
Temporal Reasoning in Historical Humanities Data: The Case of Muzio Clementi and the Music Trade

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Abstract

Historical data are crucial for understanding the past; however, they often lack precise temporal details, which complicates both narrative reconstruction and formal data modeling. This study addresses these challenges by applying temporal reasoning based on Allen's interval logic to data related to the life and activities of Muzio Clementi (1752-1832), a key figure in London's musical and intellectual scenes during the late 18th and early 19th centuries. Utilizing the CIDOC CRM ontology to structure the data, the research employs Allen's interval logic expressed in the RDF-based logic language Notation3 (Notation3), along with the EYE reasoner for inference. This approach enables precise modeling and inference of relationships among events. The study qualitatively evaluates the results of this method, demonstrating its potential to reveal deeper insights from a complex historical dataset.

Keywords

temporal reasoning, Allen's interval algebra, EYE reasoner, historical event modeling

Introduction

Historical data plays a central role for historians in reconstructing and interpreting past events and actors. Both factual claims and interpretative narratives are grounded in such data. Beyond narrative reconstruction, data serves as the foundation for building arguments and analyzing connections and causality. For digital historians, it also enables them to formally represent and reason about the relative timing of different events. However, this shift from narrative to data modeling also brings the limitations of historical data into sharper focus, most notably its temporal imprecision. Many historical records do not contain exact dates or durations, instead offering vague references—"early spring," "shortly after the coronation," or "between 1790 and 1795." On the other hand, some events are recorded with precise details, such as the hour of occurrence. This coexistence of vagueness and precision complicates the modeling of historical events, requiring approaches that account for uncertainty while still supporting automated reasoning about event sequences, overlaps, or causal relationships.

This study applies temporal reasoning to historical data drawn from the life and activities of Muzio Clementi (1752-1832). As a prominent pianist, composer, conductor, pedagogue, musical instrument maker, music seller, and music publisher, Clementi played a central role in the musical and intellectual life of late 18th- and early 19th-century London. His music publishing firm, *Clementi and Co.*, flourished for more than three and a half decades, leaving behind a wealth of historical records. These materials, rich in detail yet rife with gaps, offer an exemplary case study for exploring the challenges posed by vague and incomplete temporal information in historical analysis.

Temporal reasoning in this study helps to derive insights from both well-established facts and partial or uncertain

temporal information. Data for this study were gathered from a variety of primary and secondary sources, including contemporary journals and newspapers, records from the registers of Stationers' Hall, Clementi's correspondence (Rowland, 2010; Rowland, 2024), biographies, memoirs, and obituaries. These materials provide rich contextual knowledge and perspectives on the time and place.

The data used in this study are modeled using the CIDOC Conceptual Reference Model (CRM), a widely adopted framework for structuring and standardizing data related to historical and cultural heritage (CIDOC CRM Special Interest Group, 2023, p. 9-11) CIDOC CRM enables a detailed and semantically rich representation of events, actors, and relationships, making it an ideal foundation for integrating temporal reasoning with historical datasets.

We build on previous work on automatic reasoning about temporal intervals using Allen's interval logic (Endelin, Aloulou, De Roo, Renouard, Tiberghien & Mokhtari, 2013). Allen's interval logic takes temporal intervals as primitive and acknowledges that significant imprecision is an inherent aspect of modeling historical knowledge (Allen, 1983, pp. 832-833), making it a suitable foundation for our study. Every interval is defined by a starting and an ending point, where the starting point is strictly less than the ending point. However, the exact value of these points may often be unknown, reflecting the imprecision inherent in historical data. Allen's interval logic provides a set of possible qualitative relations that may hold between such intervals. The rules for inferring these possible relations are encoded using the RDF-based logic language Notation3, and inference is handled using Jos de Roo's Eye reasoner ([EYE homepage](#)), a Notation3 reasoner available under

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the open source MIT license. Our contribution focuses on modeling events with greater nuance and precision to support the inference of detailed event sequences and qualitatively assessing the results.

Background

Time, as a category of historical data, presents a challenge. While chronology underpins much historical interpretation, historical temporal data is often imprecise, incomplete, or inconsistently recorded. Accurately modeling temporal relationships is not merely a technical concern—it fundamentally shapes the interpretations and conclusions historians can draw. For example, a court meeting recorded simply as taking place in “May, 1799” carries very different implications than one precisely noted as “noon, on May 4th, 1799.” This disparity between vague and specific temporal information in historical data raises questions about how best to represent such data formally, and how inference mechanisms can accommodate uncertainty without distorting the historical meaning.

Temporal vagueness arises when dealing with time-related information is incomplete or imprecise. A key challenge in dealing with qualitative temporal details is that the relationships between temporal intervals are known, even when their exact boundaries—such as start or end times—are unspecified or only partially specified. In some cases, the duration of an event may be known quantitatively, even if its starting or ending point remains vague. Despite this, the event’s qualitative position relative to other events can still be inferred, allowing for meaningful temporal reasoning even in the absence of precise timestamps. This problem is not new. Historian David Fischer, for example, warned against the “fallacy of misplaced precision,” a mistake that arises when “an empirical statement is made precise beyond the practical limits of accuracy” (Fischer, 1970, p. 45, 61). In modeling historical events, it is essential to acknowledge such limitations.

Our approach to modeling time directly shapes how we interpret the relationships between historical events—whether one event preceded or followed another, whether they overlapped, and how earlier development influenced later outcomes. Because of this, time is not only a structural feature of historical narratives but also a central concern for automatically inferring relationships, not only among temporal intervals but among the people and places and things that interact over time. As historical documents and primary sources are increasingly digitized, the volume and accessibility of historical data have grown exponentially. This expansion underscores the need to formalize temporal information in ways that support automated reasoning and interpretation. Formal models such as the CIDOC Conceptual Reference Model (CRM) offer structured ways to represent temporal relationships and handle vagueness, forming a bridge between humanistic interpretation and computational inference. We explore one such model, CIDOC CRM, in greater detail in the method section.

Related Works

Temporal reasoning is the task of representing and inferring temporal relations among events. Approaches to automating temporal reasoning fall into three categories: symbolic methods (rule-based temporal inference), and neural methods that learn temporal dynamics, and temporal reasoning with large language models (LLMs). To contextualize our contribution, we review each paradigm in turn.

Symbolic Temporal Reasoning

Classical symbolic reasoning systems are grounded in formal logic and declarative rule specification. Allen’s interval algebra provides a foundational framework for representing temporal relations, and its formal semantics make it well-suited for rule-based inference. Within the Semantic Web community, ontology-based reasoning has advanced through standards such as OWL, which leverages fragments of descriptive logic to maintain decidability and computational tractability under the open-world assumption (OWA). While OWL-based reasoning offers strong theoretical guarantees, its expressivity is deliberately constrained to preserve decidability (Batsakis, Petrakis, Tachmazidis & Antoniou, 2009).

