Sequence Analysis in Routine Dynamics

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Sequence analysis in routine dynamics

Abstract

Implicitly or explicitly, sequence analysis is at the heart of research on routine dynamics. Sequence analysis takes many forms in many different disciplines, because sequence is central to temporality, process, language, and narrative. In this chapter, we focus on sequence analysis in routine dynamics research. The goal of this chapter is to help researchers use sequence analysis in their research on routine dynamics. Hence, the chapter reviews prior literature that has used sequence analysis, it shows how to carry out sequence analysis and it provides implications as well as an agenda for future research.

1 Introduction

Sequence analysis can be defined as a family of methods that can be used to identify, describe, compare and visualize patterns in sequentially ordered data. The disciplinary origins of these methods include computer science (Sankoff and Kruskal, 1983), bioinformatics (Durbin *et al.*, 1998), history (Griffin, 2007), life course sociology (Aisenbrey and Fasang, 2010) career research (Abbott and Hrycak, 1990), research on decision making (Levitt and Nass, 1989) and innovation research (Van de Ven *et al.*, 1999). Sequence is essential to concepts like progression, temporality, and flow that are central to process organization studies (Langley and Tsoukas, 2017) and routine dynamics (Feldman *et al.*, 2016).

In this chapter, we focus on sequence analysis as it applies to routine dynamics. The goal of this chapter is to help scholars use sequence analysis in their research on routine dynamics. We begin by considering the kinds of questions we can address with sequence analysis. We review prior routine dynamics research and show how it has used sequence analysis. Excellent resources are available for the mechanics of particular methods (e.g., Sankoff and Kruskal, 1983, Cornwell, 2015, Poole *et al.*, 2017). Hence, rather than zooming in on particular sequence analysis methods (e.g., optimal string matching), we are zooming out to consider how sequence analysis can help ***identify***, ***describe***, ***visualize*** and ***compare*** routines and their dynamics. We show how scholars can get started with sequence analysis with any kind of sequential data (e.g., from ethnographic observation, interviews or digitized event logs). Finally, we suggest avenues for future research.

To illustrate our arguments, we draw on the example of Scrum software development routines in a medium-sized high-tech manufacturing company (Mahringer, 2019, Mahringer, Dittrich and Renzl, 2019). Scrum is a software development framework which splits the software development process into phases of two to four weeks (i.e., sprints) (Schwaber and Beedle, 2002). The study includes ethnographic fieldwork of how the software development teams enacted the Scrum routines over a period of 12 months. The software development teams organized their work by using a software tool called Zoe (all names are pseudonyms). that recorded approximately 4.500 sequences and 90.000 events in a database. Sequence analysis can be used with any or all of this data.

2 How does sequence analysis help to understand routine dynamics?

Abbott (1990: 375) identifies three kinds of questions where sequence analysis can be useful: “(1) questions about whether a typical sequence or sequences exist, (2) questions about why such patterns might exist, and (3) questions about the consequences of such patterns.” Of these, he argues that the first question is most important. To the extent than an organizational routine contains recognizable patterns of action, we expect to find typical sequences in any routine. Sequence analysis can help us identify, describe, visualize and compare those sequences.

Abbott's (1990) questions are generic to any kind of sequential data, but there are more specific questions that are relevant to the analysis of organizational routines. By definition, routines are repetitive, so they generate multiple performances (Feldman and Pentland, 2003). To the extent that each performance of an organizational routine can be treated as a sequence of actions, we can ask the following kinds of questions (Salvato, 2009b):

- **What are the typical patterns of a routine?** Because routines are patterns in variety (Cohen, 2007) they can potentially generate a large number of different performances. Some of these performances occur more often and, hence, are more typical while other performances are less typical. Abbott (1990: 378) refers to these as "typical-sequence/families-of-sequences" questions; he argues that these are "the central questions of the sequence area."
- **How varied are the performances of a routine?** While the performances of some routines are more similar to each other, the performances of other routines differ tremendously. Pentland (2003a) offers metrics for measuring sequential variety.
- **How does sequence matter?** The sequential relations among actions of a routine performances are essential (LeBaron *et al*., 2016). Sequence analysis can be used to unpack sequential relations between actions.
- **How does the pattern of a routine change?** Sequence analysis can also be used to show how the pattern of a routine changes over time. Dittrich, Guérard and Seidl (2016), for instance, analyze how the routine pattern changed, and identify reflective talk as a critical mechanism of routine change.
- **How do different action patterns influence performance outcomes?** Sequence analysis provides opportunities to better understand how different patterns influence performance outcomes. For example, first writing an exam and then learning the relevant content most likely results in a different performance outcome than the other way round.

