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# Temporal Ontology Learning: Artificial Intelligence That Discovers New Dimensions of Time

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**Abstract:** ***The combination of artificial intelligence (AI) and knowledge representation, and more particularly temporal reasoning, creates an integration which is a monumental shift toward systems that can conceptualize and understand time in new ways. In this paper, we discuss the emerging area of temporal ontology learning which concerns the automated acquisition and incremental formalization of conceptual models with explicit temporal semantics. We construct the foundational terms, strategies, and various uses of this interdisciplinary field by integrating contemporary works in AI, machine learning, natural language processing and ontology engineering. We discuss how AI methods aid in the continuous modeling of arbitrary points in time, the discovery of concealed temporal structures, and the representation of intricate recurring time patterns. We present difficulties with expressiveness, the incompleteness of data, and the complexities of evaluation, all with the scope of future advancements. This synthesis illustrates how important temporal ontology learning is for the advancement of intelligent systems that need to understand, reason, and adapt to the nature of the relationships and events in different science and technology domains.***

**Keywords:** Temporal Ontology, Temporal Knowledge Graph, Representation Learning, Temporal Reasoning, Deep Learning for Time-Series, Spatio-Temporal Modeling, Knowledge Tracing, Explainable AI

## 1. Introduction

Time is an essentially complex component of human experience which influences everything from language and memory to planning and prediction. In order for Artificial Intelligence systems to achieve enhanced understanding in interactions within dynamic environments, they need to abandon static knowledge viewpoints and adopt temporal information fluidity. Coming at a critical juncture, the research of temporal ontology learning is evolving to endow AI with the capacity to understand, express, and reason about time across all dimensions [9]. By concentrating on the intentional learning of temporal concepts, relations, and axioms from heterogeneous sources of data, this research goes beyond the traditional methods of ontology learning [1].

Temporal phenomena pose challenges for many AI tools, many of which use informal or ad hoc techniques which restrict broader applicability [9]. AI ontologies accomplish this by introducing formalisms for knowledge representation ontologies as formally specified fames of shared domain concepts descriptions [6]. Relating the temporal aspects of such ontologies helps AI systems comprehend processes like causality, evolution and even predicting phenomena at a deeper level. This paper will explore the fundamentals and approaches underlying the capacity of AI to "discover new dimensions of time," and discuss current use cases, while predicting future lines of inquiry.

### Foundations of Temporal Ontology Learning

Ontology learning typically refers to knowledge conceptualization extraction from different sources to build, enrich, or adapt ontologies [1]. The disadvantage of many current ontology- building methods is that they do not recognize the implicit temporal characteristics of domain concepts [9]. Temporal ontology learning deals with the metamorphosis of conceptual models over time and their interaction throughout this period.

The initial phases of AI temporal reasoning recognized the necessity of having time indicated in representing some concepts change and the relation between these concepts, causality, and action. Different systems, for example, consider time placed in an ontology as points or intervals and time tracks as linear, branching or cyclic [9]. A case in point, the Human Time Ontology (HuTO), models complex time expressions by non-convex intervals and offers rich temporality [9]. The addition of the geometry of time and space gives rise to spatio-temporal ontologies. Such ontologies are important to phenomena in the world and many branches. including Geographic Information Systems (GIS), and Computer Aided Design and Manufacture (CAD/CAM), as these branches recognize the spatio-temporal dynamics of ontologies [18].

Temporal ontology learning requires mathematical tools for representing, analyzing, and understanding data. These include the core mathematical science of machine learning: linear algebra, calculus, probability, and optimization [17]. Bearing further on this are the mathematical tools needed to come up with algorithms that actually learn and reason about temporal relations.

## 2. Methodological Approaches

Temporal ontology learning leverages a blend of advanced AI and machine learning techniques:

### Natural Language Processing (NLP)

Scientific literature and textual data abound in implicit temporal properties. NLP properties must be extracted for instance, fine-grained named entity typing with temporal context of the entities, or probabilistic topic models, for discovering time-sensitive concepts and their relationships within text corpora [9]. This complex task, which relies on NLP, usually involves the implementation of a range of linguistic levels, including at minimum, a lexical, a syntactic, a semantic, a discourse, and a pragmatic level, to arrive at a conceptual model [4].