Rule-based systems using Notation3 (N3) allow greater flexibility in rule expression and support constructs for reasoning about statements, albeit without the same global decidability as OWL DL. N3-based reasoning, therefore, complements ontology reasoning by enabling more expressive rule-driven inference while retaining a formally defined semantics (Endelin, Aloulou, De Roo, Renouard, Tiberghien & Mokhtari, 2013).

Neural Approaches: Temporal Knowledge Graphs and GNN-based reasoning

Graph Neural Network (GNN) methods have been explored for temporal reasoning in the form of temporal knowledge graphs (TKGs), where facts are time-dependent and commonly represented as quadruples that encode *when* a relation holds (Trivedi, Dai, Wang & Song, 2017). GNNs are tailored for graph data and have emerged as a prominent approach for drawing inferences from dynamic graphs. This is useful in any domain where relationships between entities change over time, and where that change can potentially be used to predict future changes, such as fraud detection, traffic prediction, recommender systems, and epidemiology.

Constructing a GNN requires structured graph data, a clearly defined task, and appropriate frameworks that for efficiently computing over irregularly indexed data. For temporal reasoning with GNNs (Longa, Lachi, Santin, Bianchini, Lepri, Lio, Scarselli & Passerini, 2023), a large amount of data is needed, since dynamics and not just structure are being learned. Furthermore, although GNNs are versatile tools for analyzing complex systems, the inherent black-box nature of deep learning makes it challenging to verify the validity of their inferences. For both of these reasons, neural approaches are not well suited to our use case.

Temporal Reasoning with Large Language Models

Recent work has examined the temporal reasoning capabilities of LLMs. Despite their broad competency across many reasoning tasks, temporal reasoning remains challenging for LLMs due to the complexity and diversity of temporal concepts and expressions, as well as the need for systematic logical inference (Xiong, Payani, Kompella & Fekri, 2024, p. 1), (Song, Liang, Sun, Zhang, Wang & Xu, 2025, p. 3040). Empirical studies (Wang & Zhao, 2024, p. 6389,6390) show that LLMs’ performance in temporal reasoning benchmarks lags behind human abilities (Song, Liang, Sun, Zhang, Wang & Xu, 2025, p. 3040), (Wang & Zhao, 2024, p. 6389), (Chu, Chen, Chen, Yu, Wang, Liu & Qin, 2024, p. 1204, 1205), particularly in interpreting implicit temporal clues.

Several efforts aim to address these limitations and enhance LLMs’ temporal reasoning abilities. Xiong et al. (Xiong, Payani, Kompella & Fekri, 2024) introduce deliberate chain-of-thought (CoT) bootstrapping and graph data augmentation to improve text-to-temporal-graph translation. Song et al. (Song, Liang, Sun, Zhang, Wang & Xu, 2025) propose the Temporal Chain of Thought (TempCoT) framework combining three-step reasoning strategies with in-context learning. However, research indicates that CoT prompting falls short in complex scenarios (Song, Liang, Sun, Zhang, Wang & Xu, 2025, p. 3040), (Chu, Chen, Chen, Yu, Wang, Liu & Qin, 2024, p. 1205, 1208, 1209). Other work explores temporal graph and LLM hybrid (TG-LLMs) (Xiong, Payani, Kompella & Fekri, 2024) and develops benchmarks such as TRAM (Wang & Zhao, 2024) and TIMEBENCH (Chu, Chen, Chen, Yu, Wang, Liu & Qin, 2024) to systematically evaluate LLM temporal reasoning. Despite these advances, substantial gaps remain in LLMs’ ability to perform robust, logically grounded temporal inference.

Positioning of This Work

Against this landscape, our work is situated within the symbolic rule-based tradition of temporal reasoning. We adopt Allen’s interval algebra encoded in Notation3 (N3) to provide deterministic, transparent, and explicitly interpretable temporal inference. This symbolic approach stands in contrast to LLM-based and neural methods, offering formal guarantees and explainability, which are essential for applications that require precise, rule-based temporal logic.

The Current State of Art

Earlier versions of CIDOC CRM (from version 3.3) adopted Allen’s Interval Logic to define temporal relationships, using properties P114-P122 (see table 1). However, in version 6.2.8 (February 2020), the model transitioned to a different strategy designed to support fuzzy temporal boundaries (CIDOC CRM Special Interest Group, 2023, p. 42). This change was justified by the claim that the newer set of properties (P173-P176 and P182-P185) provides less rigid and more semantically nuanced constructs, better suited to modeling historical data.

Table 1. CIDOC CRM Temporal Properties Related to Allen’s Interval Logic

Property	Label
P114	is equal in time to
P115	finishes
P116	starts
P117	occurs during
P118	overlaps in time with
P119	meets in time with
P120	occurs before
P121	overlaps with
P122	borders with
P132	overlaps with
<i>Fuzzy temporal relations introduced in version 6.2.8</i>	
P173	starts before or with the end of / ends after or with the start of
P174	starts before the end of / ends after the start of
P175	starts before or with the start of / starts after or with the start of
P176	starts before the start of / starts after the start of
P182	ends before or with the start of / starts after or with the end of
P183	ends before the start of / starts after the end of
P184	ends before or with the end of / ends with or after the end of
P185	ends before the end of / ends after the end of

We plan to investigate and compare the use of the new CIDOC CRM temporal relations in future work. Here we focus on Allen’s Interval Algebra (also known as Interval Logic) (Allen, 1983; Allen & Hayes, 1985; Allen, 1984; Allen & Hayes, 1989), introduced by James F. Allen in 1983, which remains one of the most influential approaches to temporal representation. This formal system defines thirteen basic relations between time intervals that are jointly exhaustive and pairwise disjoint: *precedes*, *preceded by*, *meets*, *met by*, *overlaps*, *overlapped by*, *starts*, *started by*, *during*, *contains*, *finishes*, *finished by*, and *equals*. Its support for disjunctions—alternative possible relations that may hold between intervals—enables the representation of uncertainty and ambiguity in temporal data. This capability is crucial in domains like historical research, where the precise start or end times of events are often unknown, and relationships between events are known only in relative terms (for example, whether one event occurs before, after, or during another).