While Abbott's (1990) primer provides a useful starting point, it has some important limitations, especially when applied to routine dynamics. First, Abbott treats events as objective, which undermines that routine participants might interpret events in different ways. However, the significance of events for participants is central to the formation and dynamics of the routine (Sele and Grand, 2016). Therefore, sequence analysis of routines should include the notion of meaning and interpretation. An event, then, can be defined as an actual happening that sufficiently coheres to be experienced as similar, but which still incorporates different points of view (Hernes, 2014).

Second, Abbott (1990) treats patterns as stable or stationary. While Abbott's own research places history and temporality in the foreground (e.g., in the formation of professions), the methodologies he discusses in his primer are a-historical. They focus on sequences of events, but not on how these sequences might change over time. In contrast, research on routine dynamics is explicitly concerned with change and temporality (Pentland *et al.*, 2012).

Third, focusing particular sequences tends to obscure the significance of multiplicity in routines. Routines are generative systems that can display a substantial number of different sequential patterns. Like other processual phenomena, routines are multiplicities (Pentland *et al.*, In Press). Hence, when comparing routines or measuring change over time, we may need to compare whole action patterns, not just particular linear sequences.

3 Sequence analysis in prior routine dynamics research

Sequence methods in routine dynamics research can be sorted into three different categories: whole sequence methods, pattern-mining methods, and network methods. These methods can be differentiated according to the length of sequence that is considered in the analysis (Table 1).

Table 1: Three types of sequence analysis in routine dynamics

	Whole sequence methods	Pattern mining methods	Network methods
Sequence length	Variable, up to length of longest performance	Variable, typically three to five actions or events	Fixed, pairs of events
Typical applications	Identifying different types of patterns	Identifying a typical pattern of actions of a routine	Identifying handoffs between actions
Major drawbacks	Only considers differences between whole sequences, not within sequences	Size of the lexicon has a critical effect on the findings; limited applicability in comparing patterns	Only considers the immediate context (i.e., one action before and one after)
Exemplary references	Salvato (2009a, 2009b)	Pentland and Rueter (1994), Hansson, Pentland and Hærem (2017)	Pentland, Hærem and Hillison (2010), Goh and Pentland (2019)

3.1 Whole sequence methods

As the name implies, whole sequence methods operate on complete sequences of action (Salvato, 2009b). These methods build on the rationale that differences between empirically observable sequences yield meaningful insights. These methods treat whole performances of a routine as the unit of analysis. They derive from molecular biology and computer science (Sankoff and Kruskal, 1983). Abbott and Hrycak (1990) pioneered the use of these methods in career research.

Salvato (2009a), for instance, analyzes new product development processes at Alessi over a period of 15 years. The author uses dossiers that report details about 90 new product development projects to identify the sequences of events for each project. He applies optimal matching (Abbott and Tsay, 2000) to identify clusters of similar sequences. To interpret the meaning of these clusters the author went back to his raw data or asked participants. A similar approach is applied by Sabherwal and Robey (1993). These authors use optimal matching and cluster analysis to develop a taxonomy of implementation processes. Analyzing 53 computer-based information system implementation processes they identify six archetypes of these processes. Pentland (2003a) also uses whole sequence methods as one way to characterize variety in routines.

It is important to note that narrative analysis, based on ethnographic fieldwork, can also be considered a whole sequence method (Pentland, 1999a). When ethnographers describe the typical performance of a routine, from start to finish, they are engaging in sequence analysis. Constructing a narrative from fieldnotes requires the same basic steps as a more formal, mathematical analysis: collecting the data, defining the lexicon, choosing a point of view, identifying the sequence and creating a representation.

3.2 Pattern mining methods

In contrast to whole sequence methods, pattern mining methods seek to identify common subsequences within performances of a routine. There is a broad class of algorithms and techniques for empirically identifying patterns (e.g., Mabroukeh and Ezeife, 2010, Fournier-Viger *et al.*, 2014).