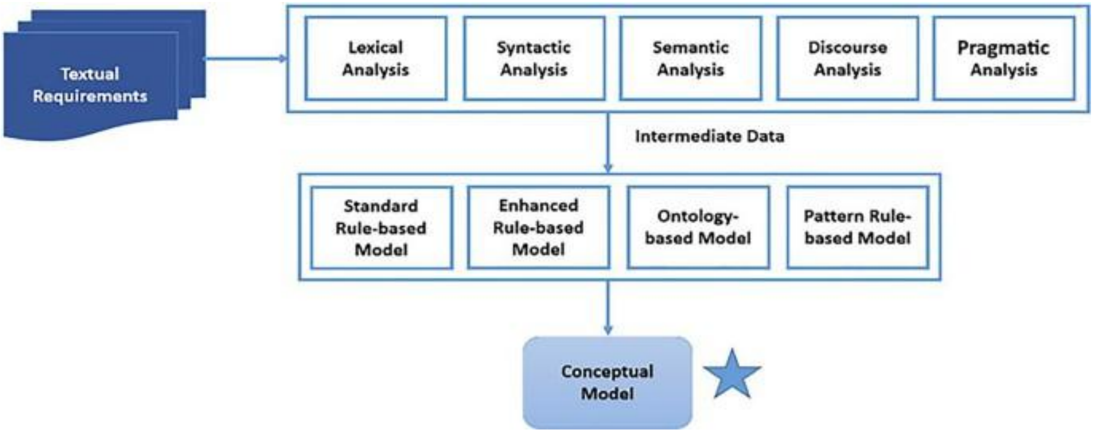


**Figure 1:** Conceptual Model Derivation from Textual Requirements [4]. This illustrates how textual requirements undergo lexical, syntactic, semantic, discourse, and pragmatic analyses to produce intermediate data. This data then feeds into various modeling approaches (standard rule-based, enhanced rule-based, ontology-based, and pattern rule-based) to ultimately generate a comprehensive conceptual model [4].

### 2.1 Machine Learning (ML) for Temporal Dynamics

Machine learning focuses on learning the patterns in time-series data and adapting to them [16]. Deep learning, specifically, comes into greater use for the acquisition and enrichment of ontologies because of the ability of deep learning to handle enormous datasets [2]. The synergistic effect of deep learning-based representation learning and deep clustering enhances time-series clustering by learning and abstracting a variety of complex spatio-temporal patterns [16].

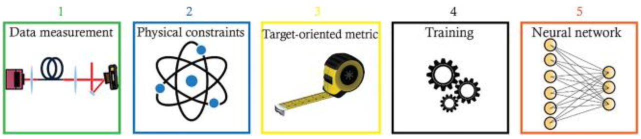


**Figure 2:** Five-step Machine Learning Process [16]. This figure outlines a typical machine learning workflow, starting from "Data measurement" and "Physical constraints," progressing through "Target-oriented metric" definition, "Training," and ultimately employing a "Neural network" for complex pattern recognition [16].

For temporal data, RNNs, LSTM networks, and GRUs are powerful in capturing and learning the sequential dependencies [8] and [10]. BiL- STM networks add the capability of processing the sequence from the two ends, thus capturing richer contextual details [8] and [10].

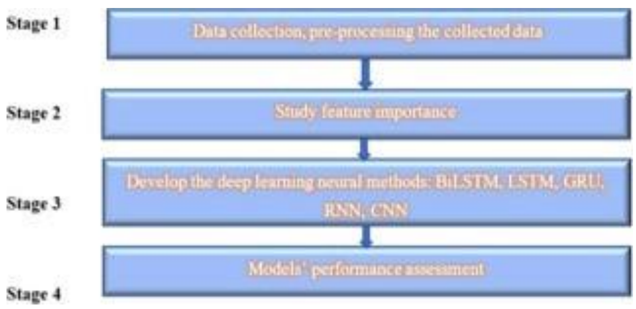


**Figure 3:** Deep Learning Methods for Time Series Forecasting [8, 10]. This figure illustrates a process including data collection and pre-processing, feature importance study, development of deep learning methods (BiLSTM, LSTM, GRU, RNN, CNN), and model performance assessment for time-series forecasting [8, 10].

