Forecasting learning in electrical engineering and informatics: An ontological approach

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ABSTRACT

This research explores the vital role of ontology in learning forecasting in electrical engineering and informatics. As formally defined models of knowledge, ontologies are critical in organizing concepts for predictive learning. More than just an inquiry, our research reveals complex interconnections centered on Internet of Things (IoT) design, the semantic web, and knowledge modeling. Applications demonstrate the practical significance of ontologies in fostering intelligent connections, advancing information production, and improving interactions between computers, devices, and humans. This research introduces a comprehensive forecasting learning ontology to highlight the importance of ontologies in education, scientific inquiry, and developing systems for predictive analysis. Ontologies provide a structured framework for understanding the essence of predictive learning, encompassing key elements such as ideas, terminology, methodology, algorithms, data preprocessing, assessment, validation, data sources, application environments, interactions with technology, and learning processes. Emphasizing ontologies as indispensable instruments that drive technological development, our work underscores structured representation, semantic interoperability, and knowledge integration. In summary, this research improves the understanding of ontologies in forecasting by explaining practical applications and revealing new perspectives. Its unique contribution lies in its specific applications and natural consequences, laying the foundation for the future progress of ontology and learning forecasting, especially in educational contexts.

1. Introduction

Ontology, as a profound branch of philosophy [1], delves into the fundamental nature of existence with a depth of conceptual exploration that extends beyond mere inquiry into what exists [2]. It serves as a window to understanding how objects and concepts interrelate within a realm of knowledge or the world's grand tapestry. This discipline aspires to furnish comprehensive answers to pivotal questions concerning actual existence [3], the discernment of reality [4], and the limits of human knowledge [5]. What makes ontology even more intriguing is its permeation into diverse fields, stretching beyond pure philosophy. It has become a foundational underpinning in various knowledge domains, including electrical engineering and informatics. Electrical engineering and informatics ontology constitute a research field that seeks to unravel the intricate conceptual framework and interconnections among entities within these domains. In today's era of information technology, characterized by rapid technological evolution shaping the course of future developments [6], an in-depth comprehension of the ontology within these disciplines is of paramount significance. The electrical engineering and informatics ontology serves as the lighthouse guiding our understanding, delineating core knowledge, concepts, and terminologies, thereby laying a robust foundation for research and development in these domains. In electrical engineering, ontologies assume a critical role in the design of the Internet of Things (IoT) [7], fostering intelligent connections between devices and enabling the generation of information in a more sophisticated manner. Previous research emphasizes the importance of ontologies in improving the compatibility and semantic comprehension of devices in IoT networks [8], [9]. However, there is a lack of detailed integration of ontologies designed for predicting electrical engineering applications. In informatics, ontologies are pivotal in developing the semantic web and knowledge modeling [10]. Research conducted by [11], [12] highlights the need to organize and organize large datasets to make them easily accessible to both machines and people. However, a noticeable lack of literature explicitly addresses the distinct difficulties associated with forecasting in the informatics field. This study aims to bridge these gaps by providing a nuanced exploration of ontologies tailored for forecasting within electrical engineering and informatics. By delving into specific challenges faced in forecasting applications and leveraging ontological structures, our research seeks to offer targeted solutions and advancements.

Employing ontologies within electrical engineering and informatics facilitates communication and cooperation, offering a more contextually rich and meaningful interaction between computers, devices, and humans. This transformative power contributes to creating intelligent systems, advanced data processing capabilities, and technology deployment in diverse contexts. However, this expansion of ontological usage in these fields also introduces new challenges, demanding solutions through a profound understanding and application of forecasting techniques. In our ever-evolving era, the need for tools and methods capable of forecasting technological developments, market trends, and fundamental electrical and information engineering shifts is paramount. This is where forecasting or prediction comes into play. Forecasting is a process that allows us to project future events based on historical data and existing knowledge [13]. Forecasting is pivotal in planning [14], decision-making [15], and the pursuit of technological advancements and innovation in electrical engineering and informatics [16], [17]. Thus, the understanding and application of forecasting is a necessity. Learning forecasting within the context of ontology in electrical engineering and informatics can be likened to adopting a formally structured knowledge model. In this case, an ontology defines the essential concepts and relationships pertinent to forecasting. Components integral to the forecasting ontology encompass Knowledge Concepts, Forecasting Methods, Data, Evaluation and Validation, Application Context, Relationships, Dependencies, and Tools and Technology.