Allen’s Interval Logic is known for its reliability and computational efficiency (Allen, 1983; Janhunen & Sioutis, 2020). Reasoning using Allen’s logic typically begins by constructing a disjunction of possible relations between two intervals. Any relations not included in the disjunction are assumed to *not* hold between the intervals. Inference involves iteratively eliminating possibilities from the disjunction, circumscribing the possible temporal orderings. This process presents a challenge for RDF-based systems, because RDF-based reasoning is designed to be *monotonic*, meaning that the addition of further triples cannot invalidate a triple in a graph. This is connected to the well-known “open world assumption” (OWA) under which not knowing something does not imply that it is false. The OWA precludes the logic of disjunction, since we cannot assume that relations missing from the disjunction do not hold, and monotonicity precludes the logic of elimination.

We rely on an implementation of Allen’s Interval Logic in the RDF-based logic language Notation3, which uses Notation3’s support for “scoped negation as failure” (SNAF) to implement reasoning about Allen intervals (Endelin,

Aloulou, De Roo, Renouard, Tiberghien & Mokhtari, 2013). SNAF is a way of defining a “closed world” with limited scope, in order to interpret the failure to find a statement within that world as a negation of the statement (De Roo & Hochstenbach, 2024). The OWA does not allow making universal declarations such as “there is no X such that Y ”, but SNAF allows making *scoped* declarations such as “this specific graph does not assert that there is an X such that Y .” This enables using rules of symmetry (*i.e.*, `owl:inverseOf` relations) and composition tables (given relations between intervals A and B and between intervals B and C , what can we conclude about the relation between intervals A and C ?) to construct disjunctions of chains of relations between two intervals, possible within the scope of the local graph. Finally, the relations common to all the possible chains between two intervals are inferred to be the only possible ones. In this way, the circumscription of possibilities typical of Allen’s logic is reconciled with RDF’s monotonicity and the OWA.

Method

To operationalize temporal reasoning over historical data, we adopt the CIDOC Conceptual Reference Model (CRM), an upper-level ontology developed for the standardized representation of cultural heritage data (Doerr, 2005; CIDOC CRM Special Interest Group, 2023). It provides a structured framework for modeling historical and cultural heritage data in a consistent, interoperable manner, including classes and properties specifically designed for modeling temporality. The CIDOC CRM distinguishes between *temporal entities* that take place in time (and space), such as events or activities, and *time spans* that express a potentially only partially known extent of time. Temporal entities are linked to time spans via the *P4 has time-span* property. Different sources may assert different time spans for the same temporal entity.

As in Allen’s interval logic (Allen, 1983, p. 834), in the CIDOC CRM, dates are treated as intervals rather than points, based on the assumption that no event occurs instantaneously or has zero duration. This holds true even for short time spans that, although perceived as instantaneous, are treated as having a non-zero duration. We have adopted CIDOC CRM’s RDF implementation guidelines for representing dates as time spans with the properties *P81a end of the begin*, *P81b begin of the end*, *P82a begin of the begin*, and *P82b end of the end* (Doerr, Light & Hiebel, 2020). All values of these properties are encoded using the `xsd:dateTime` datatype. Together, these four properties allow us to define a given time span as definitely “ongoing throughout” the time between two “inner” date-times (*P81a* and *P81b*) and possibly happening “at some time within” two “outer” date-times (*P82a* and *P82b*). In other words, each time span consists of a narrower, possibly empty interval that it *definitely* covers, and a wider interval that it *possibly* covers.

We applied the *P81a* and *P81b* property pairs to time spans with known start times, such as court meetings in bankruptcy cases. These meetings were typically advertised in *The London Gazette*, the official publication for legal notices related to insolvency and bankruptcy in the UK.

When the exact start time was known, that is, when a meeting was scheduled to begin at a specified hour, we used *P81a* to record the meeting start time and *P82a* and *P82b* for the beginning and ending of the day of the meeting: the outer bounds. In these cases, we assumed the meeting lasted at least one hour and used *P81b* to represent the conservative end time under that assumption. For example:

```
# Longman and Broderip bankruptcy case
# hearings, first sitting

[] a ecrm:E52_Time-Span ;
  ecrm:P82a_begin_of_the_begin
    "1795-05-30T13:00:00"^^xsd:dateTime ;
  ecrm:P81a_end_of_the_begin
    "1795-05-30T13:00:00"^^xsd:dateTime ;
  ecrm:P81b_begin_of_the_end
    "1795-05-30T14:00:00"^^xsd:dateTime ;
  ecrm:P82b_end_of_the_end
    "1795-05-30T23:59:59"^^xsd:dateTime .
```

Figure 1. Time span with known start hour and bounding day

Some events in our dataset are known only by their dates, without any definitive indication of the time of day at which they occurred. In these cases, we relied exclusively on the *P82a begin of the begin* and *P82b end of the end* properties, which define outermost temporal boundaries within which an event took place. Specifically, property *P82a* records the earliest point at which the event may have started, and *P82b* marks the latest point in time by which the event is known to have concluded.

While *P82a* and *P82b* provide essential temporal anchors for uncertain or imprecise temporal information, on their own, they only support quantitative reasoning about the relative ordering or overlap of time spans. For reasoning about the relative ordering or overlap of time spans, we need to supplement quantitative reasoning with qualitative reasoning about possible temporal relations. While the CIDOC CRM now recommends implementing qualitative temporal reasoning based on their own “fuzzy” relation primitives, we are unaware of any attempts to implement automated reasoning based on these primitives. Since Allen’s interval logic remains highly relevant for temporal reasoning on the Semantic Web and there is a high-quality reasoner that supports it, we chose to stick with it.

Our methodology involves modeling uncertain temporal intervals, defining commonsense assumptions, and using automated reasoning to infer temporal relationships. This enables us to examine not only what is logically possible, but also what is plausible or meaningful within a given historical context. Our initial exploration focuses on how varying assumptions, such as limits on event duration or bounded intervals, affect the outcomes of temporal reasoning. By comparing different inference results under these changing assumptions, we aim to gain insight into the stability, reliability, and interpretive value of each approach.

Analysis

Assumptions made

Time spans are modeled based on natural language expressions, which are often implicit and vague. Temporal phrases are assigned predefined interpretations based on a conventional and intuitive notion of time. For example:

1. *Early-to-mid-October 1802*. We decided to include October 20th as part of early-to-mid-October because we divide each month into three roughly equal parts: early October (1st-10th), mid-October (11th-20th), and late October (21st-31st).
2. *Late 1802 or early 1803*. We defined the period as spanning from October 1, 1802, to March 31, 1803. We divide the year into three four-month segments: early (January-April), middle (May-August), and late (September-December).
3. *Summer of 1804*. We adopted a conventional approach to seasonal boundaries. For example, the term "Summer 1804" was interpreted as referring to the period from June 1, 1804, to August 31, 1804. While no universal rule defines seasonal timeframes with exact dates, this interpretation reflects a commonsense understanding aligned with meteorological norms in the Northern Hemisphere.
4. *Towards the end of 1808*. Similarly, the phrase "towards the end of 1808" was taken to mean the period from November 1, 1808, to December 31, 1808. These interpretations were made for the sake of consistency and clarity in temporal analysis.
5. *When a precise meeting start time is given*. In some cases, specific event times are known, for example, a scheduled meeting at the bankruptcy court or a lunch meeting. For such events, we make practical assumptions about their duration based on contextual knowledge. Specifically, we assume that a court meeting lasts at least one hour, while a lunch meeting lasts no more than two hours. These assumptions provide bounded intervals that support more precise temporal reasoning within the overall framework.