Transformer-based models are also gaining prominence for their ability to handle long-range dependencies in sequential data, exemplified in Tunnel Boring Machine (TBM) penetration rate prediction [23].

### 2.2 Graph-based Learning

Temporal Knowledge Graphs (TKGs) are essential to understanding the evolution of knowledge and events [13]. Models such as Polynomial Approximation for Temporal Knowledge Graph Embedding (PTBox) facilitate the reasoning over evolving facts occurring over time by assuming a continuous model for arbitrary defined timestamps [13]. Moving along the timeline and reasoning through text models, dynamic knowledge graphs can identify newly formed knowledge communities [22]. There is a growing application of GNNs to the analysis of spatio temporal data, including the simulation of central air conditioning systems (Li et al, 2024 13).

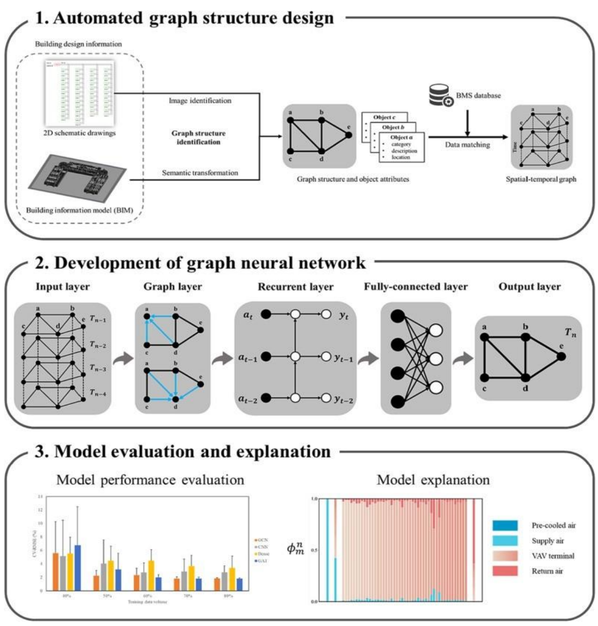


**Figure 4:** Graph Neural Network for Central Air Conditioning Systems [12]. This figure illustrates a graph neural network workflow, from automated graph structure

design using building information to development of the GNN, encompassing input, graph, recurrent, fully-connected, and output layers, concluding with model evaluation [12].

### 2.3 Hybrid AI Approaches

The combination of symbolic AI (ontologies) and connectionist AI (machine learning) is a powerful hybrid system. These techniques integrate the reasoning of formal knowledge representation and the learning ability of neural networks [6]. For example, prediction tasks can be solved using Bayesian networks as they provide a probabilistic graphical model [5]. The subsequent integration with other AI models can add to the learning process [15].