The utilization of ontologies in learning forecasting within electrical engineering and informatics is instrumental in enhancing our comprehension of forecasting methods, facilitating the integration and analysis of data, and bolstering the development of intelligent systems capable of automating forecasting in various application contexts. These ontologies are indispensable tools for streamlining communication and fostering knowledge exchange within these disciplines. The importance of forecasting, as imbued within the ontological structure of electrical engineering and informatics, is indisputable. It not only empowers us to foresee the direction and impact of future technologies but also underpins the vitality of technology development, research, and innovation. To summarise, whereas ontologies have achieved substantial advancements in IoT design and knowledge modelling, its use in forecasting within the fields of electrical engineering and informatics has not been thoroughly investigated. This study aims to address this gap by presenting a customised ontological framework that offers specific answers to the distinct issues encountered in predicting within these particular areas.

2. Method

The method involves several essential steps in forecasting electrical engineering and informatics ontology. First, collecting and analyzing historical data includes technological developments, trends, and changes in these sciences. In order to guarantee the precision and dependability of our research, we employed stringent criteria for data selection. Emphasis was placed on datasets encompassing a wide range of historical, technical, market, and user data in electrical engineering and informatics domains. This inclusion aimed to encompass the intricate and diverse nature of forecasting challenges across several domains. Furthermore, the datasets were obtained from reputable archives, scientific articles, and industrial reports, ensuring the authenticity and reliability of the utilized content. Subsequently, ontology is utilized as a framework to represent conceptual knowledge, including concepts, entities, and relationships, in a structured and semantic way. It integrates machine learning and data mining techniques to identify patterns that may not be detected manually and machine learning algorithms to help forecast trends based on historical data. Data used includes historical, technical, market, and user data. The study employed analytical methodologies to get a thorough comprehension of forecasting techniques in the fields of electrical engineering and informatics.

The selection of machine learning techniques, such as regression, artificial neural networks, and decision trees, was based on their capacity to detect patterns that may not be easily identifiable through manual analysis and predict future trends using previous data. The reason for using these particular methods is based on their appropriateness for analyzing time-series data, which is a crucial component of predicting in these fields. Regression models offer a direct approach to comprehending and representing the connections between variables. Artificial neural networks are highly adept at capturing deep connections within datasets due to their ability to learn complex patterns. Decision trees, renowned for their interpretability, provide valuable insights into the decision-making processes underlying predicted outcomes. The analysis steps involve data processing, modeling, evaluation, implementation, and regular monitoring and updating. Apply various tools, including machine learning algorithms, ontology software, and data analysis tools. The criteria for data selection were meant to guarantee a strong and varied representation of essential information, while the chosen analytical methodologies were motivated by their effectiveness in tackling the specific issues of forecasting in electrical engineering and informatics. These factors jointly enhance the dependability and relevance of the outcomes from our investigation. This method provides significant knowledge for predicting patterns and alterations in electrical engineering and informatics, enhancing technological advancements and facilitating more efficient decision-making in the ever-evolving nature of these domains.

3. Results and Discussion

A forecasting learning ontology refers to a formally defined knowledge model for understanding, describing, and structuring the concepts, relationships, and entities involved in the forecasting learning process. Such an ontology defines forecasting as a learning subject in various fields, including electrical engineering and informatics. The main components of the forecasting learning ontology are shown in Table 1.