Different types of time spans

The categories listed below represent different types of time spans along with their corresponding levels of certainty and uncertainty.

1. *Known date, but uncertain year*. This applies when the day and month of the event are known, but the year cannot be established, either due to the source material being damaged, faded, or otherwise uncertain. For example, a letter from Muzio Clementi to Mr. Camille Petit is dated September 30, but the year is not decipherable in the original document. Based on other contextual clues, it could have been written in 1817, 1820, 1821, or 1826, but none can be confirmed definitively. In this case, we have given the likely date range as

```
[ ] a ecrm:E52_Time-Span ;
    ecrm:P82a_begin_of_the_begin
        "1817-09-30T00:00:00"^^xsd:dateTime ;
    ecrm:P82b_end_of_the_end
        "1826-09-30T23:59:59"^^xsd:dateTime .
```

Figure 2. Known date, but uncertain year

2. *Known or bounded by terminus ante quem (establishes the upper bound or the latest possible date)*. This applies when the exact date of an event is unknown, but evidence shows that it must have occurred before a specific, documented point in time. For example, Muzio Clementi wrote to Nicola Clementi before 1785. We don't have the exact date of the letter, but we know it was written sometime prior to 1785—possibly because of dated references, known events, or other letters that help set that upper boundary. Similarly, John Preston published the first edition of Clementi's Op. 12. It was entered at Stationers' Hall on May 10, 1784. Since music typically was entered at Stationers' Hall on or very shortly after publication, this entry date sets the latest possible date for the publication. The time span for the publication event is:

```
[ ] a ecrm:E52_Time-Span ;
    ecrm:P82b_end_of_the_end
        "1784-05-10T23:59:59"^^xsd:dateTime .
```

Figure 3. Known or bounded by terminus ante quem

3. *Known or bounded by terminus post quem (i.e., the lower bound and the earliest possible date is known)*. This applies when the exact date of an event is not known, but we know it must have happened after a certain point, e.g., Thomas Holcroft, a friend of Clementi, went into exile in 1799. He hosted a dinner attended by Clementi and others in his intellectual circle on February 17, 1799. Since we know he left after this gathering, February 17, 1799, serves as the lower bound for his departure.

```
[ ] a ecrm:E52_Time-Span ;
    ecrm:P82a_begin_of_the_begin
        "1799-02-18T00:00:00"^^xsd:dateTime .
```

Figure 4. Known of bounded by terminus post quem

4. *Date known, time unknown / date-level precision without sub-day specificity*. This applies to cases where the exact date of an event is known, but the specific time of the day is not. In other words, the event is temporally fixed to a particular day, but lacks finer temporal granularity, e.g., Muzio Clementi writing to Nicola Clementi on December 24, 1781.

```
[ ] a ecrm:E52_Time-Span ;
  ecrm:P82a_begin_of_the_begin
    "1781-12-24T00:00:00"^^xsd:dateTime ;
  ecrm:P82b_end_of_the_end
    "1781-12-24T23:59:59"^^xsd:dateTime .
```

Figure 5. Date known, time unknown

5. *Uncertain interval with approximate bounds.* This applies to fuzzy bounded interval uncertainty. For example, a publication dated *ca. 1790-95* reflects uncertainties about both ends of the interval. Both the terminus post quem (1790) and the terminus ante quem (1795) are approximate.

```
[ ] a ecrm:E52_Time-Span ;
  ecrm:P82a_begin_of_the_begin
    "1790-01-01T00:00:00"^^xsd:dateTime ;
  ecrm:P82b_end_of_the_begin
    "1795-12-31T23:59:59"^^xsd:dateTime .
```

Figure 6. Uncertain interval with approximate bounds

6. *Unbounded or fully indeterminate time.* This category refers to events for which no specific date is known, and no concrete temporal boundaries can be established without additional evidence. For example, the writing of a letter from Muzio Clementi to Miss Dean with no recorded date has an entirely indeterminate time span. However, the temporal context may be refined later through indirect evidence, such as watermarks or other related correspondences.

7. *Potentially bounded but not explicitly stated.* Muzio Clementi and Caroline Clementi left Rome for Berlin in early January 1805 and returned by February of that same year. For temporal modeling, we interpreted *early January* to refer to the first two weeks of the month. The phrase “arrived back in Berlin by February 1805” implies a *terminus ante quem* of 28 February 1805, meaning the return must have occurred on or before that date. In this context, “by February 1805” is taken to include the entirety of February, not excluding its final day. Therefore, the time span of their return could be modeled as:

```
[ ] a ecrm:E52_Time-Span ;
  ecrm:P82b_end_of_the_end
    "1805-02-28T23:59:59"^^xsd:dateTime .
```

Figure 7. Potentially bounded by not explicitly stated

The time span of their leaving Berlin can be modeled as

```
[ ] a ecrm:E52_Time-Span ;
  ecrm:P82a_begin_of_the_begin
    "1805-01-01T00:00:00"^^xsd:dateTime ;
  ecrm:P82b_end_of_the_end
    "1805-01-14T23:59:59"^^xsd:dateTime .
```

Figure 8. The timespan of the Clementi’s departure from Berlin

8. *Indeterminate interval (fuzzy temporal bounds).* This category applies when only part of the temporal interval is known, leaving the other end open-ended. For example, the partnership between Clementi, Collard, Davis and Collard was dissolved, but the exact date of dissolution was never publicly announced in *the London Gazette*. However, we know that David Davis passed away on January 9, 1822. Therefore, the dissolution must have occurred before this date. Therefore, this indeterminate interval can be expressed as:

```
[ ] a ecrm:E52_Time-Span ;
  ecrm:P82b_end_of_the_end
    "1822-01-09T23:59:59"^^xsd:dateTime .
```