Hansson *et al.* (2017) investigate the application of these methods to organizational routines. They examine the use of regular expressions and inductive pattern mining. Regular expressions are a pattern matching tool that is available in nearly every modern computing language. Regular expressions provide a flexible tool for searching a corpus of sequence data (typically in the form of text) for particular combinations of letters and words. Hansson *et al.* (2017) refer to regular expressions as a deductive method because the search pattern must be defined in advance. In contrast, inductive pattern mining methods are algorithms that search through a corpus of text to find patterns that do not need to be defined in advance.

Keegan, Lev and Arazy (2016) analyze editorial events in Wikipedia articles. The authors use pattern mining to identify the most frequent sub-sequences of how articles are edited. The authors are interested in different contribution styles to Wikipedia articles, such as solo contributing or reactive contributing. They emphasize the opportunities that sequence analysis offers to better understand routines in online knowledge collaboration.

Pentland and Rueter (1994) apply a simple pattern mining approach to identify grammatical rules that could be used to describe organizational routines. The authors use a sample of 335 calls from a software support hotline. They define grammars (i.e., patterns) for the data set based on observations of the routine. Subsequently, they use the grammatical patterns to rewrite (i.e., substitute) the events in the actual sequences. This analysis led to the insight that a large number of performances could be described by a small number of patterns.

3.3 Network methods

In contrast, network methods operate on adjacent pairs of actions or events within a sequence or set of sequences. Because they do not require whole sequences, network methods can be used where fragments of performances are observed, as often occurs in fieldwork (Pentland and Feldman, 2007). Network methods provide a convenient way to describe what Cohen (2007) referred to as the "pattern-in-variety" of organizational routines. There are repetitive, recognizable patterns, but there may also be a large number of variations.

Pentland and Feldman (2007) propose that sequences of events can be used to compute narrative networks, a special class of network in which nodes represent events and edges represent sequential relations between those events. "A narrative network is an analytical device for describing, visualizing, and comparing these patterns." (Pentland and Feldman, 2007: 782). This method has been used to visualize routine patterns from observational data (Danner-Schröder and Geiger, 2016, Dittrich *et al.*, 2016), but it also offers the possibility to compute event networks from digitized digital trace data.

Pentland *et al.* (2010) analyze 4781 invoice processing sequences in four Norwegian organizations. They aggregate those performances into an event network that represents the routines in each organization, and they compare those networks to determine whether the routines in these organizations are different. Note that this method is not comparing specific performances of the routine. Rather, it is comparing the relative frequency of sequential pairs of action in all observed performances of the routine. Pentland *et al.* (2011) extend these insights by showing that patterns change over time due to endogenous factors.

In summary, the network approach can be used to better understand the variability of routine patterns (Pentland, 2003b), complexity (Hærem, Pentland and Miller, 2015, Hansson, Hærem and Jeong, In Press) and multiplicity of routines (Pentland *et al.*, In Press).

4 A guide to sequence analysis in routine dynamics research

In this section we step-by-step show how to analyze sequential data based on the example of Scrum software development. As with any routine, in practice these steps may not follow a fixed, linear sequence. Rather, it may be necessary to jump back and forth.

4.1 Collecting the data

As with any empirical work, sequence analysis starts with collecting data. The predominant empirical approach to understand routine dynamics is ethnographic fieldwork (Feldman *et al.*, 2016). It should be evident from the prior review that sequence analysis can be applied to many different kinds of data, including observational data collected during fieldwork. Indeed, any source of data that includes temporal sequence can be used for sequence analysis. A major strength of ethnographic fieldwork is that it enables scholars to capture the mundane everyday actions and the meaning that actors associate with specific events (Dittrich, In Press). However, a drawback of ethnographic fieldwork is that it is limited to specific times and places.

Digital trace data is gaining popularity (Berente, Seidel and Safadi, 2019). It offers possibilities for extending ethnographic data in two important ways. First, digital trace data can extend the *temporal scope*, because these data oftentimes extend across several years or decades. This enables seeing patterns of stability and change over longer periods of time. For example, while the first-author of this chapter spent twelve months observing the Scrum routines, the digital trace data covers a period of approximately four years. Taking earlier periods into consideration shows that the actors used different functions in Zoe than they used during the observation period.

