The Why, the What and the How to Model a Dynamic Relational Learning Process with Temporal Networks

Mohammed Saqr [1] and Sonsoles López-Pernas [2,1]

[1] *University of Eastern Finland, Joensuu, Finland*
[2] *Universidad Politécnica de Madrid, Madrid, Spain*

Abstract
Research on online learning has benefited from intensive data collection to understand students' online behavior and performance. Several learning analytics techniques have been operationalized to examine the temporal nature of learning that includes changes, phases, and sequences of students' online actions. Moreover, to account for the relational nature of learning, researchers have harnessed the power of network analysis to model the relational dimensions of data, mapping connections between learners and resources, and discovering interacting communities. However, prior research has rarely combined the two aspects (temporal and relational), but rather most researchers rely on aggregate networks where the time dimension has been ignored. To combine both these aspects, temporal networks provide a rich framework of statistical and visualization techniques that allow to fully understand, for instance, the evolution and building up of learning communities, the sequence of co-construction of knowledge, the flow of information, and the building of social capital, to name a few examples. Since temporal networks have been rarely used in educational research, with this study, we aim to provide an introduction to this method, with an emphasis on the differences with conventional static networks. We explain the basics of temporal networks, the different subtypes thereof, and the measures that can be taken, as well as examples from the few existing prior works.

Keywords
temporal network analysis, learning analytics, social network analysis

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1. Introduction

A learning process involves interactions between learners, teachers, and machines. Students' actions are interdependent on each other as well as facilitated or constrained by their peers while they negotiate their roles, organize their tasks or develop their common goals [1]. Learning as a process is regulated and influenced by time at many levels, starting from the attention span and the individual lessons, up to the course schedules and finally the whole program [2]. Therefore, accounting for time using accurate dynamic models that incorporate the different factors that influence learning and how they interact together is both necessary and timely [3].

To account for the relational nature of learning, researchers have harnessed the power of network analysis to model the relational dimensions of data [4]. Using networks, researchers can chart relations, map connections, and discover interacting communities, as well as study a whole networked group to mention a few examples [5,6]. Network mathematical analysis enabled researchers to quantify interactions, find important actors, study students' roles as well as group interactivity [6,7]. The wealth of network methods, theoretical foundations, and research traditions have helped researchers across different domains of education study various phenomena [8].

The emergence of big data analytics has kindled the quest to explore their applications in learning. The premise of learning analytics was that studying learners' data may lead to a better understanding

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EMAIL: mohammed.saqr@uef.fi (A. 1); sonsoles.lopez.pernas@upm.es (A. 2)
ORCID: 0000-0001-5881-3109 (A. 1); 0000-0002-9621-1392 (A. 2)
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of learning [9]. The initial applications have succeeded in modeling and profiling students' performance using trails of their online behavior. Recently, efforts have been directed to using learners' data to understand learning as a dynamic and complex process, i.e., understanding the temporal nature of learning that includes changes, phases and sequences as well as the complex interactions between learners, learning resources, and environments [10]. Such an approach has emerged to address one of the shortcomings of using the data in "aggregate", i.e., counts of static discrete events with no connection to time or temporality [11–14].

Yet, researchers have rarely combined the two aspects (the dynamic and relational aspect) in an analytics framework. Most of the existing literature uses aggregate networks where the time dimension has been ignored [11]. Considering how important the timing and order of the learning process is, it is imperative that our analysis lens is not time-blind [3]. Time-blind methods flatten a temporal process by compressing the temporality thereof [12,13]. By relying on time-blind methods, we miss the rhythm, the evolution and devolution of the process as well as overlook the regularity and the irregularity of human behavior and, therefore, may fail to capture the moments that matter [12,13].

Temporal networks, which have been witnessing a rising trend across many fields to model dynamic phenomena, for instance, information exchange, the spread of pandemics or the reach of viral memes on the Internet [5, 9], holds the promise for enabling the modeling of a temporal and relational process such as learning. Yet, temporal networks have so far been rarely used in educational research, which can be seen as a limitation. This rising adoption has been coupled with an evolution of methods and applications as well as a rich framework of statistical and visualization techniques that deserve further scrutiny in the field of education. Taking advantage of time-dynamics allows us to fully understand the evolution and building up of learning communities, the sequence of co-construction of knowledge, the flow of information and the building of social capital, to name a few examples. What is more, temporal networks allow the longitudinal modeling and analysis of interactions across the full duration of a course, project or meeting using time-respecting paths [11,15].