Figure 9. Unbounded or fully indeterminate time

9. *Known by relative dates.* Muzio Clementi, a leading composer, pianist, and music publisher of the late eighteenth and early nineteenth centuries, made several extended tours of the European continent while maintaining London as his professional and personal base. We know some details about Clementi’s first continental tour, which commenced in 1780. On May 26, 1780, he performed in a concert in London. Shortly thereafter, he departed for Paris. We also know that after his time in Paris, Clementi traveled through Strasbourg and Munich en route to Vienna. Clementi was in Munich by November 15, 1780, and arrived in Vienna on December 19, 1780 (Rowland, 2010; Rowland, 2024, p. liv; p. xxxiv). From Mozart’s letter to his father, we also know Clementi left Vienna on May 9, 1782 (Rowland, 2010, p. lv). He then went to Lyon; the exact date of arrival is unknown. He performed at a concert on August 29, 1782, and remained there in the fall of 1783. Then, he went to Zurich before returning to London.

```
:clementi_s_last_concert_in_1780
  a ecrm:E7_Activity ;
  ecrm:P4_has_time-span [
    a ecrm:E52_Time-Span ;
    ecrm:P82a_begin_of_the_begin
      "1780-05-26T00:00:00"^^xsd:dateTime ;
    ecrm:P82b_end_of_the_end
      "1780-05-26T23:59:59"^^xsd:dateTime .
  ] .
```

Figure 10. Clementi’s final concert of the 1780 season in London

```

:clementi_in_paris
  a ecrm:E7_Activity ;
  ecrm:P183_starts_after_the_end_of
    :clementi_s_last_concert_in_1780 ;
  ecrm:P183i_ends_before_the_start_of
    :clementi_in_strasbourg .

:clementi_in_strasbourg
  a ecrm:E7_Activity ;
  ecrm:P183i_ends_before_the_start_of
    :clementi_in_munich .

:clementi_in_munich
  a ecrm:E7_Activity ;
  ecrm:P183i_ends_before_the_start_of
    :clementi_in_vienna .

:clementi_in_lyon
  a ecrm:E7_Activity ;
  ecrm:P183_starts_after_the_end_of
    :clementi_in_vienna .

:clementi_in_zurich
  a ecrm:E7_Activity ;
  ecrm:P183_starts_after_the_end_of
    :clementi_in_lyon .

```

Figure 11. Known by relative dates

He was confirmed to be in London on February 11, 1784, as he performed in a concert. Given this, we infer that his arrival in London occurred no later than February 10, 1784. If we assume *late 1783* to be the period between October and December 1783, his return can be modeled as

```

[] a ecrm:E52_Time-Span ;
  ecrm:P82a_begin_of_the_begin
    "1783-10-01T00:00:00"^^xsd:dateTime ;
  ecrm:P82b_end_of_the_end
    "1784-02-10T23:59:59"^^xsd:dateTime .

```

Figure 12. Clementi's return to London timespan

10. *Known dates and known starting time.* Muzio Clementi was closely associated with the London music publishing firm, Longman & Broderip—initially in a limited capacity, but his involvement became more direct over time. The firm's bankruptcy proceedings, including scheduled meetings of creditors, were publicly announced in *the London Gazette*. In some instances, both the exact date and starting time are documented. For example, a creditors' meeting with assignees was scheduled to begin at 1 pm. on March 1, 1802. Because this event has a precisely known start and a reasonably inferable minimum duration, we modeled it as a temporal interval with fixed inner bounds in addition to the outer bounds.

```

[] a ecrm:E52_Time-Span ;
  ecrm:P82a_begin_of_the_begin
    "1802-03-31:13:00:00"^^xsd:dateTime ;
  ecrm:P81a_end_of_the_begin
    "1802-03-31:13:00:00"^^xsd:dateTime ;
  ecrm:P81b_begin_of_the_end
    "1802-03-31:14:00:00"^^xsd:dateTime ;
  ecrm:P82b_end_of_the_end
    "1802-03-31:23:59:59"^^xsd:dateTime .

```

Figure 13. Known dates and known starting time

There are also dates associated with when Clementi dined with his intellectual circles (thanks to William Godwin's diary). However, the source does not indicate whether the meal was lunch or dinner, so we cannot narrow down the time.

The strongest relations inferred

The implementation of Allen reasoning in (Endelin, Aloulou, De Roo, Renouard, Tiberghien & Mokhtari, 2013) calculates the “strongest” Allen relation that can be inferred, if any, between each pair of intervals. Reasoning proceeds as follows:

1. Known endpoints of intervals are used to quantitatively calculate Allen relations between pairs of intervals, where possible. For example, if interval A ends at A^{end} , and interval B begins at B^{begin} , and $A^{\text{end}} < B^{\text{begin}}$, then A precedes B and B is preceded by A . These known relations are the only possible relations for these pairs of intervals.
2. Symmetric relations are added to the set of possibilities. For example, if it is possible that interval A occurred during interval B , then it is possible that interval B contains interval A .
3. Relations via composition are included. For example, if interval A possibly overlaps interval B , and interval B is possibly during interval C , and $A \neq C$, then any of the following are possible: A overlaps C , or A starts the same time as C , or A is during C .
4. Because intervals may be related via composition in multiple ways, at this point, there may be multiple sets of possible relations that could hold between any two intervals. The final step in the reasoning process is to take the intersection of these sets, which, if it is not empty, contains the single possible relation common to all the sets of possible relations between the intervals. This relation is the “strongest” inferable relation between the intervals.

We examined the strongest Allen interval relations inferred by EYE. Specifically, when the relations are known between two intervals A and B and two intervals B and C , but the relation between A and C is not explicitly given, the reasoner can infer the most constrained (*i.e.*, the strongest possible) relation between A and C even though there is no direct relation between A and C asserted in the source data.

The reasoner inferred a total of 387,400 temporal relations between pairs of historical events, identifying the

most specific (strongest) Allen relation applicable to each pair. This large-scale application of Allen’s interval logic produced a distribution that reflects a meaningful temporal structure within the data.

The most common relations were `precedes` (186,896) and its inverse `precededBy` (186,896), reflecting clear sequential ordering across much of the dataset. The high frequency of `precedes/precededBy` likely reflects their relatively low logical constraints compared to other interval relations. These two relations require only that the end of one interval occurs strictly before the start of another, without needing any shared endpoints or overlaps.

Additionally, the reasoner identified more complex interval relations including `starts` (163), `startedBy` (163), `finishes` (146), `finishedBy` (146), `during` (5,682), `contains` (5,682), `overlaps` (222), `overlappedBy` (222), and `equals` (1,182). Notably, the `meets` and `metBy` relations were not inferred—a point that is addressed in detail later in the discussion.