Second, analysis of digital trace data can extend the *spatial scope*. Ethnographic fieldwork oftentimes focuses on local settings (Marcus, 1995). Digital trace data, however, particularly when provided by digital software tools that are used by actors in different locations, enable scholars to analyze sequences that extend across many locales. In the Scrum study, for instance, the Product Owner (i.e., the actor who was responsible for the software to be developed) typically spent some time in his private office space in the early morning to check the product backlog (i.e., a list of issues to be resolved). During this time he also clarified issues in Zoe and communicated with customers. These events are tracked in Zoe while they had not been directly observed.

By extending the spatial and temporal scope of research, digital trace data provides researchers with methods that can identify otherwise hidden patterns and dynamics. Computing a network of events from the Scrum sequences showed how events typically connected to each other. This network showed that the event 'PrioritizeIssue' (i.e., an event that signifies changes in the order of issues in the product backlog) took a central position in the network and connected with many other events. This made us reflect the relevance of prioritizing issues.

4.2 Selecting software tools

Data in hand, the next step is to determine if any kind of software is needed to assist in the analysis. With a small amount of data, it is perfectly possible to identify, describe, visualize and compare patterns by hand (Barley, 1986, Pentland, 1999b). With larger amounts of data, and for specialized questions, it may be necessary to find a software tool that helps to analyze sequential data, such as TraMineR or ThreadNet.

TraMineR is a software package for R. After having installed R the TraMineR package can be downloaded. TraMineR offers many different methods, including whole sequence analysis, pattern mining and network models. Gabadinho *et al.* (2011) offer a detailed user guide that explains the methods available.

ThreadNet is also a software package in R, available on GitHub (https://github.com/ThreadNet/ThreadNet). As the name implies, it converts threads (sequential data) into networks based on sequentially adjacent pairs of events. ThreadNet allows users to define events in a flexible manner, based on any combination of contextual factors. This allows users to quickly explore action patterns from different points of view (e.g., the actor, the location, etc.). ThreadNet itself is limited to visualization, but it can export network structures for analysis in TraMineR and other software packages. In analyzing the Scrum data, for example, we started with ThreadNet and later extended to TraMineR when more specific functions were required.

We suggest the use of specialized tools rather than general qualitative analysis tools, like nVivio or Atlas/ti because sequence analysis poses some unique challenges. We are not just trying to sift and sort categories; we are looking for patterns of sequential relations between categories. The number of possible relations grows exponentially (as the square of the size of the lexicon). As a result, sequential relations can be difficult to keep track of without some kind of specialized, computerized help.

4.3 Identifying the limitations of your data

All kinds of data have limitations. These limitations shape which kinds of questions can be answered and where additional inquiry is required. As we have discussed before, ethnographic data is limited in its temporal and spatial scope. Because ethnographic fieldwork requires the researcher to observe a setting in detail, the data typically covers a period of several months, and sometimes few years, but rarely extends to a longer time horizon such as decades. The degree of detail of ethnographic fieldwork also requires researchers to make choices on what to observe and what not to observe (Van der Waal, 2009). Hereby, it is necessarily limited to a specific setting.

By contrast, digital trace data also face several limitations. First, trace data are *limited to events that are captured 'on-line'*, as part of the digital environment. Hence, they do not capture events that happened 'offline'. In the Scrum case, for instance, the daily standup was a routine which the developers enacted to synchronize their work. Even though this routine was an important part of software development, the developers did not use Zoe when performing it. Hence, the digital trace data did not contain information about the daily standup routine.

Second, trace data may not capture the *differences in meaning* associated with events. For instance, the same event in the digital trace data can have different meanings depending on the situation in which it is performed. A major feature of Zoe was the product backlog, which was an extensive list of issues to be resolved. When actors dragged an issue from the product backlog and dropped it to another position this resulted in an event which we called 'PrioritizeIssue'. The actors oftentimes coincidentally dragged and dropped and issue to another position when they were discussing about the product backlog. In other cases, by contrast, actors intentionally dragged issues from the bottom of the product backlog to its top. Since issues at the top of the product backlog had the highest priority and were added to the next sprint this was a significant event. Zoe, however, did not allow us to account for such differences. Above we noted that this event took a central position in the event network. We considered the possibility that coincidentally moving an issue could be an explanation for the central position of the event in the network. However, depending on the data it might also be possible to take account of such differences by considering additional data sources (e.g., fieldnotes).

