to the same products, customers, and suppliers. Therefore, scalability is no problem using a two-tier architecture, where only the events and objects related to a profile are loaded

into the process-mining engine. Consequently, scalability is comparable to (and often even better than) traditional process mining.

Although OCED logs are more complex than traditional flat event logs, organizations are eager to adopt this new technology. Next to new capabilities, such as discovering object-centric process models and powerful insights spanning multiple departments and processes, it greatly simplifies data management. Operational processes tend to leave data in different systems. OCPM provides a layer on top of these systems unifying the data in a format much closer to the actual business operations. Instead of storing the data in a format close to the source system (e.g., SAP with its 800.000 tables), data should be stored in a *well-defined unified* format using names for object types and event types that end-users understand. Definitions of object types and event types and their attributes need to be standardized. It is possible to define *taxonomies* of object types and event types using inheritance notions.

This requires a mind shift. Instead of loading the data as they are stored in the different source systems, it is better to pull the data from these source systems using a specific target format (i.e., well-defined object types and event types). This provides unified semantics. Having semantically enriched OCED, new forms of querying and reasoning can be used. It is possible to train large language models (LLMs) that use publicly available data (Wikipedia, websites, etc.) and semantically enriched information about objects and events. It is already possible to generate process-mining queries using general-purpose LLMs, such as GPT-4. However, for more precise results, structure and semantics are key.

Next to these new opportunities provided by OCPM, also, existing process-mining techniques need to be reinvented to deal with multiple object types. Because the notion of an instance is more flexible, tasks such as filtering, clustering, and prediction are more challenging. Whereas traditional process-mining algorithms deal mostly with sequences, OCPM techniques often work on graphs.

6. Conclusions

Process-mining technology is used to drive efficiency, improve operational excellence, and address performance and compliance problems. Although more and more organizations are seeing the value of process mining and have started to use it, there are also some challenges. As explained in this paper, (1) extraction is often time consuming and needs to be repeated when new questions emerge, (2) interactions between objects are not captured and objects are analyzed in isolation, and (3) a three-dimensional reality with multiple object types needs to be squeezed into two-dimensional event logs and models focusing on individual cases.

This tutorial-style paper illustrated these problems by first presenting the normal process-mining tasks and the object-centric event data meta-model (OCED-MM), which introduces the core concepts. Using this, it was possible to precisely explain the convergence and divergence problems. We also provided a rigorous formalization of these concepts. Moreover, we could explain such concepts as the contingency table, profiles, and flattening events logs by picking one object type. We also explained the basic principles that can be used to lift process discovery and conformance checking from traditional event logs to object-centric process mining (OCPM). This was illustrated using the open-source OC-PM tool and Celonis Process Sphere. However, the goal was not to present specific tools and algorithms. This is outside the scope of this paper. Instead, we presented the "bigger picture" and "growing relevance" of OCPM.

By implementing OCPM, it is possible to view *all* operational activities from any perspective using a *single source of truth*. Organizations should steer away from system-specific event logs; ideally event data are *system agnostic*. A process supported by SAP should leave the same footprint as the same process supported by Oracle. This requires taking control of data management. There is no need to extract the data when changing the viewpoint. This allows for *flexibility* using "on demand" process-mining views. OCPM will reveal novel and valuable improvement opportunities for problems that live at the

intersection points of processes and organizational units. This helps to transition from two-dimensional views of processes to a three-dimensional and dynamic view of the entire organization and its processes. Traditional process mining can be seen as taking two-dimensional X-rays of processes. These are static and limited to one particular viewpoint (i.e., the angle is fixed). OCPM is more like taking an MRI, thus creating a three-dimensional representation that can be viewed from any angle. Therefore, we expect that OCPM will become the "normal" way of performing process mining and that the ideas presented in this paper will be adopted by most tool vendors. Moreover, existing research approaches will need to be lifted to include this third dimension. This provides interesting new scientific challenges.

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