Although these relations are the ones determined to be possible under Allen’s interval logic, not all are equally useful in practice. Their interpretive utility varies: some align closely with meaningful patterns in the data, while others are less analytically or narratively significant. Among the highly constraining relations in Allen’s interval algebra, `starts`, `finishes`, and especially `during` offer the most interpretive value. In particular, the high frequency of the `during` relation can be viewed as both logically precise and contextually rich. For instance, 923 events were inferred to occur during the interval representing Muzio Clementi’s time in London (i.e., `muzio_clementi_in_london`). This interval, which encompasses Clementi’s career phase, comprises 923 events, all of which are nested within the broader professional and biographical period during which London served as his central base. Importantly, while the interval captures the geographical context of Clementi’s professional life, it does not refer to his continuous physical presence in the city, but rather to a span of time, during which London was his primary hub of activity—an era marked by his emergence as a freelance musician, composer, pedagogue, and later, a music publisher.

The high number of `during` relations in our temporal graph is not merely a statistical anomaly but reflects the nested event hierarchies that shaped Clementi’s life and career. For example, events related to his performances, publishing ventures, and professional activities are all temporally anchored within the interval of `muzio_clementi_in_london`. This interval spans a distinct phase of Clementi’s career, defined by his activities in the city, irrespective of his travels across Europe during this period. Although Clementi undertook extensive travels, including multi-year absences from London, his professional base remained in the city, underscoring the temporal significance of this interval.

The `during` relation in Allen’s interval algebra is highly constrained, holding only when one interval starts after and ends before another. This strict temporal condition eliminates a wide range of other relations, such as `starts`, `startedBy`, `finishes`, `finishedBy`, `overlaps`, `overlappedBy`, `meets`, `metBy`, and `equals`, which do not fit within the bounds of the `during` relation.

As such, the `during` relations serve as a logically precise and interpretively rich way to capture temporal constraints within a broader context. In the case of `muzio_clementi_in_london`, it represents a significant phase of Clementi’s life, marked by his career development in London. The inferred “during” relations thus map neatly onto the historical and biographical context, reflecting meaningful event hierarchies tied to Clementi’s professional milestone.

The prevalence of “during” and “contains” relations in the temporal graphs is not incidental but rather a reflection of meaningful temporal structures that mirror the significant, nested nature of Clementi’s life events. These relations serve as anchors, contextualizing key developments and offering insight into the broader trajectory of his career. In effect, the high number of “during” relations supports the interpretation that temporal nesting — while seemingly abundant — is a critical aspect of understanding Clementi’s professional and historical context, providing a rich and layered view of the unfolding of his career over time.

Additionally, a relatively high number of `equals` relation ($n = 1182$) further suggests a substantial number of co-extensive events—those that share identical start and end times—likely due to synchronized events, such as the sale of Longman & Broderip’s stock-in-trade comprising business premises, music engraved plates, musical instruments, and unsold copies of music. The sale of the stock-in-trade to Broderip and Wilkinson, and Clementi and Co., occurred as part of the same transaction.

In contrast, shared boundary-based relations such as `starts` or `startedBy` (163 each) and `finishes` or `finishedBy` (146 each) were less frequent but meaningfully inferred, indicating that only a subset of events begin or end exactly with another. Specifically, `starts` holds when one interval begins at the exact moment as another but ends earlier. In contrast, its inverse `startedBy` holds when one interval starts at the exact moment as another but extends beyond it. This structural alignment excludes configurations such as complete containment (as in `during/contains`), endpoint matching (`finishes/finishedBy`), `overlaps`, and `equals`.

Muzio Clementi’s arrival in Dorset in 1766 is widely regarded as the start of his time there. This event can be associated with the `starts/startedBy` relationship. Similarly, a good example of `finishes/finishedBy` relationship is seen in the connection between Clementi’s burial and his marriage to Emma Clementi. The end of Clementi’s life naturally signifies the conclusion of his marital relationship.

The relatively lower incidence of partial overlaps, as seen in relations `overlaps` and `overlappedBy` (222 each), is consistent with the structured nature of temporal datasets where such asymmetric overlaps—those that neither fully contain nor are fully contained—occur less often.

For example, Clementi began composing his Op. 7 Sonatas during his stay in Vienna, which lasted from December 19, 1781, to May 9, 1782. Thus, his arrival in Vienna, V^{begin} , precedes the creation of Op. 7, C^{begin} . The work may not have been fully completed by the time he left Vienna, V^{end} , since the first advertisement for its publication by Artaria & Co. did not appear in the *Wiener Zeitung* until

September 25, 1782 (Tyson, 1967, p. 43). By the time the advertisement appeared, Clementi was back in London.

During his time in Vienna, Clementi was likely exposed to the music of Joseph Haydn, who was based at the Esterházy court, where he served as kapellmeister. Although there is no definitive proof, biographers have speculated that Clementi may have met Haydn around the same time he met Mozart for the well-known piano duels before the Viennese Emperor Joseph II (De Saint-Foix, 1932, pp. 252). Therefore, any meeting with Haydn is best understood as an interval that occurred during Clementi’s stay in Vienna. Formally, if M represents the meeting and V the Vienna stay, then:

$$\begin{aligned} M \text{ during } V: & V^{\text{begin}} < M^{\text{begin}} < M^{\text{end}} < V^{\text{end}} \\ & V^{\text{begin}} = \text{December 19, 1781} \\ & V^{\text{end}} = \text{May 9, 1782} \end{aligned}$$



Figure 14. Clementi meeting Haydn during his stay in Vienna

Given that Haydn was twenty years his senior, Clementi likely regarded him as a significant influence. The influence is evident in Clementi’s *Opp.* 7, 8, 9 and 10—works often referred to as his Viennese compositions—both in terms of timing and stylistic features. In particular, *Op.* 7 displays thematic variation, lyricism, motive development, and contrapuntal textures (Stewart-MacDonald, 2019, p. 125) marking a departure from Clementi’s earlier Parisian style and shift towards a more rigorous Viennese idiom.

Clementi’s decision to have Artaria send a copy of *Op.* 7 to Haydn on his behalf, “as a token of respect and admiration,” (De Saint-Foix, 1932, pp. 252-253) further underscores their connection and Haydn’s impact on Clementi’s works. These compositions reflect a new style that was undoubtedly adopted during his stay, highlighting how the environment and possible interactions with Haydn shaped his music. Thus, in this context, Clementi’s time in Vienna overlaps with the creation of *Op.* 7 both temporally and stylistically:

$$V \text{ overlaps } C: V^{\text{begin}} < C^{\text{begin}} < V^{\text{end}} < C^{\text{end}}$$

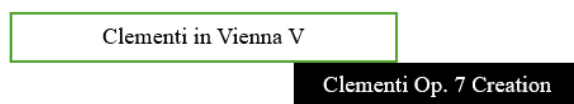


Figure 15. Clementi in Vienna and the creation of *Op.* 7

However, it is important to note that the “overlaps” relation in interval algebra is non-transitive. That is, although V overlaps C and M occurring during V , we cannot automatically infer that C overlaps M . This non-transitivity means that while the Clementi-in-Vienna interval intersects both the creation of *Op.* 7 and the meeting with Haydn, and the intervals for composition and the meeting may

not intersect. For example, Clementi may have composed significant portions of *Op.* 7 after the meeting, or the meeting may have occurred early during his stay, so temporal overlap cannot be assumed. Recognizing this prevents overgeneralizing connections between events solely on the basis of their shared overlap with a third interval.