The aim of this paper is to introduce the principles of temporal networks, how they are conceptualized and what makes them different from "traditional" social networks and in what makes temporal network modeling different (e.g., edges, paths, concurrency, and reachability). Then, the paper introduces some of the temporal measures with some examples, a literature review and how to start your journey with temporal networks.

2. Temporal networks: The basics

Temporal networks are not a simple extension of the traditionally used social networks, nor are they time-augmented networks, time-stamped or time-weighted network edges. Nonetheless, temporal networks are conceptually and fundamentally different from typical social networks (i.e., static or aggregate networks) [12,13,16]. As Holme puts it, "temporal-network modeling is far from a straightforward generalization of static networks—often, it is fundamentally different" [17]. Temporal networks are based on different representations of data, have a different mathematical underpinning, and use distinct visualization methods. In temporal networks, edges emerge (get activated or born) and dissolve (get deactivated or die) compared to always-present edges in social networks. Edges represent a temporary interaction, contact, co-presence or concurrency between two nodes existing at the same time. The paths are unidirectional or time restricted, i.e., follow the forward moving direction of time [12,13]. Such features make temporal networks more tethered to the real-life nature of human behavior. What is more, a static network tends to exaggerate connectivity and interlinks by showing all nodes connected to each other at any time [18]. For illustration see Figure 1, where a temporal network is represented along with a static network at each given time point. The figure clearly shows that real-life networks are sparse (i.e., less connected). The next section discusses these differences in detail.

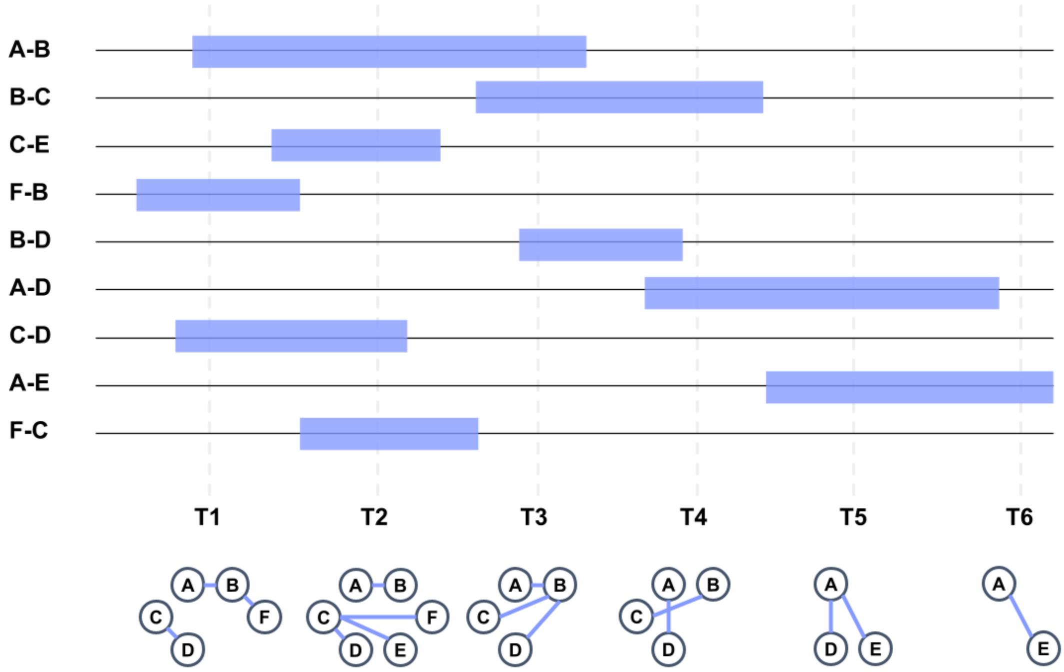

Figure 1: Example of a temporal network (top), and the corresponding network at the given time point.