Table 1. The main components of the forecasting learning ontology

Component	Description
Concepts and Terminology	The ontology contains definitions of essential concepts and terminology related to forecasting, such as "time series," "forecasting models," "error metrics," "statistical methods," "machine learning," "accuracy measurement," "feature engineering," and so on.
Methods and Algorithms	The ontology describes various forecasting methods and algorithms, including regression, ARIMA, exponential models, artificial neural networks, decision trees, and others. Information on how these methods work and when they should be used is also included.
Data and Preprocessing	The ontology includes concepts related to the data used in forecasting, such as "time series data," "preprocessing," "cleaning," "data transformation," and "data clustering." The ontology also describes how data is prepared before being applied in a forecasting model.
Evaluation and Validation	The ontology includes definitions of evaluation metrics used to measure the accuracy of forecasting models, including MAE, MSE, MAPE, and others. In addition, the ontology also includes concepts related to model validation, such as cross-validation and hypothesis testing.
Data Source	Ontologies describe various data sources that may be used in the forecasting learning process, such as historical, sensor, market, and other external data.
Application Context	Ontologies introduce various application contexts where forecasting learning is used, such as sales forecasting, network traffic forecasting, weather forecasting, and other electrical engineering and informatics applications.
Interaction with Technology	Ontologies cover how technologies, including data analysis software and computing hardware, interact with the forecasting learning process.
Learning Process	The ontology describes the stages and processes of forecasting learning, from data collection to model evaluation, including data preprocessing, method selection, model training, and accuracy testing.
Concept Dependency	Ontologies show the relationships and dependencies between concepts in the forecasting learning domain, such as how time series data is used to train forecasting models or how forecasting methods are selected based on data characteristics.

From Table 1, the forecasting learning ontology helps understand and present structured information needed to develop, apply, and understand the forecasting process. Such ontologies can be used in teaching, research, and developing intelligent systems focused on forecasting. Thus, electrical engineering and informatics ontologies have a crucial role in supporting the understanding, development, and implementation of technologies in these disciplines and continue to contribute to advancing science and technology. Following the ontology, several essential components must be known and understood in learning forecasting, as shown in Fig. 1.

Fig. 1. Basic components of forecasting

From Fig. 1, it is known that ontologically, the essential components of forecasting that must be known are data types, data patterns, methods, optimization, time, and evaluation. There are two types of data: univariate and multivariate. Univariate is a data set consisting of a series of attributes of past observations to predict future values [18]. Meanwhile, multivariate forecasting has more than one set of attributes (many attributes) that change over time to make predictions based on historical patterns of data sequences [19]. Four kinds of data patterns are horizontal, seasonal, cyclical, and trend. The horizontal pattern is an unexpected and random event, but its occurrence can affect the fluctuation of time-series data [20]. Trend patterns are trends in the direction of data in the long term, which can be in the form of increases or decreases [21]. Seasonal patterns are fluctuations in data that occur periodically within one year, such as quarterly, quarterly, monthly, weekly, or daily [22]. At the same time, cyclical patterns are fluctuations in data for more than one year [23]. So, regarding univariate and multivariate forecasting, it must consider the data type from the four data patterns.

Following Fig. 1, forecasting methods can be grouped into several categories: traditional statistical methods [24], [25], Machine Learning (ML) methods [26], [27], and Deep Learning (DL) [28], [29]. A more complete explanation of these categories is in the next sub-chapter according to each category. Using statistics is a way to understand a phenomenon more simply through statistical measures. In statistical methods, there are several methods that are widely used, namely Moving Average (MA), and its variations (ARIMA and SARIMA) [30]–[33]. Forecasting using Machine Learning (ML) is the subject of how machines can learn on their own so that they can do forecasting without being explicitly programmed [34]–[36]. In ML, methods that can be used for time-series analysis are of the supervised learning type. These methods include linear regression, Support Vector Machine (SVM), and Artificial Neural Network (ANN). In forecasting, the application of DL is used for anomaly detection [37]. Anomaly detection is a stage to identify irregular patterns that do not match the predicted behavior [38]. Anomalies can be interpreted as unnatural behavior or patterns and indicate an error in the system. DL is currently a popular research reference.