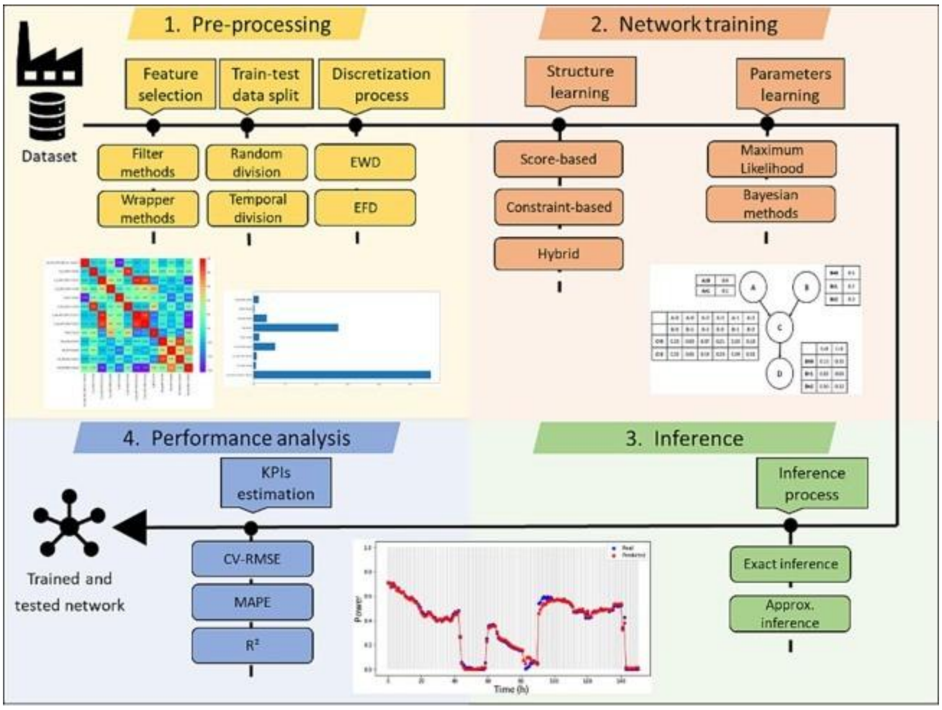


**Figure 5:** Bayesian Network Workflow [5]. This figure details a Bayesian Network workflow, covering pre-processing, network training (score-based, constraint-based, hybrid methods), inference (exact, approximate), and performance analysis using metrics like CV-RMSE, MAPE, and R-squared [5].

## 3. Discovering New Dimensions of Time

The notion of "discovering new dimensions of time" within temporal ontology learning goes beyond merely logging timestamps. It encompasses:

### 3.1 Continuous Modeling of Arbitrary Timestamps

Existing TKGE methods often struggle with continuous modeling of arbitrary timestamps. Novel approaches utilize techniques such as polynomial decomposition-based temporal representation, enabling a more continuous and fine- grained understanding of temporal evolution [13]. This allows for temporal reasoning to handle events that do not align with discrete intervals.

### 3.2 Uncovering Hidden Temporal Dynamics

Time-series data frequently contain intricate temporal patterns that are not immediately ap- parent [16]. Temporal data mining aims to ex- tract interpretable patterns, correlations, and trends. This involves machine learning algorithms for time-series decomposition, anomaly detection, and predictive modeling, revealing previously unrecognized temporal dimensions [16]. High-order temporal correlation model learning can identify complex dependencies in multiway arrays of time-series data, extending beyond simple sequential correlations [16].

### 3.3 Representing Complex Recurring Temporal Patterns

Standard temporal ontologies, such as OWL- Time, often lack the expressiveness to model complex recurring temporal patterns tailored to specific domains [9]. Omitting such intervals disfigures the model's integrity and is, thus, a worthwhile ontological enrichment. Adding structures for user-defined periodicity and discrete time and event control constraints among repeated occurrences goes a step ahead to enhancing the granularity and coherence of the model [9].

### 3.4 Spatio-temporal Semantic Information

The models employed in predicting the urban flow often ignore the nested spatio-temporal semantic structures in them [11]. Having separate latent spaces for disjoint time intervals for the entire length of the prediction enables the AI models to learn varying temporal patterns, elucidating the domain's temporal structures and, thus, introducing a semantic dimension to time [11]. Domain-specific trajectory ontologies, for example, extract semantic structures from raw movement data via the spatio-temporal lens and thus impose higher level understandings onto the data [21].

**Algorithm 1:** Training Algorithm for STUP

**Input:** The observed traffic data $\mathbf{X}_{t-T:t}$; Learnable temporal embedding $E^T$; Learnable spatial embedding $E^S$; Training epoch $M$; Model layer $L$;

**Output:** The forecasting traffic output $\hat{\mathbf{X}}_{t+1:t+P}$ and traffic uncertainty $\hat{\sigma}_{t+1:t+P}$;