2.1. Edges

Edges are the building blocks of networks, in temporal networks those are commonly referred to as events, links or dynamic edges. Two types of temporal networks are commonly described:

- **Contact temporal networks:** In contact temporal networks, edge duration is negligible or almost instantaneous. An illustrative example is the exchange of messages in a chat, where the messages are instant with no meaningful duration. Figure 2 shows a contact temporal network where the edges are represented as sequences of contacts between nodes with no duration.

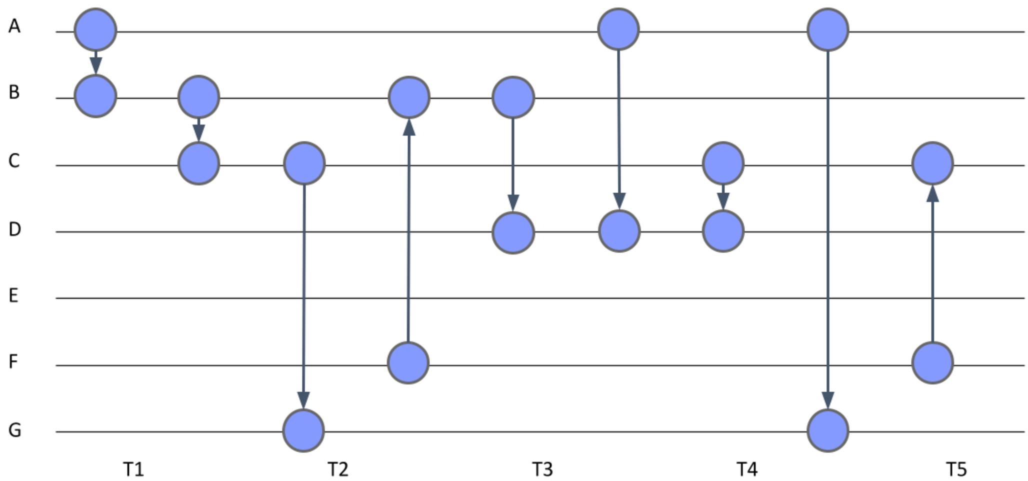

Figure 2: Example of a contact temporal network

- **Interval temporal networks**: In interval temporal networks, each interaction has a duration. An example of such a network would be a conversation where each of the interlocutors talk for a certain length of time. In the interval temporal network, the duration of interactions matters, and the modeling thereof helps understand the process. In Figure 3, we see an interval temporal network where each edge has a clear start and clear end; for instance, an edge forms between node A and node B at time point 1 and dissolves at time point 3.