The lead time in forecasting depends on the unit of data value used. Generally, the most minor units commonly found are seconds and a maximum of years. In forecasting, ooptimization can also be done [39]. Optimization can be said to be a process to achieve ideal or practical results. Optimization can also be interpreted as optimizing something already existing by producing a new, better value [40]. Based on Fig. 1, existing methods in forecasting can be optimized in preprocessing, process, or a combination of both (hybrid) [41]. Evaluation in forecasting can be seen from three sides: accuracy, error, and correlation [42]. Accuracy is used to determine the accuracy of the forecast results with actual data, which Mean Absolute Error (MAE) or Mean Absolute Percentage Error (MAPE) can usually use [38], as in (1) and (2). Error is used for outlier detection (sensitivity), which can use Mean Squares Error (MSE) or Root Mean Squared Error (RMSE) [43], as in (3) and (4). Correlation determines how significant the forecasting results are to the actual data [44], as in (5), which can be calculated using R2. A_i is the actual value, F_i is the predicted value, n is the number of predictions, SS_{res} is the residual sum of squares, and SS_{tot} is the total sum of squares.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i} \tag{1}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i} \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(F_i - A_i)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(F_i - A_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{5}$$

It is necessary to master some basic supporting knowledge and skills to learn forecasting well. Based on the Association for Computing Machinery (ACM) Curricula, in curriculum development in electrical engineering and informatics, especially those covering topics such as signal processing, data analysis, and software development, forecasting elements can be included as an essential part of the curriculum [45]. Thus, some basic knowledge and skills should be provided in learning forecasting for electrical engineering and informatics students. These basic knowledge and skills can be seen in Table 2. Although ACM does not have a curriculum that explicitly covers forecasting, curriculum development in electrical and information engineering can include elements of forecasting to prepare students with relevant and applicable skills in data analysis and intelligent decision-making in various electrical and information engineering contexts. Therefore, based on ontology, continuous learning and keeping abreast of developments in the discipline is also very important to remain relevant in forecasting. In connection with the basic knowledge and skills of forecasting learning in Table 3. In this study, a survey of the existing electrical engineering and informatics curriculum at public and private universities in Malang was conducted, each with 3. These universities include Universitas Negeri Malang (UM), Universitas Brawijaya (UB), Universitas Islam Negeri (UIN) Maulana Malik Ibrahim Malang, Universitas Muhammadiyah Malang (UMM), Universitas Merdeka (UNMER), and Institut Teknologi Nasional (ITN). From the existing observations, the results can be seen in Table 3.

Table 2. Basic knowledge and skills of forecasting learning

Basic Science and Skills	Description
Statistics	Understanding concepts such as mean, median, standard deviation, regression, probability distribution, etc.
Math	Basic math skills, including algebra, integral and differential calculations, and an understanding of mathematical functions

Data Analysis	Ability to collect, clean, and analyze data and understand concepts such as time series data, panel data, and data analysis methods. Learn how to evaluate and test the accuracy of forecasting models. Metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), and prediction accuracy.
Economics and Business	Understanding of economic and business principles. Practice forecasting with actual data to understand the challenges and errors that may occur in the forecasting process.
Financial Math	Understanding of stock price forecasting, revenue forecasting, or cash flow forecasting
Technology and Software	Mastery of data analysis software such as Python, R, or specialized tools for forecasting and use of spreadsheets (excel)
Machine Learning	Understanding of machine learning and predictive models such as linear regression, logistic regression, and neural networks
Big Data Analytics	With extensive and diverse data volumes, big data analytics makes it possible to extract deep insights and improve forecasting accuracy. Understanding of the domain at hand
Artificial Intelligence	To process large and complex data in ways that humans may find difficult or incapable of doing, making it a potent tool for forecasting.

From the results in Table 3, it is known that all universities (UM, UB, UIN, UMM, UNMER, ITN) teach statistics as a basic science in learning forecasting. Statistics is used to analyze data, identify patterns, and make predictions based on historical data. All universities have provided the essential knowledge and skills to learn forecasting during students' undergraduate studies. Most universities have taught at least 7 of the nine required sciences for learning forecasting. UNMER, in particular, has provided its students with nine supporting sciences for learning forecasting. By teaching these basic sciences and skills, universities in Malang prepare students with relevant and applicable data analysis and forecasting knowledge. This helps students to understand basic concepts, select appropriate methods and algorithms, and develop skills in analyzing and making predictions based on data.