Third, trace data may be limited in *capturing the duration of events*. The start of an event may be recorded with a specific time stamp, but the duration might not be recorded. This might be challenging if researchers try to interpret time lags between events, assuming that events do not have a specific duration. In the Scrum case, each issue in Zoe contained a description field. When an actor pushed the 'safe' button Zoe created an event which included a specific time stamp. Whereas sometimes a description change was minor (e.g., correcting a spelling mistake) in other cases such an event could signify an extensive discussion about a complex issue. The duration of this discussion, however, was not captured in the event log data.

In summary, it is essential to identify the limitations of the data set. Ethnographic data might be limited to particular times and places. Digital trace data is limited to what happens on-line, might not capture meanings associated with events and is limited in capturing durations of events. Sometimes it may be possible to gather additional data that helps to resolve such limitations, but often it is not. This limits the kinds of questions that can be answered. Most likely, the list of limitations is continuously revised during the course of analysis, as new limitations are discovered and old limitations are resolved.

4.4 Defining the lexicon of events

Another critical step in sequential analysis is defining the lexicon of events (Berente *et al.*, 2019). The lexicon is the set of event types that are used to depict the sequences. The key point is that there does not need to be a one-to-one correspondence between the raw data collected and the lexicon that is analyzed. For example, some items in the raw data may be 'filler'. In the Scrum case, for instance, simultaneously adding multiple attachments to an issue in Zoe produced sequences of similar events in the event log data. Moreover, several different items in the raw data may be used as indicators of the same higher order category (Gioia, Corley and Hamilton, 2013). In general, the move from raw data to the lexicon of events is an essential part of making sense of your data (Abbott, 1990, Pentland and Liu, 2018).

The move from raw data to higher order constructs affects the granularity of the data. Selecting the granularity of events is a major challenge, because granularity can have a tremendous impact on the findings (Pentland, 2003a). Selecting a finer granularity (i.e., a larger lexicon) increases differences between sequences and makes it more difficult to identify patterns. Selecting a coarser granularity (i.e., a smaller lexicon) makes the sequences more similar, but might lead to the false assumption that there is only minor variation in routine performances. Hence, it is important to define granularity based on one's understanding of the setting and the phenomenon of interest. In the Scrum case actors used different functions in Zoe to indicate interdependencies. This resulted in different events in the raw data such as ‘component’, ‘link’ and ‘epic link’. Since all of these events were used to indicate interdependencies, we aggregated them into the event ‘AddInterdependency’.

4.5 Defining sequences

The next step is to define according to which rationale events are sequenced. Similarly to ethnographers who have to make choices on ‘what to follow’ (Marcus, 1995), digital trace data may provide several ways of defining sequences, which could yield different insights into the phenomenon. For example, one could follow the Product Owner on a regular work day. From that point of view, one would see how the Product Owner interacts with customers, the developers, and Zoe. Alternatively, one could follow an issue in Zoe (i.e., a bug to be resolved or a new feature to be developed in the software). From that point of view, one would see how a customer reports the issue in Zoe, how the Product Owner specifies the description of the issue and how the developers resolve it. Either point of view presents a partial view of the overall routine, which is why Feldman and Pentland (2003) emphasize that the ostensive and performative aspects of organizational routines are multiple.

In general, it is worthwhile to think about different ways of sequencing the data and which insights this could yield. In the Scrum case, we explored different ways of sequencing the data such as actors, weekdays and issues. Issues were promising because they described the sequences of events that were performed in order to implement new features in the software or resolve bugs.

4.6 Identifying, describing, comparing and visualizing patterns

Now that your data are ready, we can apply sequence methods. Three major questions are important for research on routine dynamics.

Identifying: is there a sequential pattern? Whole sequence methods are useful to *identify* different types of sequences, but they cannot be used to identify common patterns of events across these sequences. Pattern mining is more useful to identify such patterns across sequences. The major challenge here is that the size of the lexicon influences the findings, because a larger lexicon makes the sequences more different. Hence, this approach has to trade-off pattern length and generalizability of patterns. The network approach overcomes this issue because it does not rely on pattern length, but on handoffs between events.