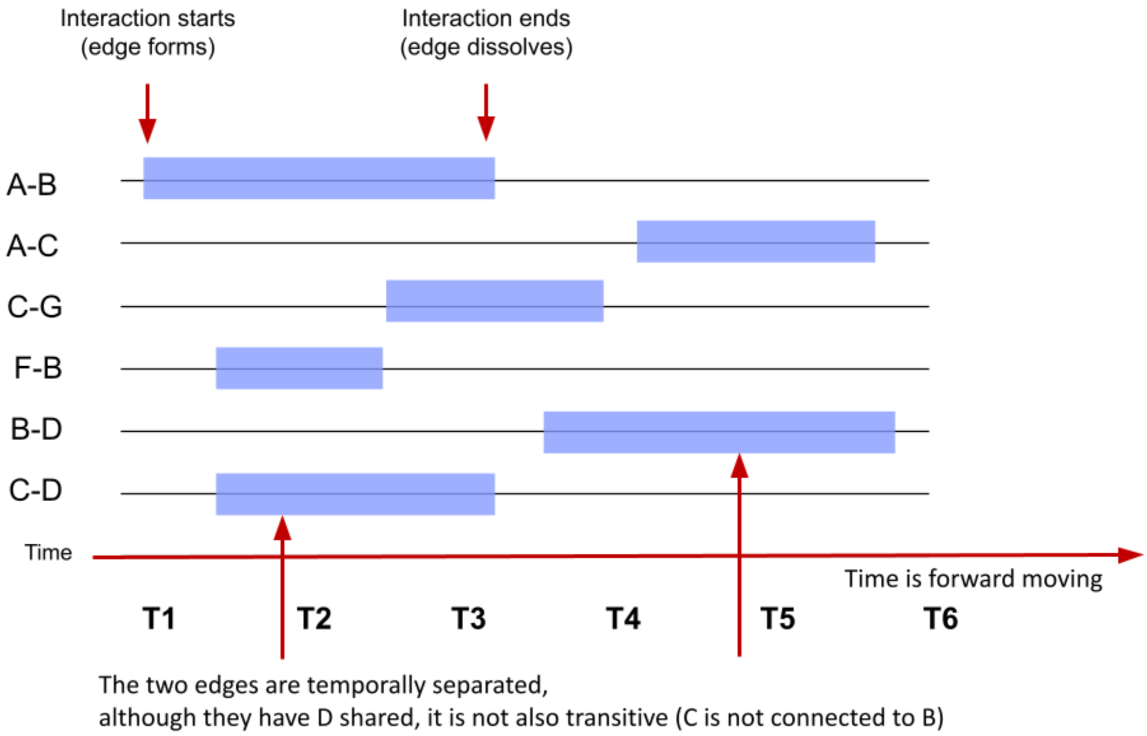

Figure 3: Example of an interval temporal network.

2.2. Paths, concurrency, and reachability

Paths represent pathways that connect nodes, the identification of which can help solve essential problems like the shortest path between two places in a route planning application (e.g., Google maps [19]). In a dynamic process, the paths represent a time-respecting sequence of edges or interactions that connect the two edges [12,13] (i.e., the timestamps are incrementally and strictly increasing). For instance, let us assume we have a group of students interacting about a problem, starting by defining the problem, arguing, debating, and finding a solution. The temporal path that would represent the sequence of interactions among students in this process will be a defining->arguing->debating->solution. As previously mentioned, the path is unidirectional, follows a time-ordered sequence, and requires that each node is temporally connected (i.e., the two nodes coexist at the same time [12]). For instance, the spread of an idea among students, the sequence of self-regulatory actions, or the progress of knowledge building interactions [17]. The concept of concurrency defines the duration of the nodes co-occurring together and therefore can be a measure of magnitude of contact between two nodes. This is particularly important when we are modeling (e.g., influence). A student is more likely to be influenced by an idea when in contact with others for longer periods of time. Similarly, self-regulation could be more meaningful when phases are more concurrent rather than disconnected [20].

2.3. Network measures

Research has shown that students' centrality measures can be used to identify students' collaborative roles, identify central actors and act as a proxy indicator for academic achievement [21]. In temporal networks, centrality measures are fine grained estimates of students' real-time centrality or importance in the form of time series data representing the centrality at each time point, compared to a single aggregate value in traditional social networks. In doing so, we can see exactly when and for how long, at what pace and with which rhythm a behavior happens. For example, Figures 4 and 5 show the density and reciprocity in a temporal network of a collaborative messaging platform [22]. Additionally, there is a growing list of temporal and time-aware centrality measures that depend on the temporal characteristics of the interactions (e.g., [16]). Similar to the centrality measures, graph properties in temporal networks are dynamic and vary by time and therefore, we get the graph level measures as time series. Such fine-grained properties allow us to understand how we can improve a collaborative group by optimizing the process. For instance, a recent paper has shown that increasing reciprocal interactions among students is more likely to improve strong ties and cohesion among them [11].