In no cases were *meets* or *metBy* inferred between intervals. This is due to the way we have encoded the Clementi dataset following the CIDOC CRM modeling recommendations. The *meets* relation in Allen’s interval algebra requires that one event ends exactly when another event begins, with no gaps in between. However, in practice, this situation does not arise because of the dataset’s temporal granularity and the encoding approach employed. For example, if event A occurred on January 1, 1795, it is typically encoded as an interval starting at 1795-01-01T00:00:00 and ending at 1795-01-01T23:59:59. Similarly, event B occurring on January 2, 1795, would be encoded as an interval starting at 1795-01-02T00:00:00 and ending at 1795-01-02T23:59:59. This means there is often a 1-second gap between the events (with A ending at 23:59:59 and B beginning at 00:00:00). As a result, *meets* cannot be established, because the two events are not adjacent with no gaps between them.

In the Clementi dataset, the most precise timing that can be determined is typically at the day level, and even when more detailed information is available, temporal information is not usually precise to the second or minute. The most granular timestamps in the Clementi dataset are typically at the hourly level, and even this level of precision is scarce. For example, if event A ends at 1795-01-01T23:59:59 and event B begins at 1795-01-02T00:00:00, there is effectively a 1-second gap between the two, making it impossible to classify them as *meets*. It may also be due to precision limitations, as *meet* and *metBy* require precise alignment of the endpoint with the start point.

Interpreting historical data through temporal logic

Temporal reasoning is most valuable when it reveals relationships that deepen our understanding of historical processes rather than merely restating what is already implicit in the sources. Useful inferences exhibit contextual relevance, temporal coherence, causal plausibility, and predictive validity, allowing us to perceive how events align, interact, and acquire meaning. By contrast, inferences that identify coincidental overlaps—such as events beginning in the same year—offer little interpretive value. For example, consider the following inferred temporal relationships.

Muzio Clementi’s leaving St. Petersburg for Vienna in mid-October 1806 **preceded** his acquisition of publishing rights for Beethoven’s works in Britain.

This inferred relation situates Clementi’s travel within a broader professional transformation from Clementi the musician to Clementi the businessman, music publisher, and musical instrument maker. Unlike his earlier continental tours, during which we saw Clementi as a musician, his

eight-year tour from 1802 to 1810 served different purposes: establishing connections with continental music-publishing firms, expanding markets for pianos manufactured by Clementi and Co., and securing rights to publish works by continental composers in Britain.

His visit to Vienna in late 1806 must therefore be read as a commercial initiative and a deliberate strategic move. Clementi was determined in his pursuit of the rights to publish Beethoven's works through direct negotiations with Beethoven, having failed to secure them during his previous visit a couple of years earlier. The inferred temporal relation between his departure from St. Petersburg and his arrival in Vienna (November 12, 1806) reflects his intent. More importantly, it was also a movement shaped by the geopolitical realities of the Napoleonic Wars. Plantinga notes that during this third continental tour, Clementi's "movement was largely improvised" (Plantinga, 1977, p. 191) because of the Napoleonic Wars.

His move from St. Petersburg to Vienna was geopolitically feasible. In late 1806, the usual westward routes from Russia into central Europe were effectively blocked. Napoleon's victory at Austerlitz placed southern Germany under French control; Prussia's collapse made Prussian territory unsafe; and the French occupation of Berlin blocked the northern corridor. Consequently, the usual westward route from Russia → Prussia → Saxony → Leipzig was no longer viable while the southern route towards Vienna was relatively stable. Clementi abandoned his initial plan to go to Leipzig (Plantinga, 1977, p. 196) to negotiate rights to publish Beethoven's work through Breitkopf and Hartel, Beethoven's Leipzig publisher and traveled to Vienna. The inferred relation that Clementi's departure from St. Petersburg directly preceded his negotiations in Vienna makes sense not only chronologically but also geopolitically.

(John) Longman, Clementi & Co. acquiring the plates for Clementi's Op. 38 **finished** (began later than, but ended the same time as) Longman & Broderip's operating at 13 Haymarket.

This inference captures a pivotal moment of transition following Longman & Broderip's bankruptcy. The firm's collapse led to the redistribution of its assets, including Clementi's own work and engraved plates, which were acquired by the newly formed Longman, Clementi & Co. This acquisition was not accidental: it was a strategic and natural move, reflecting Clementi's expanded professional role as both composer and publisher. The purchase meant the work could be reprinted with minor corrections to the publishers' imprint on the title page—a customary practice where engraved music plates were typically included in the transaction of stock-in-trade.

Longman & Broderip's operating at 195 Tottenham Court Road also **finishes** (began later than, but ended the same time as) Longman & Broderip's operating at 13 Haymarket.

The temporal relation *finishes* indicates that the Tottenham Court Road location was acquired after the shop at 13 Haymarket, but both locations ceased operation simultaneously when the business was sold. Longman &

Broderip acquired 13 Haymarket premises on November 2, 1782, and 195 Tottenham Court Road premises were acquired five years later on September 29, 1787, to serve as a musical instrument manufactory (Nex, 2011, p. 4). By inferring a *finishes* relation, the reasoner reveals a broader institutional and personal transformation. Clementi's transition from composer to publisher was actively expressed through business acquisition, asset consolidation, and the reassertion of ownership over his intellectual property. The inference thus reflects not only a change in companies but also a shift in agency, influence, and commercial power in early nineteenth-century music publishing.

Ignaz Pleyel's correspondence with Clementi & Co. **started** (began the same time as, but ended before) Muzio Clementi's stay in Vienna during his third Continental tour.

The *starts* relation in Allen's Interval Algebra indicates that both events began at simultaneously, although the timespan for Pleyel's correspondence with Clementi & Co. concluded earlier. This timing aligns with the established chronology: Clementi left Paris in early September after a documented stay from July 8 to September 1. It is plausible that Pleyel—a prominent Parisian music publisher, composer and a close friend of Clementi—met with him in person in Paris, particularly given letters exchanged between them in June 1802, which strongly suggest that Clementi stayed with Pleyel during his visit to Paris (Rowland, 2010, p. 89-92). A subsequent letter from Pleyel to Clementi & Co. (rather than directly to Muzio Clementi, who would remain on the Continent rather than returning to London) has not survived but was referred to in a letter from Clementi and Co. to Pleyel dated October 26, 1802.