Describing and visualizing: what is the pattern? The most common method for describing sequential patterns in routine dynamics research is via narrative (i.e., texts, stories). Sequences of action have a natural narrative structure, and different characters or roles can enter and exit the story as needed. However, narrative tends to portray routines as having a specific, linear structure. It is difficult to capture the pattern-in-variety (Cohen, 2007) in narratives. Of course, one can describe exceptions and variations, but this quickly becomes tedious if the routine has a large number of variations.

Visualization is another common strategy for describing routines. However, as Feldman (2016) notes, most published visualizations are abstract simplifications. They may be easy to grasp, but they convey less information than a linear textual description. Visualizations based on detailed empirical data are starting to become available through software tools like TraMineR and ThreadNet.

Comparing: how do patterns differ? Identifying a pattern of events is useful to gain an understanding of the routine, but it does not yield further insights. *Comparing* patterns across contexts can yield further insights into what influences these patterns. We could, for instance, ask whether the Scrum routines show more or less regularities in more or less institutionalized contexts. We could also look at whether differences in complexity and multiplicity (e.g., more or less complex software, more or less actors involved) shape the patterns of events.

More specifically, patterns can also be compared for different time periods. Because we are interested in change over time, routine dynamics creates an additional requirement for conventional sequence analysis. Where Abbott (1990) emphasized synchronic methods, routine dynamics suggests the need for diachronic analysis (De Saussure, 1916). Diachronic analysis not only considers a pattern at a specific point in time, but takes its development over time into consideration (Barley, 1990, Berente *et al.*, 2019).

All three methodological approaches could be used in the context of diachronic analysis. The whole sequence approach identifies differences between entire sequences. Comparing sequences across different time windows could help to understand that the sequences are changing over time. What is missing here is how the pattern changed. The network approach can be used to compare patterns for different time windows. Pattern mining methods face similar challenges, but could be suitable to understand whether routines become less or more patterned over time. The question whether patterns are changing over time requires iterating between synchronic and diachronic approaches (Berente *et al.*, 2019).

4.7 Interpreting

Identifying, describing, comparing and visualizing patterns of action provides us with either numerical or visual results. However, we need to interpret these visualizations and numbers (Keegan *et al.*, 2016). Interpreting results shows that we need an in-depth understanding of the context that we are analyzing. We need to tell a story about the patterns. Even though this chapter presents interpreting as a discrete step in the analysis, we rather see it as a process that continuously unfolds during the analysis.

5 Implications and agenda for future research

Clearly, sequence analysis has helped advance our understanding of routine dynamics and will continue to do so in the future. In the final section of this chapter, we offer some ideas for future research.

5.1 Mutually contextualizing visualizations and narratives

The most common way to describe routines is through narrative (Feldman *et al.*, 2016). Well written textual descriptions can be very detailed and compelling. Narrating is particularly valuable, because it strives to convey the researcher's experience of local meanings in the field (Yanow, 2012). However, narratives are limited as a way to describe processual phenomena (Mesle and Dibben, 2017), because it is difficult to portray variety, and the linear quality of narrative tends to lead to an understanding of routines as unitary sequences of action.

As our capability to analyze and visualize sequential data improves, we are beginning to have visualizations (and metrics) of action patterns, as well. Network methods, for instance, provide a particularly promising source of visualizations (Moody, McFarland and Bender-deMoll, 2005). A strength of visualizing lies in depicting multiplicity. Moreover, visualizing can help to structure and process complex data, which might reveal patterns that we did not see before. However, visualizations are impossible to interpret without some form of narrative explanation.

As shown in Figure 1, sequence analysis can provide narratives and visualizations (or metrics) of routines, both of which should contextualize each other. Many kinds of data can be used to create visualizations (or metrics) and narratives. These outputs mutually contextualize each other: visualizations add a sense of structure to narratives, and narratives help interpreting visualizations. Sequence analysis informs both sides of this equation. It is the foundation for both the visualizations and the narratives.

In a sense, we are specifying Feldman *et al's* (2016: 511) statement that "[e]thnographic fieldwork will always be needed to interpret archival results, but digitized trace data provide a way to visualize and compare patterns of action that have not previously been available." While Abbott (1992: 430) argues that "[t]here is nothing about thinking processually that requires interpretive attention to complexity of meaning," we argue that in routine dynamics, the opposite is usually true. Thus, we encourage future research on routines that embraces and integrates both approaches, since they are not mutually exclusive, but mutually contextualizing.