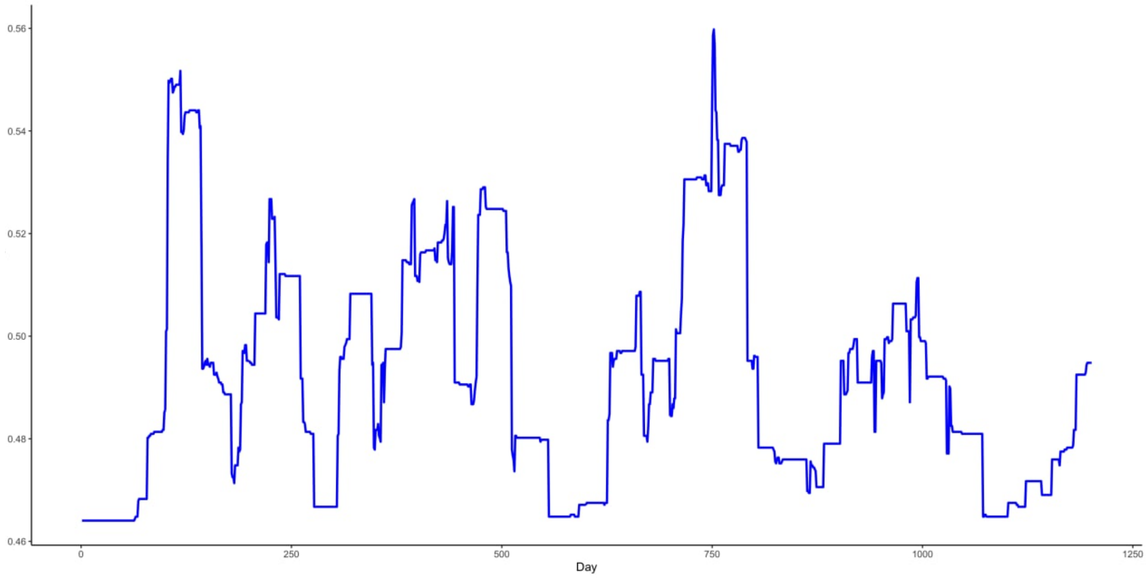

Figure 4: A graph depicting the changes in temporal density values over a full course. Note that in static network, density is commonly represented as a single value

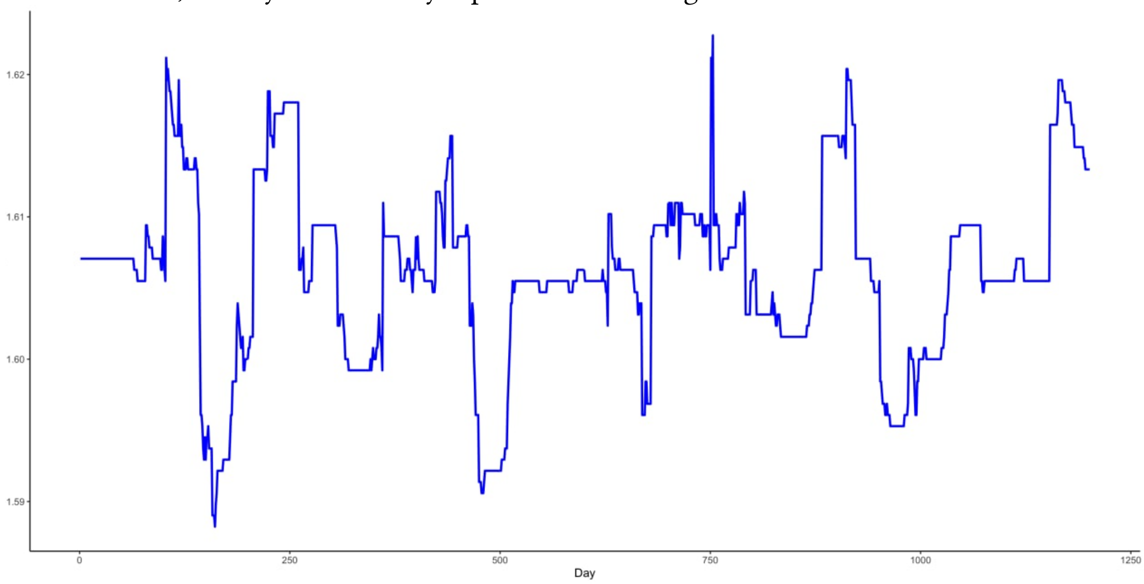

Figure 5: A graph depicting the changes in temporal reciprocity values over a full course.

2.4. Modeling dynamic relational processes with temporal networks

Due to the recency of temporal networks and the face evolution of the methods, few are the studies that have harnessed the technique. Yet, we see a vast potential for several aspects of learning and teaching that could benefit from temporal network modeling. Such potentials include collaborative learning and interactions among students, but of course extend to other aspects and student behaviors. For instance, temporal networks could enable the tracing of the flow of ideas, information, knowledge building as well as the diffusion of knowledge [11]. Temporal networks can be also used to unveil the temporal aspects of how students form ties, how they interact and how they build learning communities [14]. The role of temporal networks extends to other social phenomena such as socially and co-regulated learning and, in fact, seems much better suited than the commonly used methods (e.g., sequence mining). Furthermore, temporal networks are naturally suited for all situations where time and relations are intertwined (e.g., temporal discourse modeling). Below we offer a review of the studies that have applied temporal networks in education.