Table 3. Result

Basic Science and Skills	**UM** [46]	**UB** [47]	**UIN** [48]	**UMM** [49]	**UNMER** [50]	**ITN** [51]
Statistics	√	√	√	√	√	√
Math	√	√	√	√	√	√
Data Analysis	√	√	√	√	√	√
Economics and Business					√	
Financial Math					√	
Technology and Software	√	√	√	√	√	√
Machine Learning	√	√	√	√	√	√
Big Data Analytics	√	√	√	√	√	√
Artificial Intelligence	√	√	√	√	√	√

Overall, it is clear that ontologies can play an essential role in data analysis and forecasting in these areas by providing structured representation, semantic interoperability, and knowledge integration. Forecasting in electrical engineering and informatics involves using techniques and methods to forecast various parameters, events, or conditions in the context of electrical engineering systems or applications. In electrical engineering and informatics, forecasting has been widely used and applied to various fields in these sciences. Its applications can be categorized based on their respective basic sciences, namely electrical engineering [52]–[59] and informatics [60]–[69]. Here are some examples of how forecasting is used in Fig. 2. Forecasting in electrical engineering and informatics involves using various statistical, data analysis, modeling, mathematical, artificial intelligence, and computational methods to produce accurate predictions. This helps in the planning, decision-making, maintenance, and optimizing systems and applications in various electrical engineering sectors and applications in a rapidly changing information technology environment. Overall, ontologies are essential in representing conceptual knowledge in data analysis and forecasting in electrical engineering and informatics. Ontologies contribute to the representation of conceptual knowledge in data analysis and forecasting by providing structured representations, enabling semantic interoperability, facilitating knowledge integration, and supporting knowledge discovery. Ontologies improve the understanding and interpretation of data, resulting in more accurate and reliable forecasting models. It also enables researchers and practitioners in electrical engineering and informatics to have a common understanding of the domain, select appropriate methods and algorithms, preprocess data effectively, evaluate model accuracy, and utilize multiple data sources. The discovery of crucial elements in the forecasting ontology has significant implications for electrical engineering and informatics professionals, leading to innovations that significantly impact their daily work. Through a methodical process of clearly defining and organizing fundamental ideas and vocabulary in the ontology, such as "time series," "forecasting models," and "evaluation metrics," we provide practitioners with a uniform framework. Using this widely understood language promotes more effective communication and cooperation and enables professionals to make better-informed choices.