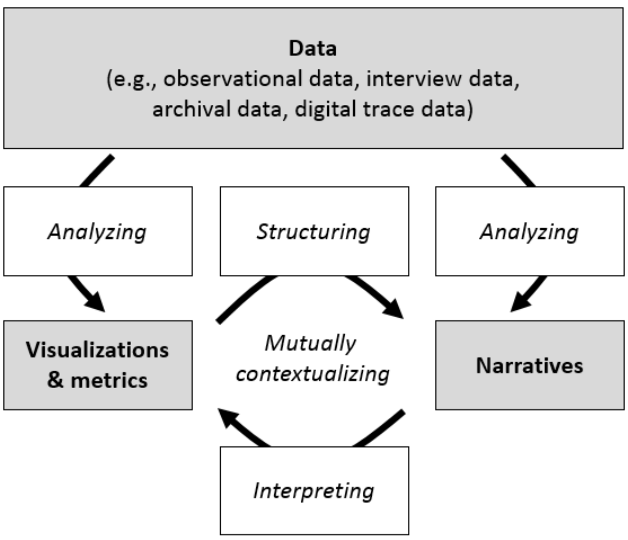

Figure 1: Mutually contextualizing visualizations and narratives generated by sequence analysis

5.2 Extending the spatial and temporal scope

The rise of digital trace data provides new opportunities to further extend the spatial scope of research on routine dynamics. Dispersed settings such as platform collaboration and open source software development make it difficult to understand how people coordinate their work through ethnographic fieldwork (Marcus, 1995). Oftentimes, however, these new ways of working are supported by software tools that provide rich data. Lindberg *et al.* (2016) is an example of a study that has taken advantage of these kinds of data to better understand routines. Because these digitized contexts become more and more important we call for more empirical research in these contexts.

Moreover, we encourage routine dynamics scholars to extend the temporal scope of their analysis. Even though ethnographic fieldwork typically studies a considerable amount of time, sequence analysis also provides opportunities that show changes and patterns over several years or even decades (Salvato, 2009a). Hence, it might be fruitful to both zoom into the details of everyday work, but also zoom out on longer time horizons to better understand routines.

5.3 Dynamics implies diachronic analysis

Ferdinand De Saussure (1916) introduced the distinction between synchronic and diachronic analysis in linguistics. Synchronic analysis refers to studies of language structure or comparative language structure within a specific period of time. In contrast, diachronic analysis refers to changes in a language over time (De Saussure, 1916). Diachronic analysis attempts to describe and understand changes over time. Barley (1986, 1990) translated these concepts for use in organizational research.

Diachronic analysis is an obvious fit for routine dynamics because it provides a way to conceptualize change in a complex system of sequential relationships over time. Pentland *et al.* (2019) offer a methodology for applying diachronic analysis to organizational routines using sequence data. As an example of diachronic analysis based on fieldwork, consider Barley's (1986) classic study of the introduction of new technology in the radiology departments of two hospitals. As a participant observer, Barley recorded the sequential interactions of radiologists, nurses and technicians, over a one year period, pre- and post-implementation. Using this data, Barley was able to conduct a diachronic analysis of the roles and action patterns (see also Barley, 1990).

5.4 Moving from singularity to multiplicity

Sequence methods make it easy to measure similarity between sequences. However, routines are multiplicities, not singular sequences (Pentland *et al.*, In Press). This ontological claim has methodological implications because we require approaches that operationalize multiplicity. Goh and Pentland (2019), for instance, introduce the notion of paths that could be used as an indicator of multiplicity of routines. More research is required to better understand multiplicity in and of routines.

5.5 Adopting methodological innovation

Business process management scholars have developed, and continue to develop, tools for analyzing sequential data (Wurm *et al*., In Press). Research on routine dynamics research has just started to recognize the possibilities of adopting these methods. These include methods for analyzing drift and variants, among other things. Research on machine learning is also providing a variety of tools for sequence analysis (Witten *et al*., 2016). There is a great deal of uncharted terrain that waits to be discovered and we hope that routine dynamic scholars will continue exploring.

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