3. Existing methods

There are several methods that can harness the temporal dimensions of a learning process such as process and sequence mining, time series methods, and epistemic network analysis. While such methods have given a wealth of information and insights about learning processes, they fall short when it comes to the relational aspects [11]. We review here, and in short, the main differences between such methods of temporal networks. Process mining is a method for the discovery and modeling of a temporal process. Yet, the relational aspect is completely ignored. The case is similar for sequence mining where the time-ordered sequences of actions can be modeled. Nonetheless, there is no possible way that sequences can offer a relational aspect. Epistemic network analysis is another method that allows the study of co-temporal interactions. However, the "temporal aspect" is limited to combining data within a temporal window and later modeling the interactions as a static network. For a comparison between the various methods see [20].

4. Literature review of prior work

The work by Saqr and Peeters [11] aimed to apply temporal network modeling to reveal the importance of the time dimension in the collaborative learning process. Using temporal networks helped the analysis of the continuous and longitudinal network properties and enabled the authors to detect when important events took place, the duration of student engagement within the collaborative group, as well as the role of mutual ties in promoting more mutuality, strong ties, and mixing of high and low achievers. The temporal features of the centrality measures showed a higher correlation with grades. Additionally, they found that reachability —the temporal reach and range of influence of nodes— had slightly higher correlation coefficients than static centrality measures.

Chen and Poquet [14] applied Relational Event Modeling (REM) to analyze peer interactions in online learning taking into account the temporal aspects thereof and not only the relational. They found that interactions between the learners seems to result from rather random processes, such as familiarity based on recency and co-occurrence, rather than homophily.

In the study by Saqr and López-Pernas [22], the authors used temporal networks to compare students' interactions in a collaborative learning setting between two platforms: an online forum and an instant messaging application. The results shows that instant messaging platforms may be associated with higher participation, both in volume and distribution among collaborators. Temporal networks also revealed that interactions in the instant messaging platform are more reciprocated, in a relatively shorter time more likely to be discussed or interacted with, and show less dominant behavior.

Saqr and Nouri [15] studied how the dynamics of students' interactions in collaborative learning settings influence co-construction of knowledge in a productive way, and how incorporating temporal features can improve predictive models aimed at supporting educators to make timely interventions. Using temporal networks allowed the authors to detect recurring patterns in collaborative learning that would not become apparent using a traditional aggregate network. For instance, they found that students were active the first days of the week and disengaged towards the end of the week. Moreover, early week engagement in collaborative interactions significantly correlated with students' academic achievement. High achievers were usually the ones initiating the interactions, and they did so earlier on than low achievers. Lastly, the authors found that a model created with aggregate dynamic centralities (based on temporal data) representing collaborative engagement during the ninth day of the course was the best performing and accurate predictive model for predicting future performance.

Kumar et al. [23] proposed the JODIE model, a coupled recurrent neural network that learns dynamic embeddings of students and learning resources via a series of temporal interactions, and predicts future interactions and changes in student status with greater accuracy.

5. Where to start

This guide may not be complete without a guide on how to start using and analyzing temporal networks. The reviewed literature in section 4 can be a starting point for previous examples. For researchers who have R statistical environment there are very informative tutorials that we can suggest. Most notably is the peer-reviewed tutorial by [24], where the author explains the structure and types of data necessary to model a temporal network, the methods of visualization of temporal networks using the NDTV package in R [25], as well as how to quantify and visualize some important network-level and node-level metrics that describe temporal networks using the TSNA package in R [26]. Another important resource comes from the workshop on Temporal network tools in statnet: networkDynamic, ndtv and tsna [27]. Another place one can get information on important functions is the R packages help pages (e.g., TSNA [26], NDTV [25] and networkDynamic [28]).

6. Conclusions

Learning can be viewed as relational, interdependent, and temporal and therefore, methods that account for such multifaceted dynamic processes are required. We have shown the main advantages of temporal networks and the potentials it offers for modeling dynamic learning processes. These potentials or features can facilitate the modeling of the complex natural processes, including the emergence, evolution, diffusion or disappearance of learners' activities, communities or social processes that unfold over time. Such features can augment the existing analytics method and help shed lights on learning phenomena.

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