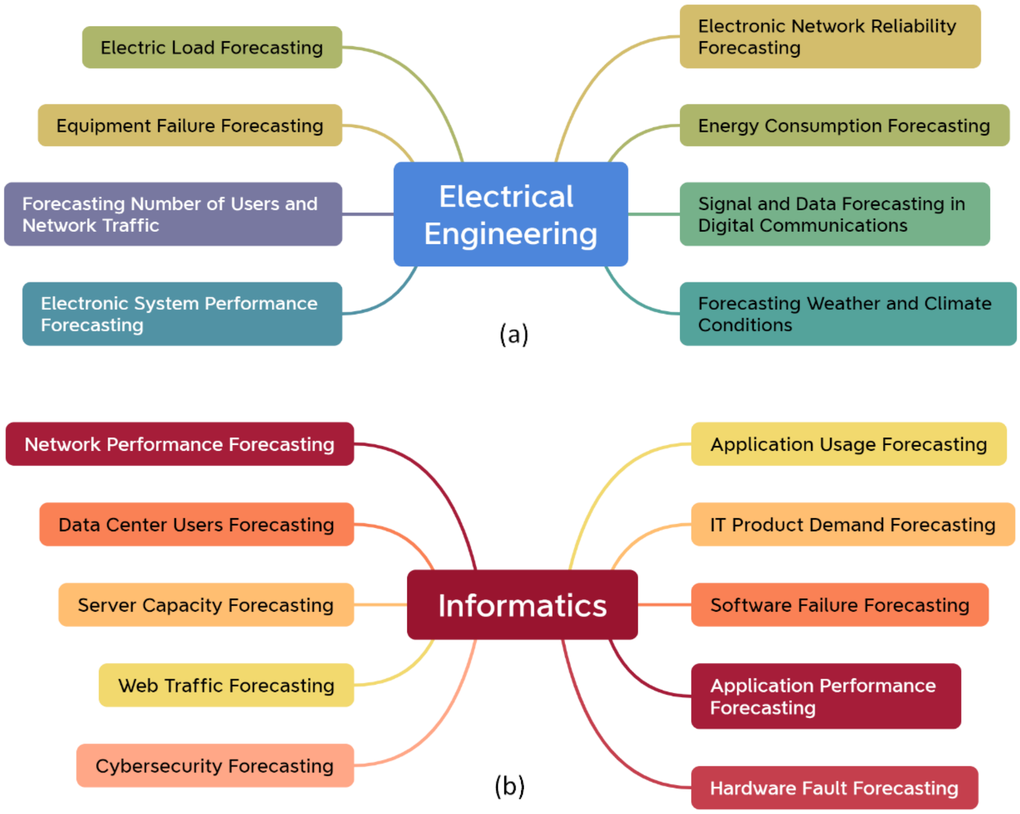

Fig. 2. Utilization of forecasting: (a). Field of electrical engineering, (b). Field of informatics

An evident consequence is observed in the domain of technological advancement. By using a wide range of techniques, such as regression, artificial neural networks, and decision trees, practitioners are equipped with a flexible set of tools for making predictions. This variety permits a more refined and customized approach to advancing technology in various domains. Gaining insight into the capabilities and uses of various techniques empowers professionals to modify their approaches in response to specific obstacles, promoting creativity and effectiveness. The ontology places significant importance on the data sources and their trustworthiness, ensuring practitioners prioritize using high-quality and accurate data in their forecasting efforts. The results of our research strongly support the use of datasets acquired from reliable archives, scholarly publications, and industrial reports. The focus on data quality improves the precision of forecasting models and strengthens the overall dependability of the forecasting process. Moreover, the ontology's inclusion of many application settings, such as sales forecasting, network traffic forecasting, and weather forecasting, recognizes practitioners' wide range of difficulties. The flexibility of these forecasting approaches enables them to be customized for the unique requirements of various electrical engineering and informatics applications, assuring their applicability in a wide range of situations. Practitioners may utilize the ontology's structured knowledge model to effectively traverse the complexities of many application scenarios, whether it be anticipating sales patterns or projecting network needs. To summarise, our work enhances the theoretical comprehension of the forecasting ontology and converts these insights into practical consequences for professionals. The ontology's organized framework and standardized language enhance communication, enable informed decision-making, foster creativity in technology development, and promote flexibility across different application settings. The practical implications of our findings are highly relevant for professionals in electrical engineering and informatics. They provide a clear path for improving forecasting procedures in these disciplines.

4. Conclusion

This study examined ontologies in electrical engineering and informatics data analysis and prediction. We found that the predicting learning ontology has a well-organized and broad knowledge structure. It defines essential concepts, linkages, and entities for predicting learning across domains. Our research of the forecasting learning ontology's principles, vocabulary, techniques, and algorithms revealed the difficulties of electrical engineering and informatics forecasting. Our focus on data quality, application settings, and technology integration in forecasting learning has deepened our understanding of these fields. There are promising future research prospects. Future research might examine the complex interaction between emerging technologies, electrical engineering, and informatics forecasts. Using advanced machine learning algorithms and analyzing massive data sets may help us understand predicting strategies in changing technological contexts. Future studies may examine ontologies' synergies with real-time forecasting. Rapid technological advancement needs research into how ontologies may adapt to dynamic real-world electrical engineering and informatics conditions. Our discoveries have practical implications for electrical engineering and informatics specialists. The forecasting learning ontology provides a systematic framework for understanding and managing forecasting complexities. Standardized language helps professionals communicate and collaborate, making sharing ideas and insights simpler. The ontology's wide range of approaches and algorithms allows practitioners to tailor their forecasting methods to specific problems. Adaptability fosters innovation and efficiency in technological development, keeping experts at the forefront of their fields. Our findings emphasize data quality and the need for reliable data sources. Forecasters should prioritize datasets from reliable archives, scientific journals, and industry reports to guarantee model accuracy and dependability. Our study improves theoretical understanding of electrical engineering and informatics forecasting and provides practical insights for practitioners in these fast-expanding fields. As technology advances and data analysis grows, our insights provide a roadmap for professionals trying to navigate and innovate in forecasting future occurrences.

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