**Initialize** the temporal and spatial embeddings $E^T, E^S$ and the model parameter $\Theta$;
**for** $m = 1, 2, \ldots, M$ **do**
  Obtain traffic state distribution with Eq. (2);
  Obtain the initial traffic state $H^{(0)}$ with Eq. (3);
  Sampling the initial traffic uncertainty $U^{(0)}$ from traffic state distribution ;
  **for** $l = 1, 2, \ldots, L$ **do**
    Learn uncertainty-aware temporal statics and dynamics, and obtain hidden traffic state $\mathbf{Z}_H^{(l)}$ and uncertainty $\mathbf{Z}_U^{(l)}$ with Eq. (4) - Eq. (9);
    Learn uncertainty-aware spatial statics and dynamics, and obtain hidden traffic state $\tilde{\mathbf{H}}^{(l)}$ and uncertainty $\tilde{\mathbf{U}}^{(l)}$ with Eq. (10) - Eq. (13);
    Adjust hidden traffic state according to traffic uncertainty with Eq. (14) - Eq. (19) ;
  **end**
  Generate traffic state $\hat{\mathbf{X}}_{t+1:t+P}$ and corresponding uncertainty $\hat{\sigma}_{t+1:t+P}$ by the prediction block with Eq. (20) - Eq. (23);
  Update $E^T, E^S, \Theta$ by minimizing the objective (28);
**end**
**return** traffic state $\hat{\mathbf{X}}_{t+1:t+P}$, traffic uncertainty $\hat{\sigma}_{t+1:t+P}$ and trained STUP model;

**Figure 6:** Spatio-Temporal Graph Neural Network Training Algorithm [11]. This figure details the training algorithm for a spatio-temporal uncertainty prediction model, illustrating inputs like observed traffic data and learnable embeddings, and outlining steps for temporal and spatial learning, hidden state adjustment, and parameter updates to generate forecasting traffic output and uncertainty [11].

## 4. Applications and Implications

Identifying new dimensions temporal ontologies is able to discover and use is an innovation that can fundamentally impact various domains:

a) **Clinical Practice Guidelines (CPGs):** In medicine, CPGs are crucial, but comorbid patients introduce complexities. Understanding interactions among different guidelines and their temporal sequencing can facilitate development of optimal, and more importantly, safer [9]. Knowledge-data integration for temporal reasoning is important in managing time-stamped datasets in systems for clinical trials [9].
b) **Topic Detection and Tracking:** Through introduction temporal dimensions to various clustering techniques, AI can identify and monitor changes in evolving topics in scholarly, yielding an understanding of how science changes over time [9]. This is done by assigning time parameters to topics and then studying their emergence and proliferation over a certain time period.
c) **Time Series Forecasting:** In economics, finance, meteorology, and business analytics, Machine Learning (ML) techniques are increasingly being used for time series forecasting [8] and [10]. A more sophisticated understanding of time enables the selection and application of the most suitable ML techniques for the future time steps, which is critical in adjusting to changing data stream patterns [8] and [10].
d) **Historical Research:** Analyzing intricate historical texts especially those which navi-gate through diverse timelines can be facilitated through the use of the TCT Ontology which helps in the integration of concepts and aids in the analysis and interpretation of past events [9]. **Robotics and AI:** Ontologies aid in the structuring of data, reasoning, and in contex- tual awareness for AI and robotics [20]. Incor-porating the temporal dimension enables robots to comprehend and devise strategies in changing surroundings and track the temporal evolution of task execution to optimize Ultra-Reliable Low- Latency Communication (URLLC) in 5G networks [20].
e) **Educational Technology:** Knowledge Tracing (KT) applies deep learning to forecast learning outcomes and offers tailored assistance [20]. Knowledge ontology-embedded models in assessments, especially in terms of the temporal advancement of the learner, lack ability to adjust and explain variables (Wang et al., 2024 19).

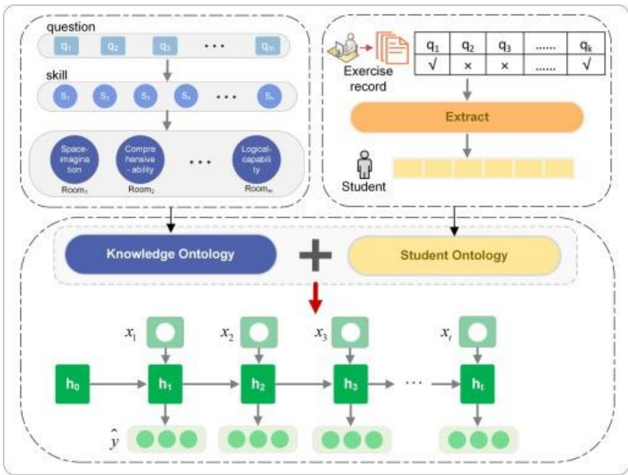


**Figure 7:** Knowledge Ontology Enhanced Model for Explainable Knowledge Tracing [20]. This figure depicts a knowledge ontology-enhanced model for explainable knowledge tracing, illustrating the flow from question and skill representation to student exercise records, integrated with knowledge and student ontologies, culminating in modeling components for prediction [20].