This scenario suggests a continuation of a business exchange, likely concerning the rights to publish Haydn's *Deux Quatuors, Oeuvre 77* in England. Pleyel published the work in Paris in October and entered it at the Dépôt Légal on 23 October 1802 (Rowland, 2010, p. 99). Pleyel likely waited until October to send Haydn's work to Clementi and Co., in an effort to ensure simultaneous publication in both France and England. Therefore, the temporal logic not only supports the simultaneous initiation of these events but also intertwines with a more intricate historical narrative of travel, correspondence, and commercial activity between two major European music publishing houses at the time.

The timespans for the publication of Clementi's Op. 44, *Gradus ad Parnassum*, Vol. II, in Paris, London, and Leipzig respectively, were **equal**.

The three publication events occurred on the same day, April 15, 1819 (Rowland, 2010, p. lxix) In the context of early 19th-century music publishing, this is a historically resonant and contextually important finding. Simultaneous publication of musical works in multiple countries was a strategic—though operationally complex—response to widespread music piracy. With limited international copyright protection, composers and publishers sought to safeguard their rights by issuing editions simultaneously in multiple jurisdictions. The temporal equality inferred here suggests not coincidence

but coordination: a deliberate effort to publish concurrently in Paris, Leipzig and London, thereby asserting legitimate authorship and deterring unauthorized reproduction.

Implications

Temporal reasoning can significantly enhance the depth and reliability of historical analysis by highlighting temporal relationships that might otherwise remain overlooked. This is particularly interesting when there is ambiguity surrounding the timing of events, which often allows multiple plausible temporal interpretations. Since our knowledge of the past is frequently incomplete, modeling historical events requires making assumptions about event timing, duration, or sequence—and differing assumptions can lead to various outcomes. A single dataset can support multiple valid reconstructions, depending on how uncertainty is addressed and the inferences that are drawn.

These inferences collectively highlight both the expressive power of Allen’s interval algebra and the capability of Notation3-based reasoning to model rich, nuanced temporal relationships in historical datasets, even faced with temporal ambiguity and interpretive plurality. This approach extends beyond the current case study and can be utilized in various areas of historical research. The same reasoning framework can be adapted to other datasets, particularly those that combine precise and imprecise temporal information, such as prosopography or cultural heritage data collections within the digital humanities.

The use of machine inference to establish the chronological ordering of undated or partially dated events represents a significant shift in practice for bibliographers and musicologists. Traditionally, the burden of reconstructing event chronology—especially when working with fragmentary or imprecise sources—rested solely on human interpretation. This often requires drawing on tacit knowledge, cross-referencing, and intuition developed through experience and domain expertise. With the ability to encode temporal logic, such as Allen’s interval logic, machines can now handle this reasoning in both a scalable and transparent manner. It makes it possible to infer temporal relationships in large datasets, uncovering temporal alignments, inconsistencies, or gaps that might go unnoticed in the manual workflow. While human remains essential, machine reasoning offers new possibilities, not just for organizing historical events, but also as a collaborator in historical analysis.

Future work

For this study, we examined the strongest Allen relations inferable based solely on (partial) information about the endpoint date-times of temporal intervals in the dataset. However, in addition to the endpoint date-times, we also have non-inferred information about Allen relations between some intervals, based on textual evidence or common sense. Incorporating this information into the reasoning process is expected to increase the number of strongest relations inferable between partially dated or even totally undated intervals (if they are involved in any non-inferred relations).

Assertions about temporal relations among intervals become hard to comprehend when there are too many of

them. In that case, seeing a timeline visualization is much easier. An advantage of calculating all of the strongest inferable temporal relations at once is that these relations can then be used to determine the layout of such a visualization. We are currently developing an interactive timeline visualization tool that can also show information about partially dated or undated intervals, even if they cannot be fully represented on the time axis, by indicating the Allen relations in which they participate. We expect this tool to be useful for further evaluating the results of temporal inferencing and possible even as a data editing interface.

Finally, we plan to investigate and compare the use of alternatives to Allen’s interval algebra. As mentioned in the introduction, the new CIDOC CRM temporal relations are designed to support “fuzzy” reasoning about intervals with imprecise boundaries (as is the case for nearly all historical temporal intervals). These may be better suited to a reasoning approach that can flexibly move between reasoning with “coarse-grained” and “fine-grained” temporal relations, rather than using disjunctions of fine-grained relations to represent coarser relations, as in Allen reasoning (Freksa, 1992).

Conclusion

In this study, we employed Allen’s interval logic encoded in Notation3 to infer temporal relationships between events in a historical humanities dataset. While the system produced correct temporal relations, we observed a few critical areas for refinement. Overall, the reasoner yielded valuable insights into the temporal dynamics of the events. Still, a significant portion of the inferred relations were historically irrelevant or redundant in the context of events under consideration. These relations were mathematically and logically valid, and therefore useful for technical purposes such as laying out elements in a timeline visualization. But they did not contribute to meaningful insights for the historian, highlighting a need for more targeted relevance filtering in temporal reasoning systems.

One unexpected outcome of our study was the impact of our encoding of start and end times—particularly for events known only at the day level—on the reasoner’s ability to infer certain temporal relations. Specifically, our approach to representing date-time introduced subtle a one-second gap between events occurring on consecutive days, which prevented the reasoner from identifying `meet` or `metBy` relationships between those events. The seemingly minor modeling choice had a significant impact, while seemingly minor, had a considerable effect on inference results, emphasizing the sensitivity of temporal reasoning systems to precision in temporal data representation.

This also explains why CIDOC CRM moved away from Allen’s interval logic and implemented fuzzy times within a space-time volume. Historical events often render Allen’s `meets` relation, which requires time point equality, inapplicable (Papadakis, Doerr & Plexousakis, 2014, p. 1).

One open question is how best to incorporate reasoning steps into the scholarly workflow. For this study, we ran “batch” inference for the entire dataset or large chunks of the dataset at once. However, it makes more sense to infer and display temporal relations as part of the data authoring

process in order to spot possible errors or inconsistencies. Alternatively, it might make sense only to infer temporal relations “on the fly” for smaller subsets of the data under examination. For example, a visualization tool might render a timeline of events with known endpoints within the currently visible time range, and then calculate what temporal relations the displayed events have to any undated or partially dated events, which can then be added to the visualization if they *possibly* fall within the visible range. Ideally, we can identify a workflow that exploits automated reasoning to find potential errors and inconsistencies and catalyze valuable insights, without flooding the historian with irrelevant conclusions, and maintaining a clear distinction between those temporal relations inductively or abductively inferred by the historian and those deductively inferred by the machine.

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