## 5. Challenges and Future Directions

Despite considerable progress, temporal ontology learning faces several challenges:

a) **Expressiveness and Consistency:** Building ontologies that can capture intricate temporal patterns and relationships in their broadest sense remains a challenge [1]. Current ontologies may not possess all degrees of flexibility in accommodating all nuances in temporal information, such as user-defined periodicity and time constraints [9].
b) **Automated Acquisition and Enrichment:** The process of automatically acquiring and enriching ontologies, in particular temporal axioms, remains time-consuming and labor- intensive (Armary et al., 2024 2). Also included are learning axioms and rules from various data sources [1].
c) **Evaluation and Validation:** One of the greatest challenges lies in the quantitative measurement of different temporal learning and their combinations' usefulness and correctness [9]. It is imperative to put forward adequate metrics to measure the degree to which temporal dimensions are illuminated and applied.
d) **Multimodal Hybrid Deep Learning Architectures:** Further developing multimodal hybrid deep learning architectures that integrate multiple data types (e.g., image, text, and time series) and multiple temporal dimensions [3].
e) **Explainable AI (XAI) for Temporal Reasoning:** Integrating explainability into tem-poral AI systems and providing insights into the rationale for their reasoning, particularly on intricate temporal relations [19]. This involves assessing XAI approaches tailored for temporal datasets, focusing on attributes like brevity and accuracy of the reasoning [14].

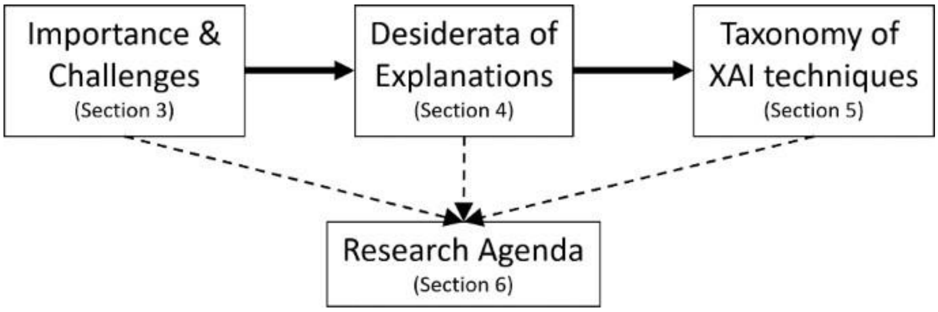


**Figure 8:** Explainable AI Research Agenda [19]. This figure illustrates a research agenda for Explainable AI, highlighting importance, challenges, desiderata, and taxonomy of XAI techniques, contributing to a comprehensive research plan [19].

f) **Interdisciplinary Collaboration:** Encouraging AI researchers, specialists (e.g., historians, doctors), and philosophers of time to work together and represent time in AI more accurately and comprehensively [9].
g) **Mathematical Formalisms for Temporal Semantics:** Improving the mathematical formalism for representing temporal semantics, perhaps using topological data analysis to derive topological invariants from high-dimensional data, which could be applied to intricate temporal systems [7].

## 6. Conclusion

Temporal ontology learning is a rapidly evolv-ing and critical field aimed at empowering AI systems to discover, represent, and reason about the intricate dimensions of time. By integrating advanced machine learning techniques, particularly deep learning and graph-based approaches, with formal ontological structures, AI can move towards a more nuanced understanding of dynamic environments. The ability to model continuous timestamps, uncover hidden temporal patterns, and represent complex recurring events significantly enhances AI's predictive and analytical capabilities across diverse applications, from healthcare and urban planning to scientific discovery. Addressing current challenges related to ontology expressiveness, automated acquisition, robust evaluation, and scalability will be paramount for realizing the full potential of AI systems capable of truly discovering and leveraging new dimensions of time.

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